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 work histories of actors, directors and producers 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 37.75% decline in an actor's subsequent movie output, with the effect being more pronounced for less experienced actors and intensifying over time. Our mechanistic analyses provide evidence for two potential channels: job referrals and career mentorship. These findings highlight the critical role of professional networks in project-based labor markets.

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 (Granovetter, 1973). Survey evidence indicates that professional connections provide an effective channel for information exchange, allowing the transmission of knowledge and private information between job-seekers and employers. For example, a survey suggests that about 85% of job openings are filled through social connections (Adler, 2016), 66% of Americans report seeking employment through friends or family members (Rainie et al., 2015), among others. Moreover, we continue to see anecdotal evidence that companies heavily rely on networks and referrals in hiring decisions (Borchers and Ellis, 2024). Although the role of social networks in job search is well supported by informal studies, empirically identifying the causal impact of network connections on career development is challenging for two reasons. 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 leverage a death shock identification strategy to resolve the endogeneity of network connections. The passing of a person is unrelated to the intrinsic ability of anyone else, but it reduces the network size of people who are connected with the deceased. Hence, it provides us with an exogenous shock to identify the impact of losing a connection.[1] 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.[2] These characteristics make the actors market suitable for measuring the impact of professional connections on career outcomes.

In this study, we focus on the deaths of directors and producers. Connections to these profes-

[1]Similar death identification strategies have been applied in other settings, including the impact of leadership on country/organization performance (Jones and Olken, 2005; Benzell and Cooke, 2021; Bennedsen et al., 2007), famous researchers on their collaborators' research output (Azoulay et al., 2010; Oettl, 2012; Jaravel et al., 2018), and worker substitutability (Jäger et al., 2025).

[2]Other professions with project-based compensation include consultants, lawyers, architects, real estate agents, house builders, and renovation specialists/designers, etc.

sionals can be highly valuable, as they may serve as mentors or facilitate referrals for auditions, directly influencing an actor's chance to be hired for a movie project. Importantly, their deaths are independent of the actors' intrinsic abilities, such as their acting skills. To conduct our analysis, we have compiled an extensive dataset on 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/producer/director over time. Leveraging this dataset and the exogenous death shocks of directors and producers, we apply 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 producer/director, our estimated average treatment effect shows that a previously connected actor experiences a 37.75% decline in future movie output. This substantial effect arises mainly because the majority of actors face sparse job opportunities and have small professional networks. The effect is not uniform; it is driven predominantly by less-established actors (those with fewer than three movies before the shock), who suffer a 48.57% decline. This group maintains a median of only four connections, and hence the loss of a single connection represents on average a significant 25% reduction in their professional network. In contrast, established actors (with at least three movies output before the shock) experience a more moderate 18.78% decline. The large average effect thus reflects that a significant portion of actors is highly vulnerable to network disruptions.

In addition, 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. Such disparities highlight how network disruptions can significantly alter career paths in the long-run.

We then empirically investigate three possible mechanisms driving this effect: (i) repeated collaboration, (ii) referral, and (iii) mentorship. First, we rule out repeated collaboration as a primary explanation, because it applies to only a small fraction (3.69%) of our sample, and its exclusion does not affect our main results. Then we show evidence of diminishing returns to network size, consistent with both referral and mentorship mechanisms. To provide evidence to support the

referral channel, we show that actors suffer a greater loss when a deceased producer/director had a higher propensity to refer actors within their professional network. Conversely, to support the mentorship channel, we show that actors still experience a significant decline in movie output after the death shock even when the referral pathway is likely inactive; specifically, we restricted our analysis to deceased producers and directors whose own producer/director connections did not launch any new movie projects following the death event. For actors connected to these deceased producers/directors, the referral pathway (i.e., the ability to get a job through a friend of the deceased) is effectively closed. Furthermore, we find evidence that the negative impact increases with the age gap between the actor and the deceased producer/director, consistent with the conventional wisdom that it is more effective for a producer/director to mentor an actor who is much younger than them. Collectively, our mechanistic analysis provides support for the roles of both referral and mentorship channels.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes our dataset and sample construction. Section 4 presents our DiD research design and the econometric model specifications. Section 5 discusses our main estimation results. Section 6 investigates the underlying mechanisms. Section 7 examines how connection losses affect access to major roles and quality-adjusted movie output. Section 8 concludes by discussing the implications of our findings for practice.

2 Related Literature

Our paper is related to two streams of literature: (i) professional network and career development; (ii) movie marketing. This section explains how our research contributes to each of them.

2.1 Professional Network and Career Development

There is a large literature that studies how one's social networks may affect their career outcomes (Topa, 2019). In particular, our research is related to Bayer et al. (2008), Hellerstein et al. (2011) and Topa (2001) who use indirectly observed social network proxy to infer how it may affect one's labor market outcome. More specifically, they argue that individuals who live in the same neighborhood are more likely to be friends (as a form of social network), and they may help each

other in job search. This argument is supported by the evidence that neighbors living in the same block are more likely to work in the same firm (or firms that are nearby). Unlike these studies, we can directly observe one's network, along with an exogenous shock to those networks: the loss of a specific connection due to death. We also observe rich characteristics of the deceased connection and track individuals' labor-market outcomes for an extended period before and after the loss. Hence, our research is able to provide much more detailed micro evidence on how social network may affect one's career path.

Our research is also related to another set of papers which study how a connection established at college or graduate school (in particular, MBA programs) would shape one's career in the long run. These papers use quasi-random assignment of dormitory roommates (Zimmerman, 2003) and class sections (Shue, 2013; Lerner and Malmendier, 2013; Hampole et al., 2025; Hacamo and Kleiner, 2022) to study the impact of such connections. In contrast, our study uses quasi-random death assignment to study the impact of losing a connection. Moreover, these papers focus on executive and corporate leadership careers which are long-term positions, while we focus on the actors market which is project-based and dominated by regular B-level actors.

2.2 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, directors and writers, to a movie's box office performance (e.g., Eliashberg et al., 2006; 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; Luo et al., 2021; Lu et al., 2023, etc.). McKenzie (2023) provides a comprehensive review of this literature. As far as we know, none of them has studied actors' productivity, let alone quantified how an actor's career prospects may be influenced by their connection to producers/directors, which is the main contribution of our research.[3]

[3]One exception is Hermosilla et al. (2018), who find that China's policies towards foreign film importation can affect Hollywood films' 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 Institutional Background and Data

3.1 Institutional Background

In this section, we describe the institutional background of hiring in the movie industry. Although not required, many actors work with Talent Agents to secure auditions. Talent agents help bridge information asymmetries by accessing restricted role listings and submitting clients for consideration, and they also negotiate contracts on behalf of actors. Casting Directors also play an important role: they typically rely on talent agents, along with their own professional networks, to identify and shortlist candidates.

Final hiring authority rests with Producers and Directors. While directors typically prioritize creative fit and performance capability, producers often enforce financial constraints by favoring "bankable" talent to secure financing and distribution. Producers, directors and casting directors all possess significant institutional memory regarding actor performance and reliability. Hence, a direct connection to them may give an actor another channel to audition opportunities.

It is important to note that we are unable to include talent agents in our analysis because comprehensive data on actor-agent relationships is not publicly available. Therefore, our study focuses on producers and directors, including casting directors. As they are key decision-makers, we believe these professionals should play pivotal roles in the hiring process.

3.2 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 comprises 86,206 movies released in the United States between 1995 and 2014. For each movie, we collect data on its actors, producers, directors, casting directors, title, release date, IMDb rating, number of votes (indicating the number of ratings received), and U.S. box-office revenue.[4] This leads to a movie dataset which features 463,688 actors, as well as 139,019 directors and producers. This is the data that we will use to construct each individual's

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

network. We consider professionals (actors, directors, or producers) as connected if they have ever worked together in a movie.[5] We assume that once a connection is formed, it persists until one of the individuals in the network passes away.

The second data category contains demographic information, including date of birth and gender, for each actor, producer, and director from IMDb. We are able to collect demographic details for 79,249 actors and 25,881 producers/directors.

The third data category consists of a list of producers, directors and casting directors who passed away between 1995 and 2014, with IMDb providing their year of death. Over this 20-year period, we identified 1,090 cases for which demographic information is also available.[6]

Table 1 provides descriptive statistics on the key characteristics of deceased directors and producers. The mean age at the time of death is 66.07, with females representing approximately 10.8% 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 producers/directors created 0.3 movies annually, with a lifetime total of 3.55 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 presented in Table 1.

3.3 Empirical Challenges and Coarsened Exact Matching

Our goal is to identify the local average treatment effects (LATEs) of losing a connection on an actor's job opportunities.[7] There are 5,309 actors (with demographic information) who faced at least one producer/director death shock. We exclude those who have experienced multiple death shocks to prevent potential bias of the treatment effect. This leads to removal of 197 actors

[5] Actors, or individuals in general, can also connect and be friends with others even though they have never worked in 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.

[6] Note that some movie professionals hold multiple roles (e.g., director, producer, and actor). IMDb categorizes individuals based on their primary role, listing their main profession first. In our analysis, we include only those listed as producers, directors or casting directors as their primary classification.

[7] 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.

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

Variable Name	Mean	SD	Min	Max
Age at Death	66.07	15.60	22	100
Female	0.108	0.31	0	1
Cum. no. of Movies	3.55	5.34	1	54
Cum. no. of Movies (weighted by rating)	18.95	29.03	0	269.50
Cum. no. of Movies (weighted by log revenue)	6.32	7.68	0	22.08
Cum. no. of Movies (weighted by log votes)	0.99	2.58	0	13.47
Ave. no. of Movies	0.30	0.46	0.05	7.71
Ave. no. of Movies (weighted by rating)	1.56	2.27	0	18.24
Ave. no. of Movies (weighted by log revenue)	5.22	6.48	0	19.82
Ave. no. of Movies (weighted by log votes)	4.04	3.00	0	12.78

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

(around 3.71% of our sample), and leaves us with a sample of 5,112 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 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, because 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 producer/director death shock during the sample period. We implement 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 the following key characteristics: (1) gender, (2) age, (3) cumulative number of movies they have appeared in (and corresponding cumulative measures weighted by rating, box office revenue and number of votes), (4) average annual number of movies they have appeared in (and the corresponding average measures weighted by rating, box office revenue and number of votes),[8] and (5) the cumulative number of connections (including connections to peer actors), (6) cumulative number of producer/director connections, and actor's network features including (7) average age of their connected producers and directors, and (8) their con-

[8]All "cumulative number of movies" and "average number of movies" variables, including all weighted measures, reflect the actor's entire career output up to that point, not metrics specific to a single actor-producer/director connection.

nected producers/directors' total cumulative movie output (summed across producers/directors), both unweighted and weighted by rating, revenue, and votes. All matching variables are actor specific and measured in the year prior to the death shock. Note that by matching on both the number of connected producers/directors and their total cumulative movie output, the average cumulative output of connected producers and directors is matched by construction. Our matching procedure is successful for 3,305 out of the 5,112 (64.65%) treated actors, corresponding to 698 deceased producers/directors (321 producers, 347 directors, and 30 casting directors).

Table 2: **Balancing of Treatment and Control in the Year Prior to Producer/Director Death**

Variable Name	**Treatment Group Mean**	**Control Group Mean**	**Std. Mean Difference**
Female	0.38 (0.48)	0.38 (0.48)	0.00
Age	43.79 (17.13)	43.43 (17.77)	0.02
Cum. no. of Movies	2.98 (3.11)	2.89 (3.15)	0.03
Cum. no. of Movies (weighted by rating)	16.86 (18.15)	16.32 (18.27)	0.03
Cum. no. of Movies (weighted by log revenue)	8.92 (8.25)	8.57 (8.24)	0.04
Cum. no. of Movies (weighted by log no. of votes)	7.45 (3.42)	7.33 (3.99)	0.03
Ave. no. of Movies	0.21 (0.19)	0.21 (0.20)	0.02
Ave. no. of Movies (weighted by rating)	1.19 (1.13)	1.15 (1.11)	0.03
Ave. no. of Movies (weighted by log revenue)	7.39 (6.97)	7.13 (6.93)	0.04
Ave. no. of Movies (weighted by log no. of votes)	5.00 (3.11)	4.90 (3.29)	0.03
No. of Connections	125.05 (144.76)	121.89 (141.71)	0.02
No. of P/D Connections	12.56 (17.64)	12.01 (16.83)	0.03
Conn. P/D Ave. Age	48.13 (8.53)	47.87 (8.74)	0.03
Conn. P/D Cum. no. of Movies	70.10 (108.63)	68.95 (98.29)	0.01
Conn. P/D Cum. no. of Movies (weighted by rating)	415.03 (649.67)	398.72 (584.92)	0.03
Conn. P/D Cum. no. of Movies (weighted by log revenue)	15.33 (7.98)	15.06 (8.24)	0.03
Conn. P/D Cum. no. of Movies (weighted by log votes)	11.12 (4.28)	11.06 (4.46)	0.01

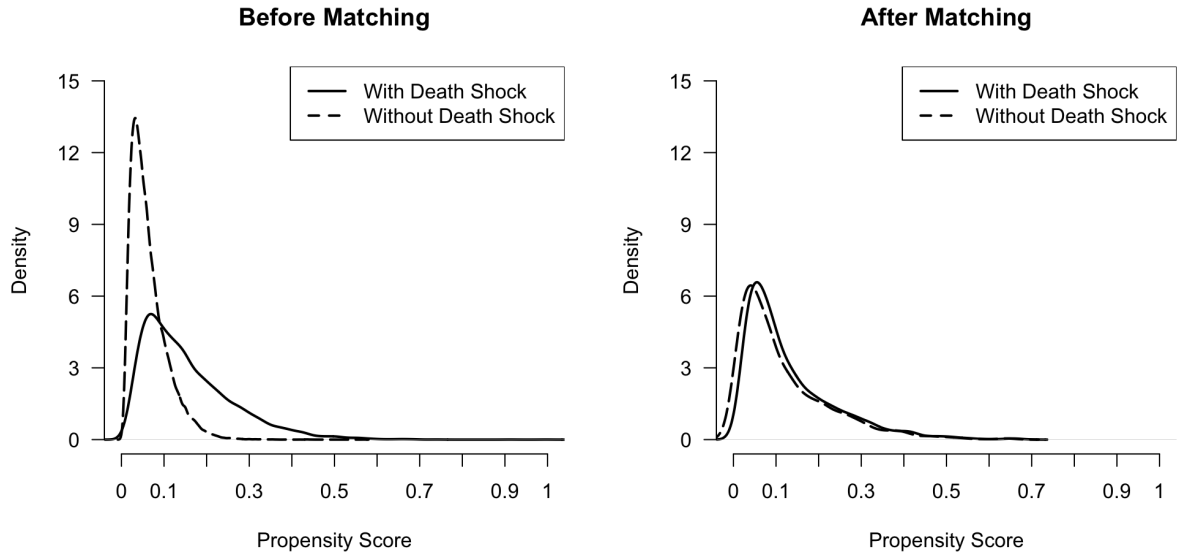
Notes: The sample comprises 3,305 actors who experienced a connection loss with a director or producer, along with an equal number of matched controls, spanning 1995-2015. Detailed information on sample construction and the matching procedure can be found in Appendix A. All variables are measured in the year prior to the connection loss, with sample standard deviations presented in parentheses. All Cum #Movies and Ave #Movies variables are actor specific and measured up to that point, not metrics specific to a single actor-producer/director connection. P/D denotes producers or directors.

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 in the year prior to the producer/director's death. It shows that the balancing requirement is satisfied.[9] To provide additional evidence on balancing, we also compare

[9]These 3,305 treated actors and their matched controls collectively participated in 18,632 movie projects,

their propensity of receiving the treatment. 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 propensity score distribution for actors with and without a death shock is displayed in Figure 1. It shows a balanced empirical distribution between the treatment and control groups after the CEM matching process, providing further support for the success of our matching procedure.

Figure 1: **Distribution of Propensity Score Before and After Matching**

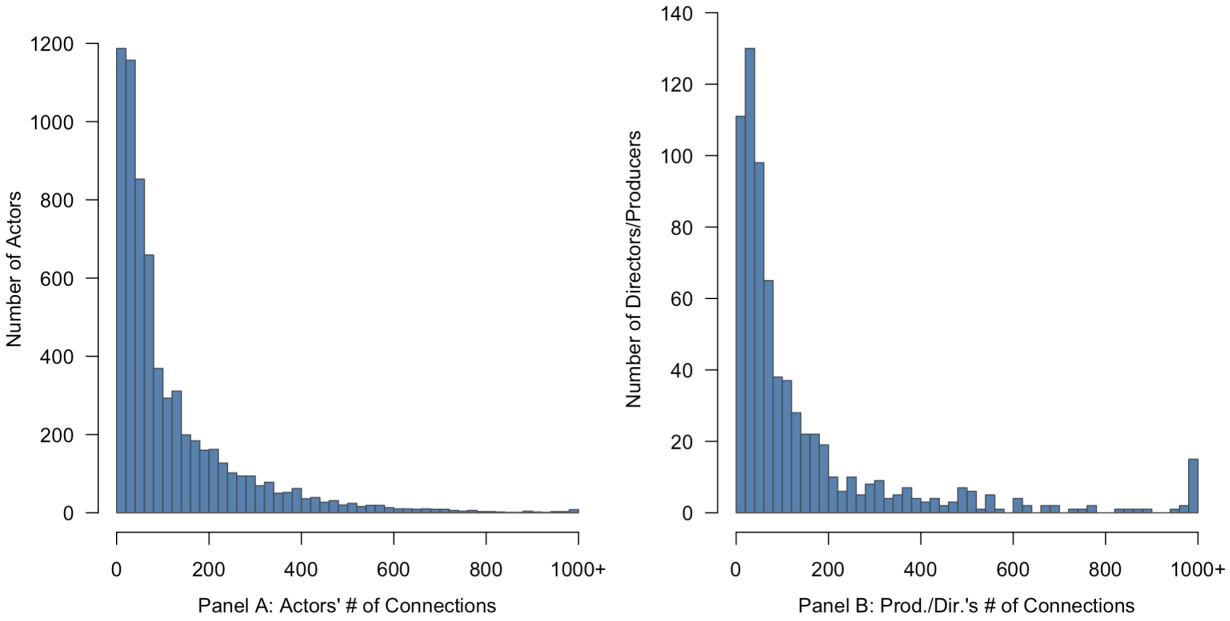


Notes: This figure plots the empirical distribution of the estimated propensity scores for the unmatched and matched samples.

Figure 2 illustrates the distribution of the number of network connections for actors (panel A) and deceased producers/directors (panel B) in the year they died. Both distributions are right-skewed with the vast majority of the number of connections below 400. The average number of connections for actors is 123.5 with a standard deviation of 143.5. The average number of connections for directors/producers is 155.7, with a standard deviation of 267.4.

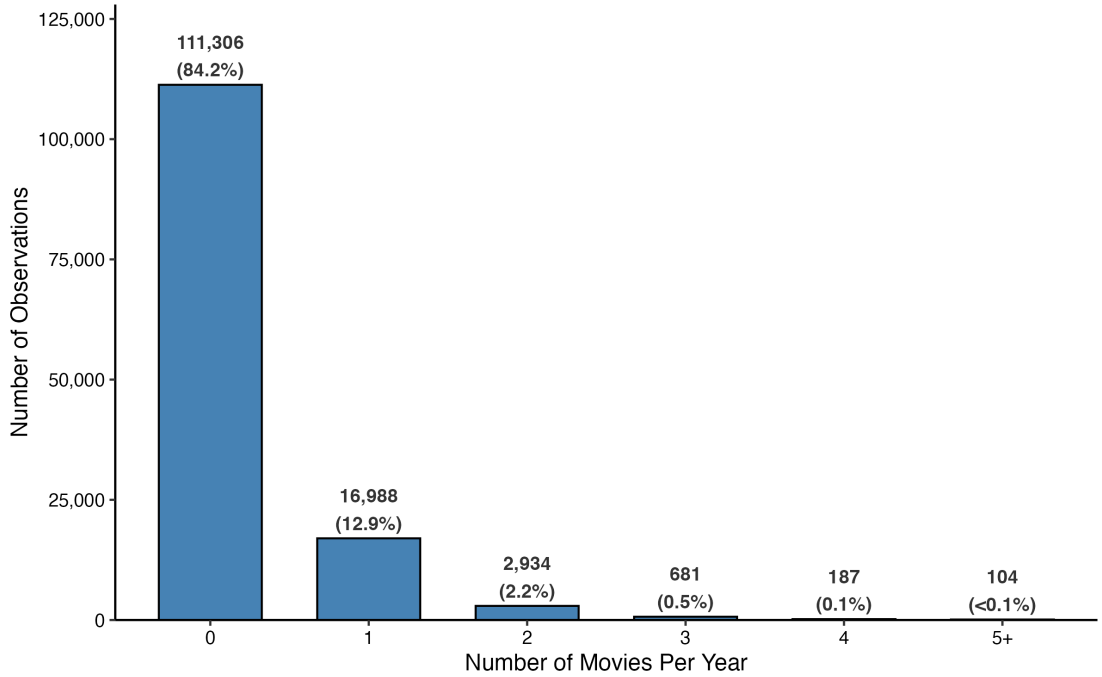
of which 10,848 (58.22%) lack box office information. Such movies, typically low-budget and less popular, are excluded from the analysis when calculating the box office-weighted number of movies but are included in other analyses.

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



Notes: This figure plots the empirical distribution of network connections for actors and for deceased producers/directors in the year the producer/director dies.

Figure 3: **Distribution of Movie Output**



Notes: This figure plots the empirical distribution of actors' yearly movie output.

Figure 3 displays the distribution of annual movie output for actors in both the control and treatment groups. The data reveals extreme right-skewness with 84.2% of the actor-year observations correspond to zero movie output (111,306 observations), and 12.9% (16,988 observations) corresponds to one movie output. This reflects the competitive nature of the movie acting market.

4 Model

To quantify the effect of a connection loss on an actor's career development, we apply a difference-in-differences (DiD) research design. Because our primary dependent variable, the number of movies actor i appears in during year t (Y_{it}), is a non-negative count variable, we estimate a fixed-effects Poisson regression. This model is particularly well-suited here as it explicitly considers the count data and provides a more robust framework for our analysis compared to a linear regression model applied to log-transformed counts (Chen and Roth, 2024).

Our main econometric specification is as follows:

$$E[Y_{it}|X_{it}] = \exp(\beta_0 + \beta_1 \cdot \text{Postdeath}_{it} + \beta_2 \cdot \text{AgeGroup}_{it} + \alpha_i + \gamma_t + \boldsymbol{\beta}_{\boldsymbol{x}}' \mathbf{X}_{it-1}), \tag{1}$$

where Y_{it} is the dependent variable that measures an actor's yearly movie output, Postdeath_{it} is a dummy variable that switches from 0 to 1 for all years after actor i experiences the death of a connected director or producer, AgeGroup_{it} represents age group fixed effects, categorized by ages < 10, $10-19$, and five-year intervals from $20-24$ to $70-74$, plus 75+, and X_{it-1} represents controls for work experience and productivity, including the actor's career-to-date average yearly and cumulative movie output, computed using all movies the actor has completed from their first credited year up through year $t-1$, as well as the corresponding quality-adjusted measures (by revenue, rating, and votes). For ease of interpretation, the quality-adjusted variables are normalized by their means. Moreover, we include the actor fixed effect, α_i, and the year fixed effect, γ_t.

We estimate our model using Maximum Likelihood. Our parameter of interest is β_1, which is interpreted as a semi-elasticity: $(\exp(\beta_1) - 1) \times 100\%$ gives the percentage change in expected movie output associated with losing a connection. To account for potential serial correlation in

outcomes for the same individual over time, we compute standard errors clustered at the actor level. 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 Web Appendix A.

Finally, we note that the recent econometric literature suggests that standard fixed-effects estimates can be biased in staggered adoption designs if treatment effects are heterogeneous over time. Although our main analysis uses the standard Two-way Fixed Effects Poisson specification defined in Equation (1), we show that our TWFE estimates are very similar to those from the staggered DID estimator proposed by Sun and Abraham (2021) in Section 5.4.2. We also run the Goodman-Bacon (2021) decomposition in Appendix C to validate that only a small percentage of treatment-control comparisons in our setting could potentially generate bias in the TWFE estimates.

5 Estimation Results

5.1 Main Results

Column (1) of Table 3 presents our main results. The dependent variable is an actor's yearly movie output. The coefficient of interest, β_1, is statistically significant and negative, indicating that the loss of a connection due to a producer/director's death leads to an average decline of 37.75% (=exp(-0.474)-1) in an actor's subsequent movie output.[10] This establishes a baseline for how professional connections shape career trajectories.

While the magnitude of this effect appears large at first glance, it is consistent with the very competitive environment of the actors market. To see this, note that the baseline level of yearly output is low; the average actor in our sample participates in only 0.21 movies per year before the treatment (Table 2). Given this low baseline, the loss of even a single acting opportunity translates into a substantial percentage decline.

Moreover, this high average treatment effect is mainly driven by the actors who participated in only a few movies before the treatment. To illustrate this, we performed a median split of the sample based on an actor's cumulative movie output prior to the death shock. This divides

[10] Unless otherwise noted, our use of the term *director* also includes casting directors.

the sample into more established actors (those with at least three movies) and less established actors (those with fewer than three). The results, presented in Columns (2) and (3), show that for actors with at least three prior movies, the decline is a more moderate 18.78% (=exp(-0.208)-1). In contrast, for those with fewer than three movies prior to the shock, the decline is much more severe, at 48.57% (=exp(-0.665)-1). For these less established actors, the median number of connections to producers and directors is only 4 at the time of the shock; thus, the loss of a single connection represents a 25% reduction in this critical professional network. Furthermore, their baseline level of output is very low, their average cumulative output over the entire post-shock period is just 0.78 movies. This combination of a small network and a low baseline means that the loss of even a single acting opportunity can result in a large percentage decline in their future movie output, highlighting the importance of each connection.

5.2 The Role of Casting Directors

We next examine the specific impact of losing a connection to a casting director. Unlike other production roles, the professional function of a casting director is explicitly focused on the hiring process; they are directly responsible for scouting talent and selecting actors for roles. Consequently, their influence on an actor's ability to secure immediate employment is likely more direct than that of directors or producers.

To test this, we construct a dummy variable, *Casting Director*, which takes a value of one if the deceased connection was a casting director, and zero otherwise. As shown in Column (4), the interaction term between the treatment and this indicator is negative and statistically significant. The estimates suggest that losing a casting director leads to a 48.57% (=exp(-0.408-0.257)-1) decline in movie output, which is 44.99% larger than the 33.50% (=exp(-0.408)-1) decline associated with other connection types. These results highlight that connections to individuals with direct decision-making power in the hiring pipeline are particularly critical for maintaining career momentum.

Table 3: **Main Results, Heterogeneity, and Robustness Checks**

	Dependent variable:						
	#Movie						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Postdeath_{it}	-0.474^{***}	-0.208^{***}	-0.665^{***}	-0.408^{***}	-0.222^{***}	-0.536^{***}	-0.511^{***}
	(0.036)	(0.052)	(0.055)	(0.037)	(0.042)	(0.035)	(0.056)
$\text{Postdeath}_{it} \times \text{Casting director}_{i}$				-0.257^{***}			
				(0.083)			
$\text{Postdeath}_{it} \times$ Years after shock_{it}					-0.078^{***}		
					(0.010)		
Average Yearly Movie Output_{it-1}	✓	✓	✓	✓	✓		✓
Cum. Movie Output_{it-1}	✓	✓	✓	✓	✓		✓
Age Group_{it}	✓	✓	✓	✓	✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓	✓	✓	✓
Observations	132,200	37,880	94,320	132,200	132,200	132,200	132,200
Pseudo R^2	0.181	0.131	0.138	0.180	0.182	0.162	0.186
Adjusted Pseudo R^2	0.090	0.071	0.010	0.089	0.091	0.071	0.091

Notes: Column (1) presents our main treatment effect. Column (2) presents results for actors who have appeared in at least 3 movies before the death shock. Column (3) presents results for actors who appeared in less than 3 movies before the death shock. Column (4) investigates the heterogeneous effect of a casting director. Column (5) investigates the temporal dynamics of the treatment effects. Column (6) shows the regression results without any control variables (except for actor and year fixed effects). Column (7) uses the estimator proposed by Sun and Abraham (2021) to address potential bias arising from staggered adoption designs. 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.

5.3 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,[11] can drive the gap between the treated and control actors wider over time.

To test this hypothesis, we created a variable *Years after Shock*, which is the number of years

[11]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.

since the treated actor experienced the death shock. We interact this variable with the *Postdeath* treatment dummy. Column (5) 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 an additional 7.50% (exp(-0.078)-1) decline in acting opportunities. This finding provides empirical support for the Matthew Effect discussed above.

5.4 Robustness Checks

5.4.1 Nickell Bias

In our model, we control for an actor's recent productivity and career establishment using their historical movie output. A potential concern with this approach is that these controls, which are functions of the lagged dependent variable, can introduce Nickell bias (also known as dynamic panel bias). This bias arises in fixed effects models with a short time dimension because the process of removing fixed effects (the "within" transformation) creates a mechanical correlation between the transformed lag of the dependent variable and the transformed error term.

To verify that our results are not due to this bias, we re-estimate the model without any time-varying controls, retaining only actor and year fixed effects. With no lagged outcome (or functions thereof) on the right-hand side, this specification is not subject to Nickell bias. As shown in Column (6) of Table 3, the treatment effect remains negative and statistically significant, and it is statistically indistinguishable from our main estimate ($p = 0.217$). This analysis indicates that our baseline findings are not driven by dynamic panel bias.

5.4.2 Staggered Treatment Adoption

It is important to note that the death 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 Goodman-Bacon (2021) and 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.

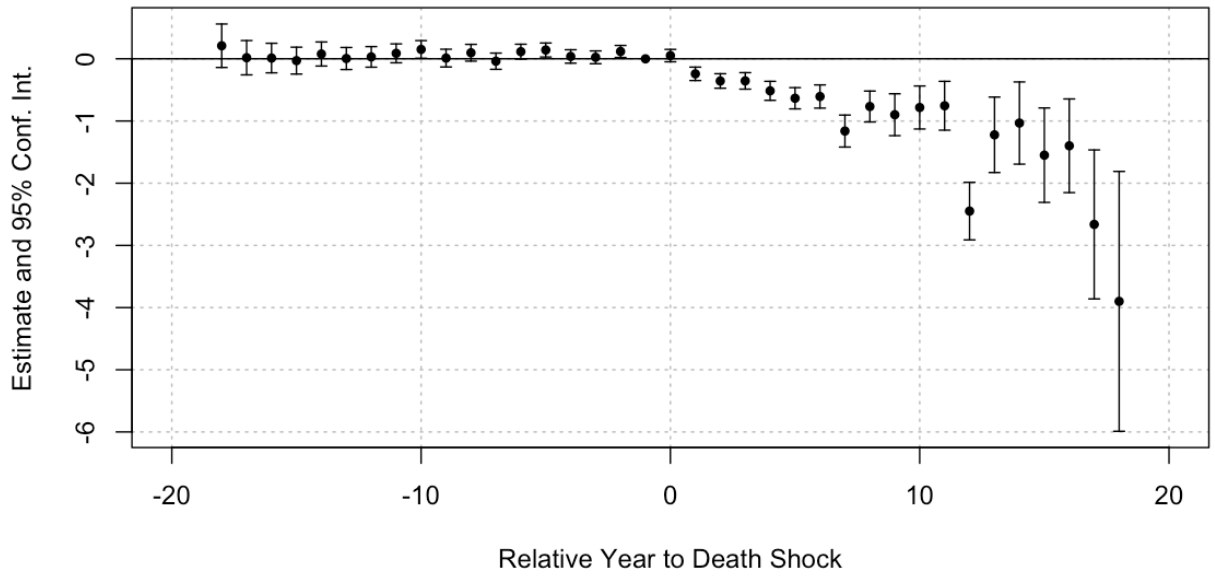
To ensure the robustness of our findings against potential biases arising from this source, we implement the estimator proposed by Sun and Abraham (2021). As reported in Column (7) of Table 3, the estimated Average Treatment Effect on the Treated (ATT) is -0.511. This estimate is statistically significant and remarkably close to our baseline TWFE estimate of $\beta = -0.474$. The fact that these two estimates are statistically indistinguishable (p = 0.578) provides strong initial evidence that our main results are robust to the staggered timing of the death shocks.

Figure 4 presents the dynamic treatment effects estimated using the estimator of Sun and Abraham (2021). The pattern in Figure 4 reinforces our main conclusions in two ways. First, the pre-treatment periods show no statistically significant differences between treatment and control groups, validating the parallel trends assumption underlying our empirical design. Second, we observe that the negative treatment effect emerges following the death shock and intensifies over time, mirroring the dynamic pattern we documented in Column (5) of Table 3. This consistency across different estimation approaches ensures the robustness of our findings.

To seek additional validation, we perform the decomposition proposed by Goodman-Bacon (2021). Intuitively, this diagnostic decomposes the standard TWFE coefficient into a weighted average of all possible 2×2 difference-in-differences comparisons between groups. It shows the specific weight assigned to the problematic comparisons, those where "later-treated" units are compared against "earlier-treated" units, which are the source of potential bias due to dynamic treatment effects. In our context, the decomposition reveals that these "Later vs. Earlier" comparisons account for only 7.6% of the total estimator weight. This minimal weighting arises structurally because the majority of treatments in our sample occur late in the panel; consequently, the pool of "earlier-treated" units available to serve as controls for subsequent units is small.

The details of the Goodman-Bacon decomposition are provided in Appendix C. Given the small weight assigned to biased comparisons and the comparable results betweenSun and Abraham (2021)'s estimate and our baseline results, we believe that the standard TWFE specification remains appropriate for our context. Accordingly, we retain this framework for our main analyses to leverage its flexibility in incorporating interaction terms.

Figure 4: **Dynamic Treatment Effect**



Notes: This figure shows the ATTs (and 95% confidence intervals) of the death shock on actor's future movie output from the Sun and Abraham (2021) estimator. Time 0 indicates the year of death shock. Other times are relative to the shock.

5.4.3 Other Robustness Checks

We conducted a series of additional robustness checks to ensure the validity of our main results. These include: (i) placebo tests to assess unobserved confounders; (ii) alternative control group construction using Propensity Score Matching; (iii) sample restrictions that exclude retired or unproductive actors and producers/directors; (iv) perturbing the year of death for directors/producers; (v) restricting the analysis to sudden deaths; (vi) assessing sampling variability from the matching procedure by repeating the matching step 1000 times and re-estimating the model. The results are reported in Web Appendix B. Across all checks, our main findings remain robust and statistically significant.

6 Mechanisms

In this section, we empirically examine three candidate mechanisms underlying our results: (i) repeated collaboration, (ii) referral and (iii) mentorship.

6.1 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 producers/directors may try to cast the same actors who worked well with them before to reduce the likelihood of internal conflicts during filming.[12] When a director or producer passes away, actors who were connected to them lose these "repeated collaboration" opportunities, which in turn could hinder their career progression.

Although there are some prominent examples of directors repeatedly casting the same actors in their movies (e.g., Martin Scorsese with Leonardo Dicaprio, Quentin Tarantino with Uma Thurman, Steven Spielberg with Tom Hanks), such repeated collaboration is quite uncommon in general. Among the 3,305 treated actors in our estimation sample, only 122 of them have repeated collaborations with the deceased producer/director (about 3.69%). To eliminate the effect due to repeated collaboration, we re-estimate the models using treated actors who have only worked with the deceased producers/directors once during her acting career.

Column (1) of Table 4 shows the regression results. The estimated treatment effect remains statistically significant, implying a 38.31% decline in movie output ($= \exp(-0.483) - 1$), which is very close to our main estimate of 37.75% (Column (1) of Table 3). This suggests that repeated collaboration is not the primary driver of the observed treatment effect.

6.2 Referral and Mentorship: Diminishing Returns of Network Size

Prior literature suggests that individuals derive career benefits from referrals and mentorship. It finds that referred applicants are more likely to be hired, exhibit lower quit rates, and earn higher wages (Burks et al., 2015; Brown et al., 2016). Similarly, high-quality mentorship has been shown to increase worker productivity (Lazear et al., 2015), improve students' math, patience/social skills and labor market orientation (Resnjanskij et al., 2024), and enhance graduates' job market outcomes

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

(Alfonsi et al., 2025). While these studies typically focus on traditional employment, we conjecture that these mechanisms are also important in the movie industry, a project-based labor market where actors face the constant pressure of securing new employment opportunities.

To investigate the potential roles of referrals and mentorship, we first test for diminishing returns to network connections, an empirical implication shared by both mechanisms. Regarding referrals, diminishing returns occur because actors face scheduling constraints that limit their ability to accept every referred project. Regarding mentorship, the marginal value declines because advice from multiple mentors eventually becomes redundant or even conflicting.

To test this hypothesis, we examine whether the negative effect of losing a connection is more severe for actors with smaller networks. We construct a variable measuring the percentage change in an actor's network size due to the death shock, defined as one (the lost connection) divided by their cumulative connections in the year prior to the shock. A larger percentage loss indicates a smaller initial network. As shown in Column (2) of Table 4, the negative and statistically significant interaction term between the treatment and this percentage change supports the diminishing returns hypothesis: actors with smaller networks suffer a disproportionately larger career setback from losing a single connection. We provide additional evidence on the diminishing returns to network size using quality-adjusted movie output in Appendix D.[13]

Note that the empirical test above does not attempt to disentangle referrals and mentorship, as both mechanisms imply diminishing return of connections. We next conduct additional analyses to search for evidence to support the presence of each mechanism.

6.3 Referral: Referral Propensity and the Extended Network

Directors/Producers may vary in their likelihood to refer actors connected with them to job openings. To capture this, we introduce *referral propensity*, and measure it for each deceased producer/director. Intuitively, it is defined as the pre-shock percentage of the deceased's connected actors who appeared in films directed/produced by someone who previously collaborated with the

[13] In our heterogeneous treatment effect analyses reported in Table D2 in Appendix D, we examine actors' cumulative work experience (measured by cumulative movie output) as moderators. We find that more experienced actors are less affected by the death shock, consistent with the hypothesis of diminishing returns to network size.

deceased, but unconnected with the actors. The goal of this variable is to measure how likely a producer/director refers actors connected to them to their extended network ("friends of friends" effect). The formal definition of our referral propensity is given in Appendix E. The average referral propensity of the deceased producers/directors in our sample is 4.05%.

We hypothesize that losing a connection to a deceased producer/director who has higher referral propensity should have a stronger negative impact on the actor's future movie output. To test this hypothesis, we interact referral propensity with the treatment dummy variable. The results in Column (3) of Table 4 show a negative and statistically significant interaction term, providing support for our hypothesis and the referral mechanism.

6.4 Mentorship: Unconnected Jobs

Regarding the mentorship mechanism, we first hypothesize that mentorship would help an actor improve their acting skills, interpersonal relationship, and professional conduct, thereby making them more competitive for roles independent of the deceased producer/director's network. Consequently, if mentorship is important, an actor's chance of landing a movie role outside the deceased producer/director's network should drop after the death shock.

To test this hypothesis, we rely on a subsample where the referral channel is likely inactive. Specifically, we only consider deceased producers/directors whose producer/director connections did not launch any new projects after their death. For actors connected to these deceased individuals, the "extended network" pathway for referrals is effectively closed. This subsample comprises 223 such deceased producers/directors and 520 treated actors (and their control counterparts). We re-estimate our baseline model on this subsample. The results, reported in Column (4) of Table 4, show a statistically significant decline in unconnected movie output. This finding suggests that the connection loss impaired the actors' intrinsic competitiveness independently of their network access, a result consistent with the mentorship mechanism.

6.5 Mentorship: Age Gap

We further hypothesize that the larger the age gap between a producer/director and an actor, the stronger the mentor-mentee relationship. A larger age gap likely signifies deeper experience

Table 4: **Mechanism Analysis**

	Dependent variable:					
	#Movie					
	(1)	(2)	(3)	(4)	(5)	(6)
Postdeath_{it}	-0.483^{***}	-0.357^{***}	-0.264^{***}	-0.581^{***}	-0.394^{***}	-0.643^{***}
	(0.037)	(0.044)	(0.045)	(0.119)	(0.054)	(0.156)
$\text{Postdeath}_{it} \times \%$ Connection Change_i		-0.620^{***}				
		(0.130)				
$\text{Postdeath}_{it} \times \text{Referral Propensity}_i$			-6.337^{***}			
			(0.916)			
$\text{Postdeath}_{it} \times \text{AgeGap}_i$					-0.003^{*}	
					(0.0017)	
$\text{Postdeath}_{it} \times \text{Deceased P/D Age}_i$						0.003
						(0.0023)
Average Yearly Movie Output_{it-1}	✓	✓	✓	✓	✓	✓
Cum. Movie Output_{it-1}	✓	✓	✓	✓	✓	✓
Age Group_{it}	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓	✓	✓
Without Repeated Collaborations	✓					
Without Connected Jobs				✓		
Observations	127,320	132,200	132,200	20,800	132,200	132,200
Pseudo R^2	0.182	0.181	0.181	0.141	0.181	0.181
Adjusted Pseudo R^2	0.090	0.090	0.091	0.001	0.090	0.090

Notes: Column (1) reports results where actors have only worked with the deceased producer/director once. Column (2) reports the moderating effect of the actor's network connection change. % Connection Change_i represents the percentage change of actor i's network connections after the death shock. Column (3) explores the moderating effect of the deceased producer/director's referral propensity (i.e., likelihood of recommending connected actors to their friends' projects). Column (4) restricts the sample to actors who might not have the chance to appear in a connected project. Column (5) investigates the moderating effect of the age gap between the actor and the deceased producer/director. Column (6) interacts the treatment with the absolute age of the deceased producer/director to test if the effect is driven by the connection's age itself rather than the age gap. 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.

and industry knowledge, which can make a senior professional's guidance more impactful and their mentorship more valuable. To test whether a larger age gap corresponds to a stronger connection effect, we define a variable, AgeGap, as the producer/director's age minus the actor's age. In our sample, the average age gap is 21.50 years (SD = 20.29), and 84.84% of treated actors were younger than the deceased connection.

We interact AgeGap with the treatment variable to examine its moderating effect. As shown in Column (5) of Table 4, the interaction term is negative and marginally significant (p = 0.058). This indicates that the negative career impact of losing a connection intensifies when the deceased producer/director was substantially older than the actor. This finding provides suggestive evidence that the mentorship mechanism may be underlying our main findings.

One potential problem of our AgeGap analysis is that it could be capturing the age effect of producers/directors. More specifically, older producers/directors might have more network connections that they could leverage for referrals. To investigate this possibility, we interact the treatment with the producer/director's age at death. The results, presented in Column (6), show a statistically insignificant interaction term. This rules out this potential confounding factor, and reinforces our AgeGap finding as evidence to support the mentorship channel.

In summary, we provide collective evidence that both referral and mentorship mechanisms are at work in explaining our empirical findings. Also, we show that repeated collaboration mechanism is not the main driver of the baseline effect.

7 Role Significance and Project Quality

Our main analysis quantifies the impact of losing a professional connection on an actor's movie output measured by the number of movie projects. However, so far we have not considered the significance of the acting role (major vs. minor) or the quality of the movies. In this section, we take such quality dimensions into account.

7.1 Effect on Major Role Opportunities

Although IMDb does not explicitly tag roles, it features a small number of actors on each movie's profile page. We consider these featured actors as the movie's major-role cast. In this specification,

we restrict our sample to individuals who played at least one major role in our sample period prior to the death shock. This restriction removes 1,850 treated actors (55.98% of the sample). The remaining sample has 1455 treated actors. Using this subsample and the number of movies with a major role as the dependent variable, we re-estimate our model. The result, reported in Column (1) of Table 5, shows that actors who experience a connection loss suffer a statistically significant 28.25% (=exp(-0.332)-1) decline in future major role opportunities. This effect is smaller than our baseline estimate for overall output, suggesting that connections to producers or directors have a greater impact on securing minor roles than on major roles.

7.2 Effects on Quality-Adjusted Movie Output

Beyond role significance, the overall quality of the movie also matters. To assess this, we use quality-adjusted movie output as our dependent variable, weighting each movie by its (i) box-office revenue, (ii) average IMDb rating, and (iii) number of IMDb votes.

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.[14] 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 (2) to (4) of Table 5. On average, the death of a producer/director leads to a 39.89% (=exp(-0.509)-1) decline in the IMDb rating-adjusted number of movies (Column 2), a 72.99% (=exp(-1.309)-1) decline in the revenue-adjusted number of movies (Column 3), and a 68.37% (=exp(-1.151)-1) decline in the votes-adjusted number of movies (Column 4). These results show that losing a professional network connection could lead to a much stronger impact on an actor's career, if we consider the quality of jobs that they received.

[14] 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 suggests that they tend to be less popular movies.

Table 5: **Effect on Major Roles and Quality-Adjusted Output**

	Dependent variable:			
	#Major Role	#Rating-Movie	#Rev-Movie	#Vote-Movie
	(1)	(2)	(3)	(4)
Postdeath_{it}	-0.332^{***}	-0.509^{***}	-1.309^{***}	-1.151^{***}
	(0.057)	(0.038)	(0.198)	(0.168)
Average Yearly Movie Output_{it-1}	✓	✓	✓	✓
Cum. Movie Output_{it-1}	✓	✓	✓	✓
AgeGroup_{it}	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓
Observations	58,200	129,680	84,220	129,680
Pseudo R^2	0.165	0.228	0.465	0.512
Adjusted Pseudo R^2	0.051	0.209	0.449	0.500

Notes: The dependent variable is an actor's number of major roles in Column (1), rating weighted yearly movie output in Column (2), revenue weighted yearly movie output in Column (3), and votes weighted yearly movie output in Column (4). 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.

8 Implications for Practice and Conclusion

Many people take for granted that having a larger professional network can lead to better job prospects. 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 producer/director'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 referrals and mentorship may be the mechanisms underlying these effects.

Our dynamic effect analysis indicates that the treatment effect amplifies over time. This highlights the importance of actors adopting a forward-looking perspective when building a 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.

Our analysis of potential mechanisms suggests that the observed effect is not primarily driven by repeated collaboration, which applies to only a small fraction (3.69%) of our sample. Instead,

the evidence points to referrals and mentorship as the key channels. We find evidence for the referral mechanism by showing that the death of a connection with a higher pre-existing propensity to refer actors within their professional network produces a significantly larger decline in an actor's subsequent movie output. Conversely, to provide evidence for mentorship, we show that actors experience a significant decline in even unconnected job opportunities and the treatment effect increases with the age gap between the deceased producer/director and treated actors.

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 3 of Table 3) and the mechanistic analysis (see Column 2 of Table 4) 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 becomes 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.

One caveat of our research is that our network measure is solely based on co-working relationships, and does not capture the role of other key intermediaries, most notably talent agents. Talent agents are a highly relevant feature of professional networks in the movie industry, often responsible for securing auditions and negotiating contracts. Unfortunately, comprehensive data on actor-agent relationships is not publicly available. We therefore leave investigating the role of talent agents for future research.

To our knowledge, this is the first study to provide causal evidence that network connections significantly influence career prospects in a sector where frequent job searching and self-marketing are essential. We should emphasize that the actors market is characterized by short-term contracts and a continuous need for self-marketing, distinguishing it from traditional sectors defined by long-term employment stability and internal promotion ladders. Hence, while our findings offer insights for other professions with similar structural features, such as consultants, contractors and real estate agents, they might not generalize to other traditional labor markets.

References

Adler L (2016) New Survey Reveals 85% of All Jobs Are Filled via Networking. *LinkedIn Pulse* .

Alfonsi L, Namubiru M, Spaziani S (2025) Meet Your Future: Experimental Evidence on the Labor Market Effects of Mentors. Working paper.

Azoulay P, Graff Zivin JS, Wang J (2010) Superstar Extinction. *The Quarterly Journal of Economics* 125(2):549–589.

Baker AC, Larcker DF, Wang CC (2022) How Much Should We Trust Staggered Difference-in-differences Estimates? *Journal of Financial Economics* 144(2):370–395.

Bayer P, Ross SL, Topa G (2008) Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Journal of Political Economy* 116(6):1150–1196.

Bennedsen M, Nielsen KM, Pérez-González F, Wolfenzon D (2007) Inside the Family Firm: The Role of Families in Succession Decisions and Performance. *The Quarterly Journal of Economics* 122(2):647–691.

Benzell SG, Cooke K (2021) A Network of Thrones: Kinship and Conflict in Europe, 1495–1918. *American Economic Journal: Applied Economics* 13(3):102–133.

Borchers C, Ellis L (2024) Landing a job is all about who you know (again). Published in *The Wall Street Journal*. Available at: https://www.wsj.com/lifestyle/careers/networking-job-search-c6f06b0c.

Brown M, Setren E, Topa G (2016) Do Informal Referrals Lead to Better Matches? Evidence from a Firm's Employee Referral System. *Journal of Labor Economics* 34(1):161–209.

Burks SV, Cowgill B, Hoffman M, Housman M (2015) The Value of Hiring Through Employee Referrals. *The Quarterly Journal of Economics* 130(2):805–839.

Chen J, Roth J (2024) Logs with Zeros? Some Problems and Solutions. *The Quarterly Journal of Economics* 139(2):891–936.

Chintagunta PK, Gopinath S, Venkataraman S (2010) The Effects of Online User Reviews on Movie Box Office Performance: Accounting for Sequential Rollout and Aggregation across Local Markets. *Marketing Science* 29(5):944–957.

Delre SA, Panico C, Wierenga B (2017) Competitive Strategies in the Motion Picture Industry: An ABM to Study Investment Decisions. *International Journal of Research in Marketing* 34(1):69–99.

Elberse A (2007) The Power of Stars: Do Star Actors Drive the Success of Movies? *Journal of Marketing* 71(4):102–120.

Eliashberg J, Elberse A, Leenders MA (2006) The Motion Picture Industry: Critical Issues in Practice, Current Research, and New Research Directions. *Marketing Science* 25(6):638–661.

Gil R, Hartmann WR (2009) Empirical Analysis of Metering Price Discrimination: Evidence from Concession Sales at Movie Theaters. *Marketing Science* 28(6):1046–1062.

Gilchrist DS, Sands EG (2016) Something to Talk About: Social Spillovers in Movie Consumption. *Journal of Political Economy* 124(5):1339–1382.

Goodman-Bacon A (2021) Difference-in-differences with Variation in Treatment Timing. *Journal of Econometrics* 225(2):254–277.

Gopinath S, Chintagunta PK, Venkataraman S (2013) Blogs, Advertising, and Local-market Movie Box Office Performance. *Management Science* 59(12):2635–2654.

Granovetter MS (1973) The Strength of Weak Ties. *American Journal of Sociology* 78(6):1360–1380.

Hacamo I, Kleiner K (2022) Competing for Talent: Firms, Managers, and Social Networks. *The Review of Financial Studies* 35(1):207–253.

Hampole M, Truffa F, Wong A (2025) Peer Effects and the Gender Gap in Corporate Leadership: Evidence from MBA Students. Working paper.

Hellerstein JK, McInerney M, Neumark D (2011) Neighbors and Coworkers: The Importance of Residential Labor Market Networks. *Journal of Labor Economics* 29(4):659–695.

Hennig-Thurau T, Henning V, Sattler H, Eggers F, Houston MB (2007) The Last Picture Show? Timing and Order of Movie Distribution Channels. *Journal of Marketing* 71(4):63–83.

Hermosilla M, Gutierrez-Navratil F, Prieto-Rodriguez J (2018) Can Emerging Markets Tilt Global Product Design? Impacts of Chinese Colorism on Hollywood Castings. *Marketing Science* 37(3):356–381.

Iacus SM, King G, Porro G (2012) Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis* 1–24.

Jäger S, Heining J, Lazarus N (2025) How Substitutable Are Workers? Evidence from Worker Deaths, Working paper.

Jaravel X, Petkova N, Bell A (2018) Team-specific Capital and Innovation. *American Economic Review* 108(4-5):1034–1073.

Jones BF, Olken BA (2005) Do Leaders Matter? National Leadership and Growth Since World War II. *The Quarterly Journal of Economics* 120(3):835–864.

Lazear EP, Shaw KL, Stanton CT (2015) The Value of Bosses. *Journal of Labor Economics* 33(4):823–861.

Lerner J, Malmendier U (2013) With a Little Help from My (Random) Friends: Success and Failure in Post-business School Entrepreneurship. *The Review of Financial Studies* 26(10):2411–2452.

Liu A, Mazumdar T, Li B (2015) Counterfactual Decomposition of Movie Star Effects with Star Selection. *Management Science* 61(7):1704–1721.

Lu S, Dinner I, Grewal R (2023) The Ripple Effect of Firm-Generated Content on New Movie Releases. *Journal of Marketing Research* 60(5):908–931.

Luo H, Macher J, Wahlen M (2021) Judgment Aggregation in Creative Production: Evidence from the Movie Industry. *Management Science* 67(10):6358–6377.

McKenzie J (2023) The Economics of Movies (Revisited): A Survey of Recent Literature. *Journal of Economic Surveys* 37(2):480–525.

Merton RK (1968) The Matthew Effect in Science: The Reward and Communication Systems of Science are Considered. *Science* 159(3810):56–63.

Moretti E (2011) Social Learning and Peer Effects in Consumption: Evidence from Movie Sales. *The Review of Economic Studies* 78(1):356–393.

Narayan V, Kadiyali V (2016) Repeated Interactions and Improved Outcomes: An Empirical Analysis of Movie Production in the United States. *Management Science* 62(2):591–607.

Oettl A (2012) Reconceptualizing Stars: Scientist Helpfulness and Peer Performance. *Management Science* 58(6):1122–1140.

Packard G, Aribarg A, Eliashberg J, Foutz NZ (2016) The Role of Network Embeddedness in Film Success. *International Journal of Research in Marketing* 33(2):328–342.

Rainie L, Smith A, Duggan M (2015) The internet and job seeking. Pew Research Center. Available at: https://www.pewresearch.org/internet/2015/11/19/1-the-internet-and-job-seeking/.

Resnjanskij S, Ruhose J, Wiederhold S, Woessmann L, Wedel K (2024) Can Mentoring Alleviate Family Disadvantage in Adolescence? A Field Experiment to Improve Labor Market Prospects. *Journal of Political Economy* 132(3):1013–1062.

Roos JM, Shachar R (2014) When Kerry Met Sally: Politics and Perceptions in the Demand for Movies. *Management Science* 60(7):1617–1631.

Shue K (2013) Executive Networks and Firm Policies: Evidence from the Random Assignment of MBA Peers. *The Review of Financial Studies* 26(6):1401–1442.

Sun L, Abraham S (2021) Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects. *Journal of Econometrics* 225(2):175–199.

Topa G (2001) Social Interactions, Local Spillovers and Unemployment. *The Review of Economic Studies* 68(2):261–295.

Topa G (2019) Social and spatial networks in labour markets. *Oxford Review of Economic Policy* 35(4):722–745.

Zimmerman DJ (2003) Peer Effects in Academic Outcomes: Evidence from a Natural Experiment. *Review of Economics and Statistics* 85(1):9–23.

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 (1) gender, (2) age, (3) cumulative number of movies they have appeared in (and corresponding cumulative measures weighted by rating, box office revenue and number of votes), (4) average annual number of movies they have appeared in (and the corresponding average measures weighted by rating, box office revenue and number of votes),[15] and (5) the cumulative number of connections (including connections to peer actors), (6) cumulative number of producer/director connections, and network features including (7) average age of connected producers and directors, (8) the connected producers/directors' cumulative movie output, both unweighted and weighted by rating, revenue, and votes. All matching variables are actor specific and measured in the year prior to the death shock. Note that by matching on both the number of connected producers/directors and their total cumulative movie output, the average output of connected producers and directors is matched by construction.

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 $75th$

[15] All "cumulative number of movies" and "average number of movies" variables, including all weighted measures, reflect the actor's entire career output up to that point, not metrics specific to a single actor-producer/director connection.

percentile), respectively.

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.[16] Our matching procedure is successful for 3,305 out of the 5,112 (64.65%) treated actors, corresponding to 698 deceased producers/directors. .

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 our study.

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

B Importance of Deceased Directors and Producers

In this section, we study the moderator role of the deceased producers/directors. On the one hand, the importance of deceased producers/directors 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 producer/director 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 producers/directors might interact with the treatment effect.

To investigate this empirical question, we first use the cumulative number of movies that they have directed or produced over their careers as a proxy of their importance. Column (1) of Table B1 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 Columns (2) to (4) of Table B1.

We next use the deceased producers/directors' 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 (5) of Table B1.

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

Table B1: **Heterogeneity by Producer/Director Status and Connection Strength**

	Dependent variable:								
	#Movie								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Postdeath_{it}	-0.494^{***}	-0.495^{***}	-0.477^{***}	-0.475^{***}	-0.471^{***}	-0.705^{***}	-0.474^{***}	-0.482^{***}	-0.328^{***}
	(0.041)	(0.041)	(0.039)	(0.039)	(0.042)	(0.135)	(0.037)	(0.037)	(0.054)
$\text{Postdeath}_{it} \times \text{P/D Cum. \# Movies}_i$	0.009								
	(0.009)								
$\text{Postdeath}_{it} \times \text{P/D Cum. Ratings}_i$		0.009							
		(0.009)							
$\text{Postdeath}_{it} \times \text{P/D Cum. Revenue}_i$			0.002						
			(0.007)						
$\text{Postdeath}_{it} \times \text{P/D Cum. Votes}_i$				0.001					
				(0.007)					
$\text{Postdeath}_{it} \times \text{P/D Cum. Connections}_i$					-0.001				
					(0.010)				
$\text{Postdeath}_{it} \times \text{Cum. Collab. Rating}_i$						0.114*			
						(0.063)			
$\text{Postdeath}_{it} \times \text{Cum. Collab. Revenue}_i$							0.0003		
							(0.004)		
$\text{Postdeath}_{it} \times \text{Cum. Collab. Votes}_i$								0.004	
								(0.004)	
$\text{Postdeath}_{it} \times \text{Relationship Tenure}_i$									-0.030^{***}
									(0.008)
Cum. $\#\text{movie}_{it-1}$	-0.270^{***}	-0.270^{***}	-0.270^{***}	-0.270^{***}	-0.271^{***}	-0.260^{***}	-0.270^{***}	-0.270^{***}	-0.276^{***}
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)	(0.061)	(0.061)	(0.062)
Cum. rating weighted $\#\text{movie}_{it-1}$	0.231^{***}	0.231^{***}	0.231^{***}	0.231^{***}	0.231^{***}	0.221^{***}	0.231^{***}	0.231^{***}	0.235^{***}
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
Cum. revenue weighted $\#\text{movie}_{it-1}$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Cum. votes weighted $\#\text{movie}_{it-1}$	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Average $\#\text{movie}_{it-1}$	0.045	0.045	0.045	0.045	0.045	0.040	0.045	0.045	0.045
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)	(0.032)
Average rating weighted $\#\text{movie}_{it-1}$	-0.061^{**}	-0.061^{**}	-0.061^{**}	-0.061^{**}	-0.061^{**}	-0.056^{*}	-0.062^{**}	-0.062^{**}	-0.063^{**}
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Average revenue weighted $\#\text{movie}_{it-1}$	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Average votes weighted $\#\text{movie}_{it-1}$	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age 10-19	0.752^{***}	0.752^{***}	0.753^{***}	0.754^{***}	0.754^{***}	0.751^{***}	0.754^{***}	0.752^{***}	0.742^{***}
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
Age 20-24	1.696^{***}	1.696^{***}	1.698^{***}	1.698^{***}	1.699^{***}	1.695^{***}	1.698^{***}	1.696^{***}	1.683^{***}
	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.126)
Age 25-29	2.101^{***}	2.101^{***}	2.103^{***}	2.103^{***}	2.104^{***}	2.101^{***}	2.103^{***}	2.101^{***}	2.085^{***}
	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)	(0.141)
Age 30-34	2.145^{***}	2.145^{***}	2.147^{***}	2.147^{***}	2.147^{***}	2.144^{***}	2.147^{***}	2.145^{***}	2.128^{***}
	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
Age 35-39	2.077^{***}	2.077^{***}	2.079^{***}	2.079^{***}	2.080^{***}	2.076^{***}	2.079^{***}	2.078^{***}	2.061^{***}
	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)

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Table B1 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age 40-44	1.993***	1.993***	1.994***	1.995***	1.995***	1.992***	1.995***	1.993***	1.979***
	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)	(0.186)
Age 45-49	1.853***	1.853***	1.855***	1.855***	1.856***	1.852***	1.855***	1.854***	1.843***
	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)
Age 50-54	1.714***	1.714***	1.714***	1.715***	1.715***	1.712***	1.715***	1.714***	1.705***
	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)
Age 55-59	1.498***	1.498***	1.499***	1.499***	1.499***	1.498***	1.499***	1.498***	1.495***
	(0.243)	(0.243)	(0.243)	(0.243)	(0.243)	(0.243)	(0.243)	(0.243)	(0.243)
Age 60-64	1.176***	1.176***	1.176***	1.176***	1.176***	1.177***	1.176***	1.177***	1.175***
	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)
Age 65-69	0.926***	0.926***	0.926***	0.926***	0.926***	0.926***	0.926***	0.926***	0.928***
	(0.286)	(0.286)	(0.286)	(0.286)	(0.286)	(0.286)	(0.286)	(0.286)	(0.286)
Age 70-74	0.487	0.488	0.487	0.487	0.486	0.486	0.487	0.487	0.491
	(0.309)	(0.309)	(0.309)	(0.309)	(0.309)	(0.310)	(0.309)	(0.309)	(0.309)
Age 75+	−0.271	−0.271	−0.273	−0.273	−0.274	−0.272	−0.273	−0.272	−0.267
	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	132,200	132,200	132,200	132,200	132,200	132,200	132,200	132,200	132,200
Pseudo R^2	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
Adjusted Pseudo R^2	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090

Notes: Columns (1)–(5) examine whether the treatment effect varies with the deceased producer/director's experience and importance. We do so by interacting the treatment indicator with their cumulative number of movies, the rating/revenue/vote-weighted cumulative number of movies, and their total number of network connections. Columns (6)-(8) test whether the treatment effect depends on the cumulative quality of all collaborations between the actor and the deceased producer/director, measured by that movie's rating, box office revenue, and number of votes. Column (9) tests the heterogeneity based on the duration of the relationship. 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.

Columns (6) through (8) investigate whether the cumulative quality of all collaborations between the actor and the deceased producer/director moderates the treatment effect. Intuitively, highly successful past projects might foster a stronger professional bond, increasing the likelihood of future assistance. We proxy movie success using ratings, box office revenue, and vote counts (summed across all shared movies). We note that for the vast majority of our sample (96.31%), this metric represents a single collaboration. As shown in the table, the interaction terms for these variables are statistically insignificant (Column 6 shows a marginally significant effect), suggesting that the success of past collaborations does not amplify the treatment effect.

A potential explanation for this null result is a 'dilution' effect caused by cast size. In our sample, high-grossing movies (higher than the mean) feature significantly more actors on average

(60.63) than lower-grossing movies (19.74). Consequently, while a connection formed in a successful movie is valuable, the producer's attention is likely split among a much larger cohort, offsetting the benefits of the film's success.

Another potential source of heterogeneity is the duration of the professional relationship between the actor and the deceased producer/director. Theoretically, the direction of this effect is ambiguous. On one hand, connections rooted in the distant past may have faded, suggesting that older ties are weaker than recent, active collaborations. On the other hand, relationships often strengthen over time, with long-standing ties representing deep social capital and trust.

To investigate this, we construct a *RelationshipTenure* variable, defined as the number of years elapsed since the first collaboration between the actor and the deceased.

As shown in Column (9) of Table B1, the coefficient on the interaction term between *RelationshipTenure* and *Postdeath* is negative and statistically significant. This indicates that the negative shock of the death is amplified by the length of the relationship. In other words, actors who had known the deceased for a longer time suffered a steeper decline in productivity, suggesting that long-term ties represent deep-seated mentorship or career dependency that is difficult to replace.

C Diagnostic for Staggered Adoption Bias

Given the staggered timing of director and producer deaths in our sample, recent econometric literature suggests that standard Two-Way Fixed Effects (TWFE) estimates may be biased if treatment effects are heterogeneous over time. Specifically, the standard estimator calculates a weighted average of all possible 2×2 difference-in-differences comparisons. Bias arises when "later-treated" units are compared against "earlier-treated" units, as the latter group's already-changing outcomes serve as a contaminated control group Goodman-Bacon (2021).

To assess the severity of this potential bias, we perform a Goodman-Bacon decomposition of our difference-in-differences estimator. The results, presented in Table C1, demonstrate that our estimates are overwhelmingly driven by "clean" comparisons. Specifically, 69.6% of the estimator's weight is derived from comparing treated actors to never-treated (or not-yet-treated) actors. In contrast, the problematic comparison—where later-treated actors use earlier-treated actors as

controls—receives a negligible weight of only 7.6%.

Crucially, the average estimates across all comparison groups are consistently negative. This uniformity indicates that slope heterogeneity does not induce a "sign flip" in our context. We acknowledge that these component estimates are derived via OLS, whereas our main analysis utilizes Poisson regression. However, this linear diagnostic provides strong suggestive evidence that the structural timing of treatment in our sample does not generate spurious results through negative weighting.

Table C1: Goodman-Bacon Decomposition Results

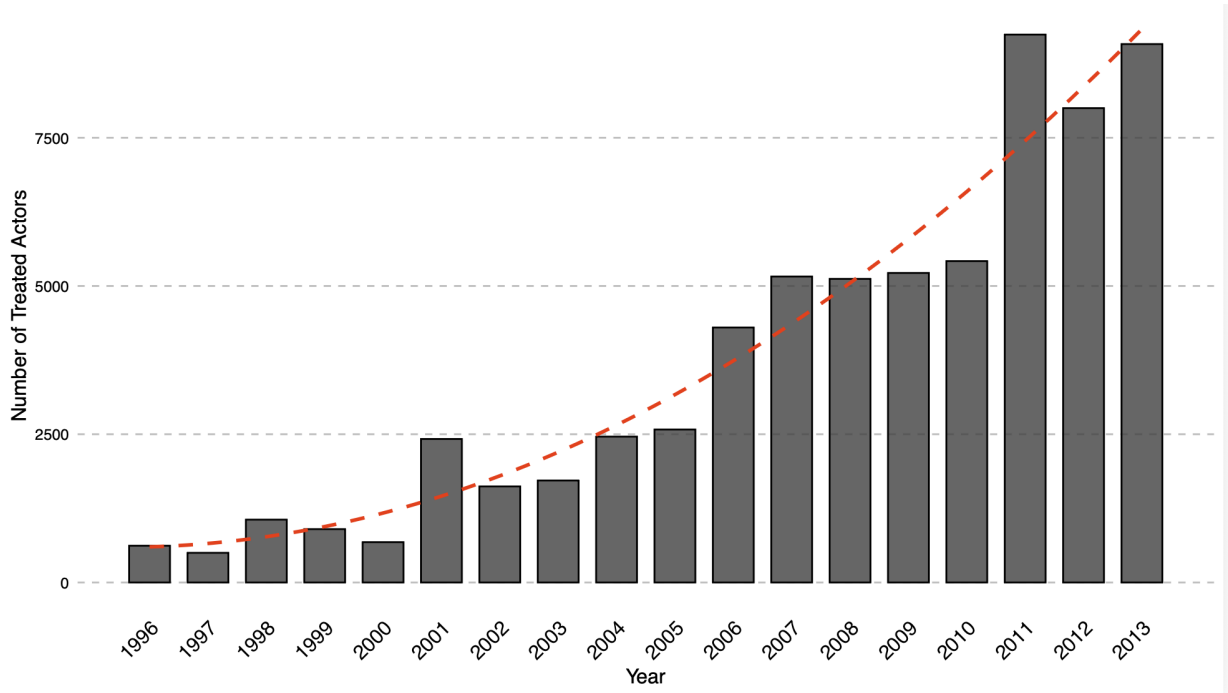
Comparison Type	**Weight**	**Avg Estimate**
Treated vs. Untreated	0.696	-0.111
Earlier vs. Later Treated	0.228	-0.150
Later vs. Earlier Treated (Potential Bias)	0.076	-0.010

Notes: This table presents the weights and average difference-in-differences estimates from the decomposition of the standard TWFE estimator as proposed by Goodman-Bacon (2021). The "Treated vs. Untreated" and "Earlier vs. Later Treated" comparisons provide unbiased estimates of the treatment effect. The "Later vs. Earlier Treated" comparison is the source of potential bias due to dynamic treatment effects.

Intuition for Low Bias. The minimal weight assigned to the biased comparison (Later vs. Earlier) is structurally determined by the distribution of treatment timing in our sample. As shown in Figure C1, the number of treated actors (those experiencing a death shock) increases significantly over time, with the vast majority of treatments occurring late in the sample period (2010–2013).

Mechanically, the Goodman-Bacon decomposition assigns weights based on the variance of treatment status. For a "Later vs. Earlier" comparison to carry significant weight, there must be a large group of "Earlier Treated" units to serve as controls for a long duration. In our setting, because most treatments are concentrated at the end of the panel, the pool of "Earlier Treated" actors available to act as controls for subsequent units is small. Consequently, the potentially biased comparisons contribute very little to the overall estimate, ensuring that our main results capture the true causal effect rather than artifacts of staggered timing.

Figure C1: **Distribution of Newly Treated Actors Over Time (1996-2013)**



Notes: This figure plots the empirical distribution of the newly treated actors in our sample.

D Diminishing Return from Network Connections

In this section, we provide further evidence on diminishing return from network connections. As shown in Column (2) of Table 4, 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 D1, 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 D1, the interaction term remains negative and 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 (2) of Table 4.

In Columns (3) and (4), 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 D1: **Diminishing Return from Network Connections**

	Dependent variable:			
	# Movie	Rating-Movie	Revenue-Movie	Votes-Movie
	(1)	(2)	(3)	(4)
Postdeath_{it}	-0.357^{***}	-0.400^{***}	-1.286^{***}	-1.121^{***}
	(0.044)	(0.047)	(0.222)	(0.186)
$\text{Postdeath}_{it} \times$ % Connection Change_i	-0.620^{***}	-0.594^{***}	-0.204	-0.280
	(0.130)	(0.148)	(0.501)	(0.661)
Cum. $\#\text{movie}_{it-1}$	-0.270^{***}	-0.043	-0.270	0.294
	(0.061)	(0.061)	(0.268)	(0.283)
Cum. rating weighted $\#\text{movie}_{it-1}$	0.225^{***}	0.006	0.226	-0.243
	(0.056)	(0.062)	(0.256)	(0.272)
Cum. revenue weighted $\#\text{movie}_{it-1}$	-0.002	-0.001	0.008	0.027
	(0.004)	(0.005)	(0.020)	(0.017)
Cum. votes weighted $\#\text{movie}_{it-1}$	-0.007	-0.007	-0.038^{*}	-0.099^{***}
	(0.005)	(0.006)	(0.022)	(0.019)
Average $\#\text{movie}_{it-1}$	0.043	0.135^{***}	-0.087	-0.355
	(0.032)	(0.031)	(0.244)	(0.301)
Average rating weighted $\#\text{movie}_{it-1}$	-0.056^{*}	-0.152^{***}	0.164	0.372
	(0.031)	(0.031)	(0.231)	(0.279)
Average revenue weighted $\#\text{movie}_{it-1}$	0.004	0.003	-0.034^{***}	-0.024^{**}
	(0.003)	(0.003)	(0.013)	(0.012)
Average votes weighted $\#\text{movie}_{it-1}$	0.004	0.004	0.010	0.013
	(0.004)	(0.004)	(0.008)	(0.010)
Age 10-19	0.761^{***}	0.732^{***}	0.590	0.380
	(0.110)	(0.113)	(0.489)	(0.363)
Age 20-24	1.703^{***}	1.644^{***}	1.011^{**}	0.974^{**}
	(0.127)	(0.131)	(0.508)	(0.413)
Age 25-29	2.107^{***}	2.031^{***}	1.142^{**}	1.171^{***}
	(0.141)	(0.145)	(0.550)	(0.455)
Age 30-34	2.149^{***}	2.063^{***}	1.070^{*}	1.085^{**}
	(0.156)	(0.160)	(0.594)	(0.500)
Age 35-39	2.077^{***}	2.010^{***}	1.091^{*}	1.158^{**}
	(0.171)	(0.177)	(0.656)	(0.557)
Age 40-44	1.990^{***}	1.925^{***}	1.129	1.036^{*}
	(0.186)	(0.193)	(0.708)	(0.598)
Age 45-49	1.851^{***}	1.780^{***}	0.875	0.746
	(0.205)	(0.213)	(0.784)	(0.669)
Age 50-54	1.715^{***}	1.659^{***}	0.609	0.630
	(0.223)	(0.232)	(0.843)	(0.735)
Age 55-59	1.503^{***}	1.417^{***}	0.362	0.265
	(0.243)	(0.254)	(0.935)	(0.819)

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Table D1 – continued from previous page

	(1)	(2)	(3)	(4)
Age 60-64	1.182***	1.108***	0.088	−0.034
	(0.266)	(0.278)	(1.021)	(0.883)
Age 65-69	0.935***	0.877***	−0.112	−0.131
	(0.286)	(0.299)	(1.166)	(1.024)
Age 70-74	0.497	0.431	−0.868	−0.648
	(0.309)	(0.323)	(1.257)	(1.104)
Age 75+	−0.247	−0.309	−1.612	−1.427
	(0.351)	(0.367)	(1.398)	(1.234)
Year FE	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓
Observations	132,200	129,680	84,220	129,680
Pseudo R^2	0.181	0.229	0.465	0.512
Adjusted Pseudo R^2	0.090	0.209	0.465	0.512

Notes: This table shows the moderating effects of an actor's network connections. The dependent variable is an actor's yearly movie output in Column (1), rating weighted yearly movie output in Column (2), revenue weighted yearly movie output in Column (3), and votes weighted yearly movie output in Column (4). Actor % 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 WA-1. 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 D2 reports the results of interacting the treatment variable with proxies for an actor's accumulated experience. We utilize four cumulative measures to capture this experience: cumulative movie output (Column 1), rating-weighted output (Column 2), revenue-weighted output (Column 3), and votes-weighted output (Column 4). All moderators are measured one year prior to the death shock

Across all four specifications, the coefficient on the interaction term is positive and statistically significant. For example, in Column (1), the interaction term between Postdeath$_{it}$ and the actor's cumulative movie output is 0.086 ($p < 0.01$). Given that the baseline treatment effect of Postdeath$_{it}$ is negative (−0.858), this positive interaction indicates that the negative impact of losing a connection is attenuated as an actor's experience increases.

This pattern holds consistent across the quality-adjusted measures reported in Columns (2) through (4). The positive interaction coefficients suggest that actors who have accumulated a larger stock of professional capital, whether measured by output volume, critical reception, box office success, or audience popularity, are more resilient to the loss of a specific connection. We

acknowledge that these metrics are likely correlated; however, the stability of the estimates across specifications confirms that the buffering effect of experience is robust to how 'established status' is defined.

These findings provide corroborating evidence for the hypothesis of diminishing returns to network size. Since accumulated work experience is highly correlated with the size of an actor's professional network, the results imply that the marginal value of a single connection is highest for less-established actors. Conversely, for experienced actors with broader networks, the loss of any single connection represents a smaller proportional shock to their overall career prospects.

Table D2: **Heterogeneous Treatment Effects (Actor Experience)**

	Dependent variable:			
	# Movie			
	(1)	(2)	(3)	(4)
Postdeath_{it}	-0.858^{***}	-0.849^{***}	-0.819^{***}	-0.968^{***}
	(0.054)	(0.053)	(0.058)	(0.083)
$\text{Postdeath}_{it} \times \text{Cum. \# Movies}_i$	0.086^{***}			
	(0.010)			
$\text{Postdeath}_{it} \times \text{Cum. Ratings}_i$		0.112^{***}		
		(0.013)		
$\text{Postdeath}_{it} \times \text{Cum. Revenue}_i$			0.133^{***}	
			(0.017)	
$\text{Postdeath}_{it} \times \text{Cum. Votes}_i$				0.214^{***}
				(0.033)
$\text{Cum. \#movie}_{it-1}$	-0.308^{***}	-0.279^{***}	-0.265^{***}	-0.265^{***}
	(0.064)	(0.062)	(0.062)	(0.061)
$\text{Cum. rating weighted \#movie}_{it-1}$	0.233^{***}	0.206^{***}	0.218^{***}	0.219^{***}
	(0.059)	(0.058)	(0.057)	(0.056)
$\text{Cum. revenue weighted \#movie}_{it-1}$	-0.001	-0.001	-0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
$\text{Cum. votes weighted \#movie}_{it-1}$	-0.007	-0.008	-0.010^{*}	-0.011^{**}
	(0.005)	(0.005)	(0.005)	(0.005)
$\text{Average \#movie}_{it-1}$	0.052^{*}	0.041	0.039	0.039
	(0.031)	(0.031)	(0.032)	(0.032)
$\text{Average rating weighted \#movie}_{it-1}$	-0.052^{*}	-0.042	-0.054^{*}	-0.053^{*}
	(0.029)	(0.030)	(0.031)	(0.031)
$\text{Average revenue weighted \#movie}_{it-1}$	0.003	0.003	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
$\text{Average votes weighted \#movie}_{it-1}$	0.004	0.005	0.006^{*}	0.006^{*}
	(0.003)	(0.003)	(0.003)	(0.003)
Age 10-19	0.757^{***}	0.757^{***}	0.740^{***}	0.751^{***}
	(0.110)	(0.110)	(0.110)	(0.110)
Age 20-24	1.702^{***}	1.703^{***}	1.677^{***}	1.691^{***}
	(0.127)	(0.127)	(0.127)	(0.127)
Age 25-29	2.113^{***}	2.115^{***}	2.082^{***}	2.097^{***}

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Table D2 – continued from previous page

	(1)	(2)	(3)	(4)
	(0.141)	(0.141)	(0.141)	(0.141)
Age 30-34	2.158***	2.161***	2.123***	2.138***
	(0.155)	(0.155)	(0.155)	(0.155)
Age 35-39	2.088***	2.091***	2.054***	2.068***
	(0.171)	(0.171)	(0.171)	(0.171)
Age 40-44	2.011***	2.015***	1.972***	1.983***
	(0.186)	(0.186)	(0.186)	(0.186)
Age 45-49	1.882***	1.885***	1.837***	1.845***
	(0.204)	(0.204)	(0.204)	(0.205)
Age 50-54	1.746***	1.749***	1.709***	1.714***
	(0.222)	(0.222)	(0.223)	(0.223)
Age 55-59	1.521***	1.528***	1.499***	1.503***
	(0.242)	(0.242)	(0.243)	(0.243)
Age 60-64	1.201***	1.209***	1.183***	1.186***
	(0.265)	(0.265)	(0.265)	(0.266)
Age 65-69	0.958***	0.966***	0.944***	0.943***
	(0.285)	(0.285)	(0.286)	(0.286)
Age 70-74	0.523*	0.533*	0.516*	0.511*
	(0.308)	(0.308)	(0.309)	(0.309)
Age 75+	−0.219	−0.209	−0.224	−0.232
	(0.350)	(0.350)	(0.351)	(0.351)
Year FE	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓
Observations	132,200	132,200	132,200	132,200
Pseudo R^2	0.183	0.183	0.182	0.181
Adjusted Pseudo R^2	0.092	0.092	0.091	0.091

Notes: This table reports heterogeneous treatment effects. Columns (1)–(4) interact the treatment indicator with the actor's cumulative movie count, as well as their rating-, revenue-, and vote-weighted movie counts, respectively. All moderating variables are measured one year prior to the death shock. Standard errors are reported in parentheses and clustered at the actor level. ***p<0.01; **p<0.05; *p<0.1.

E Construction of Referral Propensity Variable

In this section, we detail the construction of the *Referral Propensity* variable. This variable is designed to capture a deceased director or producer's tendency to facilitate job opportunities for actors within their professional network (i.e., a "friends-of-friends" effect). We define this measure as the proportion of actors directly connected to the deceased individual who subsequently appeared in films led by that individual's professional peers (directors/producers), provided those actors had no prior direct connection to those peers.

We calculate this measure for each deceased producer/director (denoted as P) who passed away

in year T. We index time by t, where $t = 1$ corresponds to the beginning of our sample period and $t = T$ corresponds to the year of P's death.

Definitions and Notation

For the deceased professional (either a director or a producer) P, we define the following sets for each year $t \in \{1, ..., T\}$:

- Let $\mathcal{A}_t = \{\text{Actor}_{t,1}, \text{Actor}_{t,2}, ..., \text{Actor}_{t,N_t}\}$ denote the set of actors who formed a *new* connection with P in year t, and N_t denote the number of newly connected actors in year t.
- Let $\mathcal{D}_t = \{\text{PD}_{t,1}, \text{PD}_{t,2}, ..., \text{PD}_{t,M_t}\}$ denote the set of producers and directors who formed a *new* connection with P in year t, and M_t denote the number of newly connected producers/directors in year t.
- Let Ω_t denote the *cumulative* network of producers and directors connected to P up to year t. This is defined as the union of all new connections from year 1 to t:

$$\Omega_t = \bigcup_{k=1}^{t} \mathcal{D}_k$$

Identifying Referrals

We define a "referral" event based on whether an actor connected to P secures a role with a member of P's established producers/directors network, Ω_t. Crucially, to distinguish a referral from a direct network effect, we restrict this definition to producers/directors with whom the actor had no prior direct connection.

Consider a specific actor $a \in \mathcal{A}_t$ (an actor who connected with P in year t). We verify if this actor collaborated with P's network in subsequent years. For any year q such that $t \leq q < T$, we define the referral indicator function $r(a, \Omega_q)$ as follows:

$$r(a, \Omega_q) = \begin{cases} 1 & \text{if actor } a \text{ appears in a movie directed/produced by any } d \in \Omega_q \\ & \text{during the period } (q+1, T], \text{ and actor } a \text{ has never worked with } d \text{ before.} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Essentially, this indicator takes a value of 1 if the actor a, after establishing a connection with P in t, subsequently works with a director or producer belonging to P's network, Ω_q, for $t \leq q < T$, provided that a and d were not directly connected prior to this collaboration.

We then aggregate these indicators to determine if the actor *ever* received a likely referral during P's lifetime. We define the actor-specific success indicator S_a:

$$S_a = \mathbb{1}\left(\sum_{q=t}^{T-1} r(a, \Omega_q) > 0\right)$$

where $\mathbb{1}(\cdot)$ is the indicator function. S_a equals 1 if the actor a successfully collaborated with P's friends-of-friends network at least once after connecting with P, and 0 otherwise.

Referral Propensity Calculation

Finally, the *Referral Propensity* (RP_P) for the deceased producer/director P is calculated as the total number of connected actors who received a referral divided by the total number of unique actors connected to P over their career (up to year T):

$$RP_P = \frac{\sum_{t=1}^{T} \sum_{a \in \mathcal{A}_t} S_a}{\sum_{t=1}^{T} N_t}$$

This ratio provides a standardized measure of P's efficacy or willingness to refer their connected actors to their broader professional network. A higher RP_P indicates that a larger percentage of actors connected to P successfully transitioned to working with P's former collaborators. The regression results using this measure of referral propensity are reported in Column (3) of Table 4.

Alternative Definition of Referral Propensity

To ensure the robustness of our mechanism analysis, we constructed an alternative definition of the referral propensity variable. While the baseline measure captures the cumulative likelihood of an actor receiving a referral at any point during a producer/director's career, this alternative approach focuses on the average yearly intensity of referral activities. Specifically, rather than calculating a single lifetime probability for each actor, this method computes a referral rate for each active year of the producer/director and calculates the average over their career. This ensures that our measure reflects the producer/director's consistent tendency to refer actors to others over time.

We define the Referral Propensity for a professional A (either a director or a producer) by calculating the rate of successful referrals within their network for each year t, and then averaging these rates over the professional's active years. Let T be the year professional A dies (or the end of the observation period). For any given year t (where $2 \leq t \leq T$), we define the following sets and variables:

- Let $\mathcal{P}_{t-1}$ denote the set of all producers and directors connected to A up to year $t-1$.
- Let $\mathcal{A}_{t-1}$ denote the set of all actors connected to A up to year $t-1$.
- Let $|\mathcal{A}_{t-1}|$ be the total count of actors in this cumulative set (equivalent to $\sum_{i=1}^{t-1} N_i$).

Referral Event (R_t)

We define R_t as the number of actors from the pre-existing network ($\mathcal{A}_{t-1}$) who appeared in at least one movie directed or produced by a member of the pre-existing producer/director network ($\mathcal{P}_{t-1}$) during year t, provided that the actor had no prior direct connection with that specific producer or director.

Yearly Referral Propensity (p_t)

The referral propensity for year t is defined as the share of the existing actor network that secured a "referral" job (as defined above) in that year:

$$p_t = \frac{R_t}{|\mathcal{A}_{t-1}|} \tag{3}$$

Aggregate Referral Propensity (RP_A)

The final Referral Propensity for professional A is the unweighted average of the yearly propensities over the period from year $t = 2$ to T:

$$RP_A = \frac{1}{T-1}\sum_{t=2}^{T} p_t = \frac{1}{T-1}\sum_{t=2}^{T}\left(\frac{R_t}{|\mathcal{A}_{t-1}|}\right) \tag{4}$$

The corresponding regression results are presented in Table E1. Again, we find that the interaction term between the treatment and the alternative referral propensity measure is negative and statistically significant. This indicates that the negative impact of a connection loss is more severe when the deceased director or producer had a higher historical tendency to refer actors to their network, thereby providing further support for the referral mechanism.

Table E1: **Robustness Check: Alternative Referral Propensity (Method 2)**

	Dependent variable:
	#Movie
	(1)
Postdeath_{it}	-0.279^{***}
	(0.053)
$\text{Postdeath}_{it} \times \text{Referral Propensity (Method 2)}_i$	-4.164^{***}
	(0.885)
Cum. $\#\text{movie}_{it-1}$	-0.275^{***}
	(0.062)
Cum. Rating w. $\#\text{movie}_{it-1}$	0.234^{***}
	(0.056)
Cum. Revenue w. $\#\text{movie}_{it-1}$	-0.002
	(0.004)
Cum. Votes w. $\#\text{movie}_{it-1}$	-0.006
	(0.005)
Average $\#\text{movie}_{it-1}$	0.048
	(0.032)
Average Rating w. $\#\text{movie}_{it-1}$	-0.063^{**}
	(0.030)
Average Revenue w. $\#\text{movie}_{it-1}$	0.004

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Table E1 – continued from previous page

	(1)
	(0.003)
Average Votes w. #movie$_{it-1}$	0.004
	(0.004)
Age 10-19	0.752***
	(0.110)
Age 20-24	1.698***
	(0.127)
Age 25-29	2.105***
	(0.141)
Age 30-34	2.150***
	(0.155)
Age 35-39	2.083***
	(0.171)
Age 40-44	1.999***
	(0.186)
Age 45-49	1.863***
	(0.205)
Age 50-54	1.720***
	(0.223)
Age 55-59	1.500***
	(0.243)
Age 60-64	1.176***
	(0.266)
Age 65-69	0.922***
	(0.286)
Age 70-74	0.479
	(0.310)
Age 75+	−0.292
	(0.352)
Year FE	✓
Actor FE	✓
Observations	132,200
Pseudo R^2	0.181
Adjusted Pseudo R^2	0.090

Notes: This table reports the regression results using the alternative definition of referral propensity (Method 2). Standard errors are in parentheses and clustered at the actor level. ***p<0.01; **p<0.05; *p<0.1.

Web Appendix A Complete Set of Coefficients

Table WA-1: **Main Results, Heterogeneity, and Robustness Checks with Complete Set of Coefficients**

	Dependent variable:						
	#Movie						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Postdeath_{it}	-0.474^{***}	-0.208^{***}	-0.665^{***}	-0.408^{***}	-0.222^{***}	-0.536^{***}	-0.511^{***}
	(0.036)	(0.052)	(0.055)	(0.037)	(0.042)	(0.035)	(0.056)
$\text{Postdeath}_{it} \times \text{Casting Director}_{i}$				-0.257^{***}			
				(0.083)			
$\text{Postdeath}_{it} \times \text{Years after shock}_{it}$					-0.078^{***}		
					(0.010)		
Cum. $\#\text{movie}_{it-1}$	-0.271^{***}	-0.339^{***}	-0.225	-0.274^{***}	-0.269^{***}		-0.273^{***}
	(0.061)	(0.064)	(0.138)	(0.061)	(0.062)		(0.063)
Cum. rating weighted $\#\text{movie}_{it-1}$	0.231^{***}	0.214^{***}	0.330^{***}	0.232^{***}	0.228^{***}		0.230^{***}
	(0.056)	(0.053)	(0.125)	(0.056)	(0.057)		(0.058)
Cum. revenue weighted $\#\text{movie}_{it-1}$	-0.002	0.001	-0.015	-0.001	-0.002		-0.001
	(0.004)	(0.005)	(0.009)	(0.004)	(0.004)		(0.004)
Cum. votes weighted $\#\text{movie}_{it-1}$	-0.007	-0.011^{*}	0.006	-0.006	-0.008		-0.010^{*}
	(0.005)	(0.006)	(0.013)	(0.005)	(0.005)		(0.005)
Average $\#\text{movie}_{it-1}$	0.045	0.101^{***}	-0.059	0.048	0.044		0.044
	(0.032)	(0.035)	(0.054)	(0.032)	(0.033)		(0.035)
Average rating weighted $\#\text{movie}_{it-1}$	-0.061^{**}	-0.052	-0.172^{***}	-0.063^{**}	-0.064^{**}		-0.075^{*}
	(0.031)	(0.035)	(0.054)	(0.030)	(0.032)		(0.040)
Average revenue weighted $\#\text{movie}_{it-1}$	0.004	0.002	0.015^{**}	0.003	0.004		0.003
	(0.003)	(0.004)	(0.007)	(0.003)	(0.003)		(0.003)
Average votes weighted $\#\text{movie}_{it-1}$	0.004	0.010^{***}	-0.018	0.004	0.004		0.005
	(0.004)	(0.003)	(0.013)	(0.004)	(0.004)		(0.004)
Age 10-19	0.754^{***}	0.575^{***}	0.951^{***}	0.770^{***}	0.734^{***}		0.718^{***}
	(0.110)	(0.185)	(0.139)	(0.109)	(0.109)		(0.108)
Age 20-24	1.698^{***}	1.503^{***}	1.939^{***}	1.712^{***}	1.666^{***}		1.646^{***}
	(0.127)	(0.209)	(0.164)	(0.126)	(0.126)		(0.125)
Age 25-29	2.103^{***}	1.897^{***}	2.357^{***}	2.115^{***}	2.060^{***}		2.038^{***}
	(0.141)	(0.225)	(0.187)	(0.140)	(0.140)		(0.140)
Age 30-34	2.147^{***}	1.888^{***}	2.407^{***}	2.157^{***}	2.095^{***}		2.069^{***}
	(0.155)	(0.241)	(0.211)	(0.155)	(0.154)		(0.154)
Age 35-39	2.079^{***}	1.759^{***}	2.359^{***}	2.090^{***}	2.029^{***}		2.009^{***}
	(0.171)	(0.260)	(0.235)	(0.170)	(0.170)		(0.170)
Age 40-44	1.995^{***}	1.593^{***}	2.345^{***}	2.005^{***}	1.951^{***}		1.927^{***}
	(0.186)	(0.278)	(0.260)	(0.185)	(0.185)		(0.186)
Age 45-49	1.855^{***}	1.432^{***}	2.199^{***}	1.868^{***}	1.811^{***}		1.788^{***}
	(0.205)	(0.303)	(0.288)	(0.204)	(0.204)		(0.205)

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Table WA-1 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age 50-54	1.715***	1.233***	2.113***	1.720***	1.676***		1.657***
	(0.223)	(0.326)	(0.316)	(0.223)	(0.222)		(0.223)
Age 55-59	1.499***	1.023***	1.902***	1.503***	1.468***		1.440***
	(0.243)	(0.353)	(0.344)	(0.242)	(0.242)		(0.243)
Age 60-64	1.176***	0.547	1.705***	1.183***	1.158***		1.136***
	(0.266)	(0.386)	(0.375)	(0.265)	(0.265)		(0.266)
Age 65-69	0.926***	0.297	1.470***	0.924***	0.906***		0.890***
	(0.286)	(0.414)	(0.404)	(0.285)	(0.286)		(0.287)
Age 70-74	0.487	−0.298	1.148***	0.498	0.471		0.461
	(0.309)	(0.451)	(0.436)	(0.309)	(0.309)		(0.310)
Age 75+	−0.274	−0.993**	0.397	−0.241	−0.267		−0.275
	(0.352)	(0.505)	(0.497)	(0.350)	(0.350)		(0.351)
Year FE	✓	✓	✓	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓	✓	✓	✓
Observations	132,200	37,880	94,320	132,200	132,200	132,200	132,200
Pseudo R^2	0.181	0.131	0.138	0.180	0.182	0.162	0.186
Adjusted Pseudo R^2	0.090	0.071	0.010	0.089	0.091	0.071	0.091

Notes: Column (1) presents our main treatment effect. Column (2) presents results for actors who have appeared in at least 3 movies before the death shock. Column (3) presents results for actors who appeared in less than 3 movies before the death shock. Column (4) investigates heterogeneous effects for casting directors. Column (5) investigates the temporal dynamics of the treatment effects. Column (6) reports estimates without any control variables (except for actor and year fixed effects). Column (7) reports estimates using the estimator proposed by Sun and Abraham (2021). Cum. #movie$_{it-1}$ represents actor i's cumulative movie output before year t. Cum. rating weighted #movie$_{it-1}$, Cum. revenue weighted #movie$_{it-1}$, and Cum. votes weighted #movie$_{it-1}$ represent actor i's cumulative rating-, revenue-, and votes-weighted movie output before year t. Average #movie$_{it-1}$ represents actor i's average yearly movie output before year t. Average rating weighted #movie$_{it-1}$, Average revenue weighted #movie$_{it-1}$, and Average votes weighted #movie$_{it-1}$ represent actor i's average yearly rating-, revenue-, and votes-weighted movie output before year t. All weighted measures are normalized by their sample means in each regression. ***p<0.01; **p<0.05; *p<0.1.

Table WA-2: **Mechanism Analysis with Complete Set of Coefficients**

	Dependent variable:					
	#Movie					
	(1)	(2)	(3)	(4)	(5)	(6)
Postdeath_{it}	-0.483^{***}	-0.357^{***}	-0.264^{***}	-0.581^{***}	-0.394^{***}	-0.643^{***}
	(0.037)	(0.044)	(0.045)	(0.119)	(0.054)	(0.156)
$\text{Postdeath}_{it} \times$ % Connection Change_i		-0.620^{***}				
		(0.130)				
$\text{Postdeath}_{it} \times \text{Referral Propensity}_i$			-6.337^{***}			
			(0.916)			
$\text{Postdeath}_{it} \times \text{AgeGap}_i$					-0.003^{*}	
					(0.0017)	
$\text{Postdeath}_{it} \times \text{Deceased P/D Age}_i$						0.003
						(0.0023)
Cum. $\#\text{movie}_{it-1}$	-0.281^{***}	-0.270^{***}	-0.273^{***}	-1.057^{***}	-0.268^{***}	-0.271^{***}
	(0.066)	(0.061)	(0.062)	(0.201)	(0.061)	(0.061)
Cum. Rating w. $\#\text{movie}_{it-1}$	0.246^{***}	0.225^{***}	0.230^{***}	0.907^{***}	0.230^{***}	0.232^{***}
	(0.060)	(0.056)	(0.057)	(0.198)	(0.056)	(0.055)
Cum. Revenue w. $\#\text{movie}_{it-1}$	-0.001	-0.002	-0.002	-0.049	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.047)	(0.004)	(0.004)
Cum. Votes w. $\#\text{movie}_{it-1}$	-0.007	-0.007	-0.008	0.065	-0.006	-0.007
	(0.006)	(0.005)	(0.005)	(0.040)	(0.005)	(0.005)
Average $\#\text{movie}_{it-1}$	0.049	0.043	0.046	-0.015	0.044	0.046
	(0.035)	(0.032)	(0.032)	(0.108)	(0.032)	(0.032)
Average Rating w. $\#\text{movie}_{it-1}$	-0.067^{**}	-0.056^{*}	-0.062^{**}	-0.199^{**}	-0.061^{**}	-0.062^{**}
	(0.034)	(0.031)	(0.030)	(0.082)	(0.031)	(0.031)
Average Revenue w. $\#\text{movie}_{it-1}$	0.003	0.004	0.004	0.057^{*}	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.033)	(0.003)	(0.003)
Average Votes w. $\#\text{movie}_{it-1}$	0.004	0.004	0.004	-0.050	0.004	0.004
	(0.004)	(0.004)	(0.003)	(0.037)	(0.004)	(0.004)
Age 10-19	0.757^{***}	0.761^{***}	0.746^{***}	1.352^{***}	0.772^{***}	0.753^{***}
	(0.112)	(0.110)	(0.110)	(0.322)	(0.110)	(0.110)
Age 20-24	1.699^{***}	1.703^{***}	1.689^{***}	2.502^{***}	1.725^{***}	1.697^{***}
	(0.129)	(0.127)	(0.127)	(0.399)	(0.127)	(0.127)
Age 25-29	2.097^{***}	2.107^{***}	2.095^{***}	3.015^{***}	2.134^{***}	2.103^{***}
	(0.144)	(0.141)	(0.141)	(0.455)	(0.142)	(0.141)
Age 30-34	2.129^{***}	2.149^{***}	2.140^{***}	3.117^{***}	2.181^{***}	2.147^{***}
	(0.158)	(0.156)	(0.155)	(0.511)	(0.156)	(0.155)
Age 35-39	2.068^{***}	2.077^{***}	2.074^{***}	3.116^{***}	2.114^{***}	2.080^{***}
	(0.175)	(0.171)	(0.171)	(0.571)	(0.172)	(0.171)
Age 40-44	1.994^{***}	1.990^{***}	1.991^{***}	3.274^{***}	2.030^{***}	1.996^{***}
	(0.190)	(0.186)	(0.186)	(0.637)	(0.187)	(0.186)
Age 45-49	1.844^{***}	1.851^{***}	1.858^{***}	3.010^{***}	1.888^{***}	1.857^{***}
	(0.210)	(0.205)	(0.205)	(0.693)	(0.206)	(0.205)

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Table WA-2 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)
Age 50-54	1.705***	1.715***	1.718***	3.097***	1.744***	1.717***
	(0.229)	(0.223)	(0.223)	(0.751)	(0.224)	(0.223)
Age 55-59	1.488***	1.503***	1.503***	3.097***	1.524***	1.500***
	(0.249)	(0.243)	(0.243)	(0.820)	(0.244)	(0.243)
Age 60-64	1.150***	1.182***	1.183***	2.951***	1.195***	1.177***
	(0.272)	(0.266)	(0.266)	(0.885)	(0.267)	(0.266)
Age 65-69	0.914***	0.935***	0.926***	2.867***	0.937***	0.925***
	(0.293)	(0.286)	(0.286)	(0.950)	(0.287)	(0.286)
Age 70-74	0.456	0.497	0.482	2.311**	0.492	0.485
	(0.317)	(0.309)	(0.310)	(1.016)	(0.310)	(0.310)
Age 75+	−0.283	−0.247	−0.285	1.394	−0.289	−0.275
	(0.361)	(0.351)	(0.352)	(1.164)	(0.353)	(0.352)
Year FE	✓	✓	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓	✓	✓
Observations	127,320	132,200	132,200	20,800	132,200	132,200
Pseudo R^2	0.182	0.181	0.181	0.141	0.181	0.181
Adjusted Pseudo R^2	0.090	0.090	0.091	0.001	0.090	0.090

Notes: Column (1) reports results where actors have only worked with the deceased producer/director once. Column (2) reports the moderating effect of the actor's network connection change. % Connection Change$_i$ represents the percentage change of actor i's network connections after the death shock. Column (3) explores the moderating effect of the deceased producer/director's referral propensity (i.e., likelihood of recommending connected actors to his friends' projects). Column (4) restricts the sample to actors who might not have the chance to appear in a connected project. Column (5) investigates the moderating effect of the age gap between the actor and the deceased producer/director. Column (6) interacts the treatment with the absolute age of the deceased producer/director to test if the effect is driven by the connection's age itself rather than the age gap. The definition of the control variables can be found in the table notes of Table WA-1. 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 WA-3: **Effect on Major Roles and Quality-Adjusted Output with Complete Set of Coefficients**

	Dependent variable:			
	#Major Role	#Rating-Movie	#Rev-Movie	#Vote-Movie
	(1)	(2)	(3)	(4)
Postdeath_{it}	-0.332^{***}	-0.509^{***}	-1.309^{***}	-1.151^{***}
	(0.057)	(0.038)	(0.198)	(0.168)
Cum. $\#\text{movie}_{it-1}$	-0.340^{***}	-0.042	-0.272	0.294
	(0.094)	(0.060)	(0.268)	(0.283)
Cum. Rating w. $\#\text{movie}_{it-1}$	0.285^{***}	0.010	0.228	-0.241
	(0.082)	(0.061)	(0.256)	(0.272)
Cum. Revenue w. $\#\text{movie}_{it-1}$	0.005	-0.001	0.008	0.027
	(0.009)	(0.004)	(0.019)	(0.017)
Cum. Votes w. $\#\text{movie}_{it-1}$	0.006	-0.006	-0.038^{*}	-0.099^{***}
	(0.008)	(0.006)	(0.022)	(0.019)
Average $\#\text{movie}_{it-1}$	0.028	0.137^{***}	-0.086	-0.356
	(0.035)	(0.030)	(0.244)	(0.302)
Average Rating w. $\#\text{movie}_{it-1}$	-0.010	-0.157^{***}	0.162	0.371
	(0.035)	(0.030)	(0.231)	(0.280)
Average Revenue w. $\#\text{movie}_{it-1}$	0.003	0.003	-0.034^{***}	-0.025^{**}
	(0.007)	(0.003)	(0.013)	(0.012)
Average Votes w. $\#\text{movie}_{it-1}$	0.002	0.003	0.010	0.013
	(0.007)	(0.004)	(0.008)	(0.010)
Age 10-19	1.114^{***}	0.726^{***}	0.586	0.377
	(0.216)	(0.113)	(0.487)	(0.362)
Age 20-24	2.204^{***}	1.640^{***}	1.007^{**}	0.970^{**}
	(0.241)	(0.130)	(0.506)	(0.412)
Age 25-29	2.697^{***}	2.027^{***}	1.138^{**}	1.166^{**}
	(0.262)	(0.145)	(0.548)	(0.453)
Age 30-34	2.678^{***}	2.061^{***}	1.066^{*}	1.081^{**}
	(0.285)	(0.160)	(0.593)	(0.499)
Age 35-39	2.500^{***}	2.011^{***}	1.089^{*}	1.154^{**}
	(0.310)	(0.177)	(0.655)	(0.556)
Age 40-44	2.269^{***}	1.928^{***}	1.128	1.033^{*}
	(0.334)	(0.193)	(0.708)	(0.597)
Age 45-49	2.115^{***}	1.784^{***}	0.874	0.744
	(0.363)	(0.213)	(0.783)	(0.669)
Age 50-54	1.807^{***}	1.656^{***}	0.608	0.627
	(0.397)	(0.232)	(0.843)	(0.735)
Age 55-59	1.596^{***}	1.412^{***}	0.360	0.263
	(0.424)	(0.254)	(0.935)	(0.819)
Age 60-64	1.275^{***}	1.102^{***}	0.087	-0.036
	(0.461)	(0.278)	(1.020)	(0.882)
Age 65-69	0.951^{*}	0.867^{***}	-0.112	-0.131

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Table WA-3 – continued from previous page

	(1)	(2)	(3)	(4)
	(0.495)	(0.300)	(1.165)	(1.024)
Age 70-74	0.538	0.419	−0.868	−0.649
	(0.535)	(0.323)	(1.257)	(1.104)
Age 75+	−0.311	−0.333	−1.612	−1.428
	(0.611)	(0.368)	(1.397)	(1.234)
Year FE	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓
Observations	58,200	129,680	84,220	129,680
Pseudo R^2	0.165	0.228	0.465	0.512
Adjusted Pseudo R^2	0.051	0.209	0.449	0.500

Notes: The dependent variable is an actor's number of major roles in Column (1), rating weighted yearly movie output in Column (2), revenue weighted yearly movie output in Column (3), and votes weighted yearly movie output in Column (4). The definition of the control variables can be found in the table notes of Table WA-1. 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.

Web Appendix B Other Robustness Checks

This appendix reports an additional set of robustness checks for our main results.

Placebo Tests

We implement two placebo tests to validate our identification strategy. First, although the staggered DiD results in Section 5.4.2 provide evidence of pre-treatment parallel trends, we further assess this assumption within our baseline DiD framework. Specifically, we restrict the sample to the pre-treatment period only; for each control actor, we define the pre-treatment window to mirror that of their matched treated actor. We then randomly assign each treated actor a placebo treatment date within this pre-period and re-estimate the baseline specification. If the design is sound, there should be no differential change in movie output between treated and control groups during this artificial pre-period. Consistent with this, Column (1) of Table WB-1 reports a placebo coefficient statistically indistinguishable from zero, indicating that our baseline effects are not driven by pre-existing trends.

Second, despite carefully implementing matching on a rich set of covariates and including extensive controls, it is still possible that residual unobservables could bias estimates. To assess this, we conduct a propensity-score placebo exercise. We estimate a logistic model for each actor's likelihood of experiencing a death shock using pre-shock characteristics and then simulate a placebo death-shock assignment among control actors with probability equal to each actor's estimated propensity. In this simulation, 5,003 control actors receive a placebo shock; we designate them as the treatment group and then re-run the full matching and estimation pipeline. As reported in Column (2) of Table WB-1, the resulting placebo treatment effect is statistically indistinguishable from zero, alleviating concerns that our findings are driven by unobserved differences between treated and control groups.

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

producer/director. Column (3) of Table WB-1 presents the results. The propensity score matching approach also yields a statistically significant and negative treatment effect ($\beta_1 = -0.475$, $p<0.01$), which is very close in magnitude to our baseline estimate of $\beta_1 = -0.474$. The consistency of these estimates across different matching methodologies provides additional support for the robustness of our main findings.

Retired Actors

Our estimated treatment effect may be biased if some treated actors were close to retirement when affected by the producer/director'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 976 treated actors (and their corresponding matched control counterparts), this amounts to 29.53% of the treated sample. The results in Column (4) of Table WB-1 show that even after excluding retired actors, the treatment effect remains statistically significant and negative. Non-retired actors experience a 32.90% (=exp(-0.399)-1) decline in movie output following a connection loss. The estimate is not statistically distinguishable from our baseline result (p = 0.158).

Retired or Unproductive Directors and Producers

Another related concern is that some producers/directors 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 226 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 (5) of Table WB-1 presents the results. The treatment effect becomes 39.16% (=exp(-0.497)-1). Although it is slightly larger than the treatment effect in our main regression (37.75%), they remain very close

and the difference is not statistically significant (p = 0.669). 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 (6) of Table WB-1, we replicate our results by excluding both retired actors and retired producers/directors. Our analysis still reveals a statistically significant and negative treatment effect, and the magnitude of the effect remains quite stable.

Year of Death

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 of whether a producer/director 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 (7) and (8) of Table WB-1, show that our main findings remain unchanged.

Sudden Deaths

A potential concern is that the impact of a death shock may depend on whether it was sudden or anticipated. For instance, a director or producer who passes away after a prolonged period of illness may have already scaled back their professional activities, potentially weakening their connection to actors prior to their death. In such cases, the death itself might represent less of a shock to the actor's network. If this is true, our baseline estimate, which includes all deaths, could be a conservative measure of the effect. To investigate this, we identify a subset of deaths that are likely to be sudden and unexpected. A death is classified as sudden if: (i) the cause is clearly abrupt (e.g., car accident, plane crash, etc.), or (ii) the deceased producer/director has more than one movie released posthumously, as this suggests they were actively working until their death. Based

on these criteria, we identified 191 sudden deaths out of the 698 cases.

We then re-estimate our main specification using only the subsample of actors affected by sudden deaths. As shown in Column (9) of Table WB-1, the treatment effect remains statistically significant and negative. The magnitude of this effect is not statistically distinguishable from our baseline estimate ($p = 0.264$), indicating that our main findings are not driven by a particular type of death shock and remain robust across different death circumstances.

Sampling Error

While we have used 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. To address this issue, we perform 1,000 iterations of the matching process and 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 -0.476, 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 0.035, with an SD of 0.0001. This provides evidence that our findings are not driven by random sampling errors.

Table WB-1: **Robustness Checks with Complete Coefficients**

	Dependent variable:								
	#Movie								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Postdeath$_{it}$	−0.033	−0.008	−0.475***	−0.399***	−0.497***	−0.431***	−0.331***	−0.521***	−0.394***
	(0.046)	(0.040)	(0.022)	(0.039)	(0.040)	(0.043)	(0.037)	(0.038)	(0.062)
Cum. #movie$_{it-1}$	−0.536***	−0.106***	−0.050***	−0.271***	−0.229***	−0.227***	−0.274***	−0.269***	−0.243**
	(0.121)	(0.036)	(0.016)	(0.059)	(0.074)	(0.072)	(0.061)	(0.062)	(0.096)
Cum. Rating w. #movie$_{it-1}$	0.295***	0.045	−0.017	0.182***	0.189***	0.144**	0.234***	0.228***	0.183**
	(0.113)	(0.030)	(0.017)	(0.052)	(0.069)	(0.066)	(0.056)	(0.056)	(0.083)
Cum. Revenue w. #movie$_{it-1}$	0.002	−0.004	−0.003	−0.001	−0.003	−0.004	−0.002	−0.002	−0.006
	(0.007)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Cum. Votes w. #movie$_{it-1}$	−0.010	−0.010	−0.004	−0.009	−0.004	−0.003	−0.007	−0.007	−0.004
	(0.008)	(0.007)	(0.004)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Average #movie$_{it-1}$	0.039	−0.001	0.021**	0.070**	0.022	0.047	0.046	0.045	0.069
	(0.036)	(0.005)	(0.010)	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)	(0.045)
Average Rating w. #movie$_{it-1}$	−0.091**	0.017	0.028***	−0.067*	−0.038	−0.036	−0.072**	−0.073**	−0.065
	(0.041)	(0.019)	(0.010)	(0.038)	(0.038)	(0.038)	(0.036)	(0.037)	(0.051)
Average Revenue w. #movie$_{it-1}$	0.001	0.005*	0.004*	0.004	0.006	0.006*	0.004	0.004	0.006
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)
Average Votes w. #movie$_{it-1}$	0.005	−0.004	−0.002	0.005	0.001	0.0001	0.004	0.004	0.004
	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)
Age 10-19	0.710***	1.101***	0.711***	0.639***	0.647***	0.584***	0.762***	0.748***	0.580***
	(0.128)	(0.097)	(0.061)	(0.123)	(0.118)	(0.130)	(0.110)	(0.109)	(0.178)
Age 20-24	1.619***	2.022***	1.557***	1.514***	1.535***	1.433***	1.712***	1.691***	1.481***
	(0.151)	(0.117)	(0.072)	(0.142)	(0.137)	(0.151)	(0.128)	(0.126)	(0.204)
Age 25-29	2.033***	2.316***	1.835***	1.905***	1.908***	1.794***	2.122***	2.091***	1.790***
	(0.166)	(0.132)	(0.080)	(0.156)	(0.153)	(0.167)	(0.142)	(0.140)	(0.228)
Age 30-34	2.109***	2.239***	1.835***	1.911***	1.917***	1.783***	2.170***	2.131***	1.797***
	(0.181)	(0.147)	(0.088)	(0.171)	(0.169)	(0.184)	(0.156)	(0.155)	(0.251)
Age 35-39	1.975***	2.032***	1.729***	1.824***	1.845***	1.712***	2.102***	2.063***	1.573***

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Table WB-1 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(0.197)	(0.163)	(0.096)	(0.188)	(0.188)	(0.203)	(0.172)	(0.170)	(0.277)
Age 40-44	1.781***	1.839***	1.619***	1.692***	1.729***	1.574***	2.018***	1.983***	1.452***
	(0.216)	(0.180)	(0.105)	(0.204)	(0.205)	(0.221)	(0.187)	(0.186)	(0.299)
Age 45-49	1.567***	1.648***	1.507***	1.539***	1.568***	1.408***	1.881***	1.842***	1.256***
	(0.240)	(0.200)	(0.115)	(0.225)	(0.226)	(0.244)	(0.205)	(0.204)	(0.329)
Age 50-54	1.329***	1.414***	1.349***	1.366***	1.379***	1.208***	1.741***	1.703***	1.008***
	(0.263)	(0.220)	(0.125)	(0.245)	(0.247)	(0.266)	(0.224)	(0.223)	(0.361)
Age 55-59	0.935***	1.142***	1.142***	1.169***	1.181***	1.032***	1.525***	1.488***	0.765*
	(0.290)	(0.242)	(0.136)	(0.267)	(0.270)	(0.290)	(0.244)	(0.243)	(0.396)
Age 60-64	0.478	0.783***	0.916***	0.792***	0.820***	0.636**	1.201***	1.171***	0.414
	(0.316)	(0.264)	(0.147)	(0.292)	(0.296)	(0.319)	(0.266)	(0.265)	(0.435)
Age 65-69	−0.002	0.379	0.607***	0.572*	0.579*	0.411	0.951***	0.918***	0.039
	(0.343)	(0.285)	(0.159)	(0.314)	(0.318)	(0.342)	(0.287)	(0.286)	(0.466)
Age 70-74	−0.557	−0.190	0.217	0.113	0.109	−0.052	0.514*	0.482	−0.530
	(0.370)	(0.307)	(0.172)	(0.341)	(0.345)	(0.372)	(0.310)	(0.309)	(0.505)
Age 75+	−1.527***	−1.163***	−0.572***	−0.647*	−0.690*	−0.889**	−0.249	−0.275	−1.495***
	(0.415)	(0.347)	(0.193)	(0.389)	(0.393)	(0.425)	(0.353)	(0.351)	(0.579)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Actor FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	84,400	200,120	359,880	93,160	104,680	80,480	132,200	132,200	44,720
Pseudo R^2	0.177	0.196	0.191	0.181	0.185	0.186	0.180	0.181	0.189
Adjusted Pseudo R^2	0.055	0.083	0.119	0.101	0.096	0.104	0.089	0.090	0.102

Notes: We check the robustness of our main results by (1) testing the pre-treatment parallel assumption by running a placebo test; (2) running a propensity-score placebo that simulates death-shock assignments for control actors based on estimated propensities and re-estimates the full pipeline; (3) matching actors according to their propensity score of losing a connection; (4) focusing on actors who did not retire; (5) focusing on producers/directors who did not retire; (6) excluding actors and producers/directors who have retired; (7) using one year before the actual death-shock year as the treatment time; (8) using one year after the actual death-shock year as the treatment time; and (9) focusing on sudden deaths. The definition of the control variables can be found in the table notes of Table WA-1. 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.