Management Science

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http://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 66, No. 2, February 2020, pp. 958–978
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Star Turnover and the Value of Human Capital—Evidence from Broadway Shows

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Received: March 8, 2017
Revised: November 6, 2017; July 1, 2018
Accepted: July 8, 2018
Published Online in Articles in Advance: August 29, 2019

https://doi.org/10.1287/mnsc.2018.3177

Abstract. Theater shows routinely turn over actors in lead roles. Otherwise, the show stays the same, including the director, the script, other actors and, the physical theater environment. Even the lines performed do not change the set. Therefore, the theater provides a unique laboratory for assessing the value of human capital to an enterprise, a question that has been studied in other contexts, including the CEO value literature. We compare revenues, capacity, and ticket prices just before and just after transitions of top cast members. We also characterize the performers in various ways and control for the attributes of the show and for team characteristics. We find that decorated theater stars significantly affect the financial success of theater shows, supporting the MacDonald version of the superstar hypothesis. Movie stars and celebrities do not seem to affect ticket prices or show revenues. Teams and seasonal effects seem to matter as well.

History: Accepted by Renee Adams, finance.

Key Words: human capital • turnover • stars • theater shows

1. Introduction

The purpose of this paper is to assess the value of human capital in a tightly controlled experiment by using the theater as a laboratory. We also characterize individuals who are important to the enterprise using superstar theories.

Most people would agree that key players in an organization or a project (leaders or stars) provide significant value added. However, precise measurement of the value of human capital has been challenging. The main difficulty is that most enterprises are team efforts, and most personnel replacements take place in an ever-changing environment. These characteristics of the problem need to be controlled for by the econometrician. Thus, for example, the chief executive officer (CEO) literature in finance uses manager fixed effects or other indirect indications of a CEO impact.

In long-running theater shows, it is often the case that one actor replaces another, whereas the other actors, the director, the script, the set, and the physical theater stay the same. Even the lines the actor performs do not change. This setup allows us to identify whether key individuals matter to the success of a theatrical enterprise in a tightly controlled experiment. When we find that some actors do make a difference (as we indeed do), we map the type of actors who "matter" to characterizations drawn from the theoretical literature on stars. Rosen's (1981) seminal paper shows how stars can emerge, even without a substantial talent differential among players. Later work by Adler (1985) suggests that stars can arise without any talent differential at all, and MacDonald's (1988) model shows how stars may evolve in an environment where experimentation leads to a dynamic revelation of talent. We find that the addition of a "theater star"—that is, a highly decorated specialized professional—can allow a theater to both increase ticket prices and attract more people, thus leading to a significant increase in revenues. In some cases, we also find that the departure of a star has some economic significance. We interpret these findings as supporting MacDonald's (1988) version of superstars. On the other hand, movie stars and celebrities do not seem to add value to the show.

Our findings can inform other work on the value of stars and support other indirect evidence on the value of key players in diverse areas of human enterprise. In the CEO space, testing the star theories is more difficult, because typically all CEOs have had a long, successful career behind them, thus almost by definition conforming to the MacDonald (1988) "star" characterization. Also, as discussed, the environments in which CEO replacements take place are less tightly controlled than ours. However, Malmendier and Tate (2009) find that media-driven "superstar CEOs" have negative effects on their respective firms. One might assume that these people are closer to Adler (1985)-type stars (i.e., people who do not have more talent than others but have good public relations), and thus their findings are consistent with our findings. Our framework can also provide some evidence for the star compensation debate, initiated by Rosen (1981) and extensively discussed in later work in different contexts—for example, in the Gabaix and Landier (2008) contribution to the CEO literature.

Additional results in this paper speak to the importance of teamwork, which has been a central theme of many studies in economics finance and strategy.

Naturally, the role of human capital varies between enterprises, and there are limitations as to how much one can generalize from one experiment to another. However, we believe our experiment is important because we show that, once you measure human capital in a tightly controlled environment, key players in an organization matter, even if they do not have much leeway in what they can do (plays are scripted). We may infer that key players in other settings who have more leeway (such as CEOs) should matter even more, and the reason for some mixed results in the literature may be the inability to control for many confounding factors.

2. Empirical Literature Review and Our Contribution

There is an extensive literature that seeks to assess the value of human capital in various settings, by using a variety of methods. We will discuss some of the relevant papers below.

In finance, much of the work on the value of human capital focuses on CEOs and on managers in general. Firms have thousands of employees and numerous moving parts, and they function in a constantly changing environment. Therefore, assessing the marginal contribution of a CEO (or a chief financial officer [CFO]) to any measure of firm performance or strategy is a challenge. Ideally, one would want to run the firm with one CEO, then roll back time, and run the firm through the same environment and challenges with another CEO. This is, of course, impossible; however, the experiment in our paper is close to this idealized setting. In the CEO realm, Bertrand and Schoar (2003) study a sample of more than 500 managers who switch firms (appear at least twice in the sample and stay at least three years at each job). Bertrand and Schoar (2003) use managers' fixed effects (as managers transition from one firm to another) to discern the impact of CEOs/CFOs and other managers on enterprise value and policies, such as capital structure, acquisitions, dividend policies, and cash holdings, as well as firm performance as measured by Tobin's Q and return on assets. Bertrand and Schoar (2003) use time-varying firm controls to explain the remaining variation. The paper shows that managers' fixed effects are significant in determining firm value and policies and have a substantial explanatory power. Although they caution against causal interpretation, Bertrand and Schoar (2003) conclude that CEOs matter. Bertrand and Schoar (2003) also relate managerial effects to CEOs' personal characteristics (specifically, MBA degrees and age), an approach that we can follow in classifying our actors according to star theories (see also Fee et al. 2013, for a different take on CEO value to organizations). Graham and Qiu (2012) show that managerial fixed effects account for much of the variation in management compensation. Adams et al. (2005) show that various types of CEOs affect variability in returns. They consider CEO power. A CEO is "powerful" if she or he is a founder, she or he is the only insider on the board, or holds multiple titles. Power measures are shown to have ambiguous (differential) effects on firm performance, but they all increase the volatility and variability of returns.

Other work on CEOs uses other indirect measures, exploiting life histories or significant events in the life of a CEO to estimate indirect effects of CEO effectiveness (see Bernile and Rau 2017 and Bennedsen et al. 2019). Schoar and Zuo (2017) find that the economic conditions when a CEO entered the labor market (turned 24) are very significant in determining career trajectory and firm decisions. Celerier and Vallee (2017) compute the return to talent, as measured by the success in the vetting process of the French engineering Grandes Ecoles and find that finance provides much greater returns to talent than other professions. Böhm et al. (2017), on the other hand, do not find such an effect for Swedish CEOs ranked by extensive army test scores. Sweden drafted (and tested) all men born between 1901 and 2010, when the draft was abolished.

Adams et al. (2018) also use Swedish army test scores. Their analysis shows that CEOs are at the top 17% in cognitive ability, the top 8% in noncognitive ability, and the top 26% in height. However, CEO pay, in particular for the largest firms, exceeds any value added that can be attributed to these characteristics and correlates more with firm size. In a sense, they agree with Gabaix and Landier (2008), who provide a model analyzing "star CEOs" outsized pay when firms grow. Malmendier and Tate (2009) find that media-driven star CEOs have negative effects on their respective firms, which in some ways supports our findings that "visibility stars" (people with more visibility than relevant talent) do not help a show. As noted, the empirical testing in all the settings we have surveyed so far has been challenging, because in most cases, the agents in question are part of large organizations, and there are numerous confounding factors that need to be controlled for and quantified. Other papers in the finance space consider the effect of "star analysts" on firms (see Groysberg et al. 2008 and Baghai et al. 2017) and show that talented individuals tend to leave firms as they approach financial distress.

In the creative arts realm, empirical work on the value of performers has been inconclusive. Hamlen (1991) measures voice quality and finds that singers with better voice quality seem to do better; however, the elasticity of record sales to an exogenously computed voice-quality measure is much less than one, presumably lower than Rosen (1981) would predict. On the other hand, Chung and Cox (1994) find that the distribution of gold records may be due to luck, applying the Yule distribution.

Much work has been done in the obvious area, namely, movies, where stars seem to be the name of the game. However, similar to the work on CEOs, the analysis falls short of an ideal experiment. The ideal experiment would be to present competing movies, identical in all respects, except for the lead actor. However, this is not possible (although this is what our experiment does in the theater). Thus, the best one can do in that space is to try some variety of fixed effects, controlling for anything else for which one can control. Ravid (1999) runs revenues and rates of return of movies as dependent variables and stars (defined as decorated actors or ones with previous economic success) as independent variables. He finds no effect of stars on the economic performance of movies. Other factors, such as budgets, genres, and critical reviews, do affect revenues and rates of return.

Other papers in this line of research (see De Vany and Walls 1999, Elberse 2007, McKenzie 2012, and others) find that movie stars, however defined, do not have much of an impact on revenues and rates of return of movie projects.

Elberse (2007) measures the value of stars by a pseudo-event study in the Hollywood stock exchange. She finds a very small increase in predicted revenues when stars join the cast. DeVany and Walls (1999) show most directly that one cannot use star presence or the hiring of individual stars to predict either rates of return or the probability of hits, although ex post, there are always some stars who are more successful than others. These studies implicitly support the notion of no visible talent differentials Adler (1985) or, alternatively, of complete rent capture (See Ravid 1999). However, it may be that the complex interactions of various elements of movie making confound the effects of individual actors on the success of the project.

The only study of the movie industry where stars do seem to add value is Filson and Havlicek (2018), where a departure of a key actor lowers the performance of the next installment in a franchise. This provides support for our view. Here, as in our case, the main elements of the franchise stay in place and one key player is switched; however, obviously sequels are different from each other in many ways (see Filson and Havlicek 2018 for a discussion; see Palia et al. 2008 for a discussion of sequel characteristics).

In another area, Mollick (2012) considers the role of various types of employees in game design firms. He uses a unique data set and follows individuals as they switch projects and firms. Mollick (2012) finds that individual producers and designers account for almost 30% of the variation in game revenues (using random effects), controlling for game-level predictors.

There are many attempts to quantify the value of human capital in other contexts. Again, an ideal experiment generally does not exist, but some work is able to carve interesting paths. Some of the most exciting new work in this area focuses on the impact of individual teachers on students' learning outcomes. Rockoff (2004) studies the effect of teachers on students' test scores using a teacher fixed effect model. Chetty et al. (2014a, b) consider the impact of teachers on students' outcomes. Chetty et al. (2014b) use a quasiexperimental design based on teacher turnover (this is similar to our approach that uses performers' transitions) and find that changes in students' lifetime outcomes (including the probability of attending college and the quality of college attended) are associated with variations in teachers' quality. We follow this creative idea, but our experiment is more tightly controlled, and the results are more direct and immediately observable. On the other hand, our institutional setting is very different. Finally, Engelberg et al. (2016) consider the assignment of pastors to churches in Oklahoma and find that individual pastors' ability can significantly affect attendance in Sunday services.

Our contribution, then, is to identify the value of an individual to an enterprise in a setting where the environment is inherently unchanged, and even what the individual does is tightly scripted.

3. Hypotheses and Research Design

3.1. Theories of the Value of Stars and Our Research Design

A good starting point for the characterization of the value added of key individuals is the labor literature beginning with Rosen (1981). Rosen's path-breaking paper suggests that stars are not necessarily individuals with significantly superior intrinsic talent, but that some characteristics of the demand and supply functions in question may award individuals with somewhat greater talent disproportionately high financial returns. In other words, people with very little additional talent can garner significantly higher payoffs. This lopsided outcome is a consequence of two phenomena—a willingness to pay that is convex in talent on the demand side (i.e., nontalented individuals are poor substitutes for talented ones) and a cost of performance that is invariant to the number of people in the audience. As a simple illustration, assume that there are only two performers, A and B. A is a bit more talented than B. For simplicity, we can assume a marginal cost of performance of zero per audience member (assuming that performances entail only fixed costs). If ticket prices to see both performers are equal, or possibly even if ticket prices for A's shows are higher, all members of the audience will prefer performer A. The result is that A will attract everybody, leading to very high payoffs (assuming she covers her fixed cost), and B will have no audience at all.

Rosen (1981)'s work has changed the way we think about the star phenomenon. From Rosen's paper, we take the implication that large financial rewards that define stars can be the result of only small differences in talent. Later work by Adler (1985) deepened the puzzle, suggesting that perhaps stars do not have any superior talent at all and that it is consumers' tastes that create them. In our previous example, assume that A and B are equally talented, but that all my friends go to see A. I thus obtain additional utility from joining my friends, and there is no reason for me to see B. From Adler's (1985) work, we take the implication that stars do not need to be more talented than other performers at all. MacDonald's (1988) dynamic model has a different take on the issue. He suggests that very-low-paid entry-level artists are compensated in equilibrium by a possibility of much higher returns should they turn out to be successful. In this model, neither early stage artists nor audiences know the identity of the talented artists ex ante. In period 1 of the two-period model, artists perform, and information about their talent is revealed. The less talented exit, and in period 2, the probability of a great performance is much higher. In other words, in MacDonald's (1988) world, the high observed payoff of stars (which occurs with a low probability) compensates actors for a high probability of accepting wages below their opportunity cost in period 1, finding out that they are not talented, and migrating to other professions. If we map MacDonald's model to a complex reality, it will translate to an ability revelation model, in which stars are people who, by a long process of elimination, turn out to be the best in their profession. In this framework, stars are very talented.[1]

Our analysis focuses on transitions between reasonably important cast members in theater shows. We look at various metrics of success just before and just after the change in cast. We also characterize the performers in various ways and control for the attributes of the show.

3.2. The Economic Setting and Hypotheses

The economics of theater transitions is very simple.

There is a monopoly element in theater shows (there is no other *Phantom of the Opera* or *Hamilton*), but it is probably more correct to think about shows as partial substitutes on the demand side. Thus, the demand curve for each show is presumably downward sloping, and so is the marginal revenue (MR) curve.

The supply (MC) curve is approximately horizontal (zero marginal cost per audience member) until we reach capacity, since it costs very little to fill an empty seat. At capacity, the marginal cost is essentially infinite (nobody else can be accommodated).

Assuming that shows are not sold out (it turns out that most of the shows in our sample sell below 100%),[2] the equilibrium quantity sold is determined by the point where the MR curve cuts the horizontal axis and the price is determined by the demand curve. If a star is added to the show and she shifts the demand curve out, then the MR curve shifts out as well, and a higher quantity (admissions) and a higher price (ticket price) are observed in equilibrium.

Similarly, if a star leaves a show, we expect a shift of the demand curve in the opposite direction.

This analysis assumes that theater owners observe the demand curve and that they are able to maximize profits. In reality, they may overshoot—increasing prices too much as a star joins the show and thus the observed quantity (number of tickets) may decrease, or when a star leaves, they may drop prices below the optimal level and observed admissions can actually increase. This can add noise to the analysis and lower the significance of our results.

Fortunately, our empirical analysis yields relatively clean findings.

Hypotheses. The hypotheses we test are then very simple:

Hypothesis H1 (Our Null Hypothesis). *Shows will perform equally well with all qualified performers (Adler 1985 or the empirical movie literature—for example, Ravid 1999, Elberse 2007).*

Hypothesis H2a. *Some types of performers will contribute more to the financial success of a show everything else equal. In particular, these performers can include celebrities with no discernible superior talent (confirming Adler 1985).*

Hypothesis H2b. *Some types of performers will contribute more to the financial success of a show, everything else equal. In particular, these performers are actors with somewhat greater talent (confirming Rosen 1981).*

Hypothesis H2c. *Some types of performers will contribute more to the financial success of a show, everything else equal. In particular, these performers are the most talented actors (confirming MacDonald 1988).*

There is a large body of literature on whether the presumed contribution of high-level players or stars can justify lopsided salaries starting with Rosen (1981), and these ideas were developed in two different research areas, namely, finance, and economics of the creative industries. In the creative industries, stars earn many millions of dollars for a movie or for a concert, whereas other artists work for practically nothing This bifurcation could not have had a more dramatic illustration than a recent rebellion against the actors' union (Equity) by Los Angeles Off Broadway actors demanding that they be allowed to work *below* the U.S. minimum wage rather than close their shows (Paulson 2015).

This protest took place practically at the doorsteps of Hollywood movie stars who make many millions of dollars for a few weeks of work. Similarly, the debate over "overpaid" CEOs and "underpaid" workers has been a recurring theme in the financial and general press.[3] We can discuss the issue further, but do not have sufficient data to answer this question directly from our experiment.

We note that even Hypothesis H1 does not suggest that every legal resident of the United States can act in every show. Landing a role in a prestigious Broadway show follows a rigorous audition process. Therefore, we expect most performers appearing on the Broadway stage to be qualified. We also assume that the audience can tell the difference between various performers and will reward them according to their tastes. However, if Hypothesis H1 is true, then the results will be consistent with the findings on movies. As discussed, Ravid (1999) and Elberse (2007), as well as De Vany and Walls (1999), find that star participation is not a predictor of the financial success of movies, which can be interpreted as a large available pool of interchangeable (or not ex-ante identifiable) qualified performers.

Adler's stars hypothesis, on the other hand (H2a), suggests that stars are "created" by the public as celebrities (perhaps people with TV experience, who are more recognizable by the general public), and audiences are willing to pay to see them on stage regardless of their "true" dramatic skills.

Hypotheses H2b and H2c suggest that it matters who the successful performers are. If they are somewhat talented, then we support Rosen's (1981) conjecture (H2b). If they are the "best" actors, this will tend to confirm MacDonald's (1988) hypothesis, which envisions a long vetting process, where only the most talented people end up in star positions (H2c). The distinction between somewhat talented and very talented is murky. However, we try to put empirical content into these characterizations by mapping actors with a theater background and accolades (theater stars) to "MacDonald stars." Actors with a movie background and accolades (movie stars) can be considered either "Rosen stars" (if you assume some but not perfect substitutability in theater and movie acting) or "Adler stars" if we only consider their fame. We map other successful performers (visibility stars) more directly to "Adler stars." We should note that a star hypothesis should suggest how stars are identified ex ante. Ex post, it is true (by definition) that some people will have done better than others (see De Vany and Walls 1999).

4. Data and Variables

4.1. Transitions

This paper considers all shows that opened between January 1, 1990, and January 1, 2013 (as covered in the database IBDb.com, a theater database) and had at least 150 performances. Our preliminary sample includes 215 shows. The reason for the cutoff is that in shows with less than 150 performances (with seven to eight shows per week, this means that the shortest run in our sample is about 20 weeks), there will rarely be any changes in the cast. Therefore, our sample essentially includes all shows with any transitions.[4]

The shows in our sample are reasonably successful, but not necessarily supersuccessful. The most successful show to date, *Phantom of the Opera*, has been running for more than 27 years, grossing as of 2014 more than $6 billion worldwide (Isherwood 2014). A show that runs for 20 weeks may not even cover its investment, keeping in mind that, unlike movies, theater shows involve a significant variable cost (per show, not per seat).

After identifying shows that ran for at least 150 performances, we use the website Playbillvault.com and look for the *Playbill* page image (see Appendix A). *Playbill* is the program distributed in the theater, and it describes the show and the actors who perform in it. In the page of "who is who" in the *Playbill* page image, we look for the first three featured actors.[5]

For example, for the long-running show *Mamma Mia*, the first actor to appear in *Playbill* for the opening night is Louise Pitre, playing Donna Sheridan. The second actor in the list is David Keeley, playing Sam Carmichael and the third is Tina Maddigan, playing Sophie Sheridan (see Appendix A for this page image). We should note that this method may omit a few important characters, but that should not affect our analysis unless these omitted character transitions are systematically different than the ones we are coding. Using the characters we identify, played by the three leading performers in *Playbill*, we find the performers who played them in the show, starting with the opening night cast. For example, as mentioned, Donna Sheridan (lead character in *Mamma Mia*) was played in the opening night by the actress Louise Pitre.

We then search for transitions—that is, changes in the cast occurring during the run. For example, Pitre performed from October 5, 2001 (the first day of the previews) until October 19, 2003. We now manually search IBDB.com for the replacement, in this example, for the actress who replaced Louise Pitre in October of

2003. We find that Dee Hoty replaced Louise Pitre and performed from October 19, 2003, to October 24, 2004.

After we identify a transition,[6] we look for several measures of economic performance around that date, including gross revenue, capacity use (i.e., the number of seats sold as percentage of the total number of seats available), and the average ticket price.[7] Weekly data are available from IBDB.com. We calculate the difference in gross revenues, average ticket price, and capacity for the three weeks before and three weeks after a transition. The transition week itself is excluded because it is a mix of both old and new performers. We later regress the type of transition and control variables on differences in economic performance.[8]

We then look for ways to identify the stars in our sample. We collect credentials of all performers involved in the transitions in several areas: theater, movies, and TV. Our theater credentials include information on (1) the number of Broadway shows in which the performer had participated by the time she or he joined the focal show,[9] (2) the number of Tony award nominations/wins the performer had earned by the time she or he joined the focal show, and (3) the number of other theater awards nominations/wins the performer had earned by the time she or he joined the focal show. We collect such information from Playbillvault.com and IBDB.com. We gather information on movie and TV credentials of performers from IMDb.com. These data include (1) the number of movies the performer had participated in by the time she or he joined the focal show, (2) the number of TV shows the performer had participated in by the time she or he joined the focal show, (3) the number of Oscar nominations/wins the performer had earned by the time she or he joined the focal show, and (4) the number of other screen awards nominations/wins the performer had earned by the time she or he joined the show. Because we only count the credentials until the time the performer joined the focal show, if a performer appears in several shows in our sample, she or he can be a "different person" in each show, depending on the number of awards and credits in between. In order to focus on professional credits that matter, we do not count appearances as "herself" in any movie or TV show. We do not count previous appearance in the same Broadway show as theater credits. We do not count shorts as movie credits. We do not count Razzies as screen awards.[10]

We try several characterizations of stars using movie awards and nominations, theater awards and nominations, theater credits, TV credits, and movie credits. Empirically, it turns out that only major awards matter.[11]

One of the issues in every test of the value of individuals within a group project is the question of proper matching or team performance. There is work on this issue in the creative industries (see Sorenson and Waguespack 2006, Cattani and Ferriani 2008, Shamsie and Mannor 2013) and in the CEO literature (see, for example, Matveyev 2017). In our case, we try to control for possible team complementarities using two variables. The first variable codes the case in which there is a cast change; in other words, several people leave a show together. Our industry sources suggest that this is not an unusual practice and the fact that cast changes occur often in our data also increases our confidence that most departures occur for exogenous reasons. If teamwork matters, then a transition involving a team may have more of an effect than a transition involving only one individual. We code a variable "cast change" as 1 if there is a cast change, and zero otherwise. We will explain below how we map cast changes into our star-transition categories.

Another possibility is that there is a team effect of people who had worked together previously. Because there are endless combinations, and following some discussions with theater professionals, we look for the director of each show where a transition is taking place. Then, we go to that director's page in IBDB.com to see if the director had worked on a different show with the same actor. We consider positions of directors, assistant directors, and associate directors in previous shows (prior to the current transition).[12] If the departing actor had participated in a previous show with the current director, our "old team" variable is coded as one; otherwise, it is zero. If the incoming actor had worked with the director before, then our "new team" variable has a value of one.[13]

We also collect variables that characterize the show—a dummy for whether the show is a musical or a straight play and a dummy for a revival versus a new production (IBDB.com). Another dummy characterizes seasonal effects. After observing the weekly grosses of Broadway shows in the last 20 years (our sample period), we find that there is a large jump in gross sales in the week between Christmas and New Year every year. Otherwise, there seem to be no discernable trends. For example, in 2011, the gross in the peak week was approximately $35 million, 3.26 SD from the mean of $20.786 million. It is also the only week where revenues exceeded the mean by more than 3 SD. For 40 weeks in a year, revenues were within 1 SD from the mean. For nine weeks, revenues were between 1 and 2 SD from the mean. For that reason, we thought that weekly fixed effects can mostly add noise—furthermore, we have weekly data, and the peak week is sometimes week 1 and sometimes week 52 of the year.

If a transition occurs within three weeks of this peak week, the change of gross revenue will be confounded by a seasonal effect. To address this concern, we use two dummies: "before-peak" and "after-peak," which identify the transitions that occur within a three-week window before or after the peak week, respectively.[14]

Finally, we create a dummy to indicate whether the show has won any award. Obviously, this variable is different than prior awards for the cast—it is just an indicator of the quality of the show itself (as opposed to being just an "audience pleaser"; by construction we do not have real failures in our data set). We also control for the number of years between the debut of the show and the time when the transition occurs, coding a variable "time of transition." We adjust all dollar figures to inflation using the annual consumer price index for the relevant year from the BLS.gov website. All dollar figures are in 2013 constant dollars.

As mentioned earlier, we clean up the data set by eliminating all transitions that occur within three weeks of each other because we cannot tell which of the transitions is related to the observed economic changes (if any). We also drop cases where performers were replaced for just a few days.

Some of the shows we started with did not have any transitions (in other words, the original cast played from the opening night until the show closed), and in other cases there were transitions, but we did not have data on transition dates or show performance. Also, multiple transitions occurring on the same day are consolidated to one transition (a cast change). We end up with 332 transitions involving 82 shows. We collected 707 performer-year combinations and 498 unique performers. All variable definitions are in Appendix C.

4.2. Definition of Stars

One of the main challenges we face is the definition of stars. We characterize three groups of performers as stars, roughly enabling us to test our hypotheses.

The first definition is of theater stars. These are the people who approximately match the MacDonald (1988) profile—that is, these are actors who have been vetted through the profession. In our main specification, we define theater stars as performers who had earned at least two Tony nominations by the time they joined the show. Tony Awards are considered the premium awards in the theater business. This definition identifies 64 out of 707 performer year combinations as theater stars. A total of 51 unique theater performers are identified as stars using this definition, out of a total of 498 performers.[15] We also tried other definitions, varying the number of Tony awards and nominations. We present the results for three Tony nominations in the paper. In other (unreported) tests, we use an alternative definition based upon the total number of theater awards received by the performer. Results remain similar to the results we report in the text.

The second type of stars we identify are "movie stars." Movie actors are in the same profession as theater actors, although acting in movies is quite different than acting in theater shows. More importantly, typically, movie stars are much more well known than theater stars and thus can fit more closely with the Rosen (1981) or Adler (1985) definitions. Specifically, we define movie stars as performers who had earned at least one Oscar nomination by the time they joined the show. This definition is consistent with prior literature (see for example, Ravid 1999 and Basuroy et al. 2003). Twenty-three performer-year combinations are identified as movie stars, and we identify 18 individual stars.[16] Again, we use various other definitions and awards for robustness checks.[17] There is some overlap between theater stars and movie stars, and we discuss this further below.

Finally, we define "well-known people" or celebrities. If it turns out that a "name" (somebody who is known from TV, writing or otherwise) is a draw, which is a common belief in the industry, this will be closer to the Adler (1985) definition. Specifically, we define "visibility stars" as the top 10% of performers in terms of the total number of appearances. As it turns out, this group includes all actors who have made at least 50 appearances in movies, TV shows, and Broadway shows. We identify 70 such performer-year combinations, including 57 distinct visibility stars.[18]

Once stars are identified, we can distinguish among three types of transitions for each star type: a type 1 transition is when nonstars are replaced by stars, a type 2 transition is when stars are replaced by nonstars, and a type 0 transition is when there is no change in the star status of the actors performing before and after the transition.

As discussed, sometimes, more than one person is replaced in a show.[19] We call such scenarios "cast transitions." We combine these changes into one record, and the transition type is determined by the overall direction of change among the cast members replaced and those who are coming in. Specifically, if the cast transition is a mixture of type1 change(s) and type 0 change(s), the cast transition is coded as a type 1 change. Similarly, if the mix is composed of type 2 change(s) and type 0 change(s), the cast transition is coded as a type 2 change. However, if the mix is composed of both type 1 change(s) and type 2 change(s), we code the transition as a type 3 change (unknown) and drop them from the analysis. These cases are very rare. We control for cast transitions in our regressions as well.

5. Analysis and Results

5.1. Summary Statistics and Means Comparisons

Table 1 shows the summary statistics of our data set. Gross change is the change in average weekly gross revenue between the three weeks prior to the transition to the three weeks following the transition, excluding the transition week. Ticket price change is the change in the average ticket price between these two periods, and capacity change is the change in the ratio of seats sold to the total seats available between the two periods.

Most of the transitions in our sample (91%) are in musicals. We find that 36% of the transitions are in revivals. In 22% of the cases, we have cast changes. The average transition in our sample occurs just over 4 years into the run, but the transitions span the lifetime of the shows we cover.

Table 1 shows that, on average, all transitions cause a drop in revenue, capacity, and ticket prices. We also see, however, that there is a significant variation among shows (high standard deviation). The capacity change is relatively small on average, consistent with the notion that, indeed, producers are trying to optimize capacity, and these aggregate statistics include cases where stars are added and cases where stars leave as well as cases where there is no change in star status.

We show the change in performance by transition type in Table 2 below. This table compares transitions when a nonstar replaces a nonstar, a star replaces a nonstar, and a nonstar replaces a star, according to various star definitions. Only theater stars seem to increase ticket prices, capacity, and revenues. When any type of star leaves the show, there seems to be a drop in revenues, ticket prices, and capacity utilization, but revenues seem to decline also when visibility stars or movie stars join the show. We should keep in mind that there are stars who are both theater stars and movie stars, and indeed the regression analysis below will show that this makes a difference.

5.2. Regression Analysis

We run a regression analysis with the performance change as the dependent variable and the type of transition as an explanatory variable, where the default is a nonstar-to-nonstar transition. We control for the year when the transition occurred, for team variables, and for seasonal effects. We run two types of controls for show characteristics. The baseline analysis is run with show fixed effects, which control for any observed and unobserved show features.[20] As a robustness check, we also run ordinary least squares (OLS) with standard errors clustered by shows, where we control for the type of show (musical versus play), whether the show is a revival, and whether the show itself had won any award (which is another proxy for overall quality).[21]

Our approach is similar to experiments in physical sciences because our environment is tightly controlled. In other ways, our approach is similar to event studies—some information comes in, and we observe a change in economic variables. However, in event studies we record changes in stock prices reflecting expectations

Table 1. Summary Statistics

	N	Unit	Mean	Standard deviation	Minimum	Maximum
Gross change	332	000 $	–22.10	156.89	–666.29	485.71
Ticket price change	331	$	–1.75	8.67	–38.10	23.34
Capacity change	331	Percent	–1.03	10.61	–38.56	26.80
Cast change	332	Dummy	0.22	0.42	0	1
Time of transition	332	Year	4.33	4.10	0.07	16.08
Nonstar to star	332	Dummy	0.05	0.22	0	1
Star to nonstar	332	Dummy	0.11	0.32	0	1
Musical	332	Dummy	0.91	0.29	0	1
Revival	332	Dummy	0.36	0.48	0	1
Award	332	Dummy	0.71	0.45	0	1
Before peak week	332	Dummy	0.05	0.22	0	1
After peak week	332	Dummy	0.09	0.29	0	1
Old team	332	Dummy	0.02	0.12	0	1
New team	332	Dummy	0.02	0.14	0	1

Notes. This table shows the summary statistics of our data set of 332 transitions. Stars in this table are theater stars (performers who have earned at least two Tony nominations by the time they join the show). Gross change is the change in average weekly gross revenues from three weeks before the transition to three weeks after the transition, in thousands of 2013 constant dollars. Ticket price change is the change in the average ticket price from three weeks before the transition to three weeks after the transition, in 2013 constant dollars. Capacity change is the change in average capacity used (percentage of seats sold) from three weeks before the transition to three weeks after the transition. Cast change is a dummy variable equal to 1 when it is a transition that involves changing multiple performers on the same day. Time elapsed from opening night is the number of years between the debut of the show and the time of the transition. Nonstar to star is a dummy variable equal to 1 if a nonstar is replaced by a star performer in the transition. Star to nonstar is a dummy variable equal to 1 if a star is replaced by a nonstar performer in the transition. Musical is a dummy variable equal to 1 if the show is a musical and 0 if the show is a straight play. Revival is dummy variable equal to 1 if the show is a revival of a previous show and 0 if it is a new production. Award is a dummy variable equal to 1 if the show has won any award. Old team is a dummy variable equal to 1 when the departing actor had participated in a previous show with the current director. New team is a dummy variable equal to 1 when the incoming actor had worked with the director before. Before peak week is a dummy variable equal to 1 if the transition occurs within the three weeks before peak week. After peak week is a dummy variable equal to 1 if the transition occurs within the three weeks after the peak week. Peak week is the week between Christmas and New Year's, when there is a huge jump in gross sales.

Table 2. Average Performance Changes by Transition Type for Different Types of Stars

	Theater star				Movie star				Visibility star			
	N	Gross change	Ticket price change	Capacity change	*N*	Gross change	Ticket price change	Capacity change	*N*	Gross change	Ticket price change	Capacity change
No change	276	−22.34	−1.58	−1.08	315	−17.49	−1.43	−0.68	283	−18.90	−1.45	−1.00
Nonstar to star	17	67.88	0.86	5.73	9	−66.94	−7.70	−5.55	23	−37.71	−3.48	−0.51
Star to nonstar	38	−62.76	−4.33	−3.86	7	−177.89	−8.95	−11.44	22	−28.96	−2.06	−1.43

Notes. This table compares the average of performance change for different types of transitions: when a nonstar replaces a nonstar (no change), a star replaces a nonstar and a nonstar replaces a star, according to various star definitions. Performance change is measured by gross change, ticket price change, and capacity change. Gross change is the change in average weekly gross revenues from three weeks before the transition to three weeks after the transition, in thousands of 2013 constant dollars. Ticket price change is the change in the average ticket price from three weeks before the transition to three weeks after the transition, in 2013 constant dollars. Capacity change is the change in average capacity used (percentage of seats sold) from three weeks before the transition to three weeks after the transition. *N* is the number of transitions by transition type.

and assessments of future cash flows, and here we measure a concrete and immediate economic impact.

Our analysis is also similar to Diff in Diff inasmuch as we observe changes due to a shock to the system. However, we are able to avoid some biases caused by omitted variables that could change after the transition because we keep all the important determinants of the show's economic success identical before and after the transition. Other actors, the director, the physical theater, the set, the music, and even the lines do not change. In Diff in Diff, an important required assumption is the "parallel trends" assumption, which says that in the absence of the treatment, the difference between the treated and nontreated groups would have stayed constant over time. Every paper in this area is careful to note that this assumption is difficult to verify. In other words, Diff-in-Diff can control for time-invariant variables before and after the shock, but it is quite likely that the control and treated groups are different in other ways that we cannot measure, and these omitted variables may affect the outcome and correlate with the treatment. In our setting, because the experiment is tightly controlled, the shows are long-running, and the outcomes are measured over a short period of time, the assumption that, absent the transition, the show would have continued exactly in the same way, is much more likely to hold.

Additionally, one may be concerned that an actor is replaced only if they fail. However, there are several reasons why we think that this may not be a major concern for our sample. First, all shows have succeeded by the time the replacement occurs. It is difficult to argue that the major stars of a successful show should be replaced because of failure (as noted we only consider long running shows). There are also no discernible trends in revenues prior to the transition—in 52% of the cases revenues increase between week −3 and week −2 (in 48% of the cases they decrease). The corresponding numbers between week −2 and week −1 are 51% (increases) and 49% (decreases). Secondly, empirically, the average impact of any replacement is negative (see below). If the average transition were a result of a failure, and show producers knew anything about the business, then the average outcome should have been positive.

To address this issue further, we look at the career of every actor who leaves a show in our sample. We check their IBDB page to see if they perform on Broadway (or in Broadway touring companies) again, and then check their IMDb page to find any TV or movie appearances. We conclude that somebody "worked again" if they performed in a show within 15 months (allowing a year + a rehearsal period) or if they had an IMDb entry the same year of the transition or the following year. Clearly, this is a crude measure, and it bundles together people who work continuously with people who have spells of unemployment. However, it is difficult to know when first readings of shows take place, or when a film or a TV show is actually shot. In other ways, however, this measure is severely biased against us, because we have no data on Off Broadway, regional theater performances, or performances overseas; for example, in London's West End. Most successful actors do appear in such venues sometime during their careers. For example, Carolee Carmello's (who is included in our sample and qualifies as a theater star) IMDB page shows her as "not having worked" since May of 2016, but she starred in a sold-out Off-Broadway show throughout 2017, with rehearsals beginning earlier. Furthermore, some of the musical theater stars perform in concerts—for example, Huey Lewis, who is included in our sample—and these appearances do not count as "worked again."

However, even our crude criterion shows that 90% of the actors worked again. This may lead to a question of whether stars only leave for a "better" job. We do not have salary data, and an actor may just get bored, but a Broadway lead is the best job in the theater business, and typically we see the actors who "worked again" leave for other, similar shows, or for movie or TV roles if they had been active in these areas before.

One may also be concerned that stars will only select into shows that match them best. However, if anything, it is theater stars who need work and may take shows just to keep on working, whereas movie stars, who generally view Broadway as a hobby, can be much more selective as to which show they appear in. Nevertheless, we find that theater stars increase revenues, and movie stars usually do not.

Also, there are several additional institutional factors that diminish possible endogeneity concerns. We learned that, typically, actors have a fixed contractual period, and should the show continue beyond that time, the contract needs to be renegotiated. Busy actors may already be committed to other projects and often cannot stay beyond the contract period, regardless of the success of the show. We have consulted several theater professionals and manually performed a press search for some replacements. We confirmed that, generally, departures were for exogenous reasons. Furthermore, because of the methodology for our sample construction, we did not use in our statistical analysis any transitions that occurred within three weeks of each other (see below). The latter should be a prime example of replacements because of failures—you come into a successful show, you underperform, and you are forced to leave. However, in the cases we checked, there was always a very legitimate reason for such replacements, either health (someone was hospitalized and could not continue in the play) or contractual (the reason for the short-term commitment was another, previous commitment for the same dates).[22] Thus, we are fairly comfortable with the view that the departures we observe are reasonably exogenous. Obviously, the show producers will try to find the best replacement for the role.

We should also note that if a transition is not a surprise (as is often the case), this should not be a problem. In fact, because most theater tickets are bought in advance of the performance (according to the Broadway League 2018 report, tickets for Broadway shows are bought on average 42 days before the performance date), a surprise is bad for our analysis. We are testing to see whether the inclusion of stars can lead to a better financial performance of a show. If, say, a star is replaced at a predetermined date by a nonstar and the theater goes empty, we prove our point. However, if the change is a surprise (say, if an actor is suddenly sick and is replaced by an understudy), then it is hard to draw conclusions because people may find out that their favorite star will not perform only when they are already in the theater, whereas all presales would have been based on the star's presence.

In Table 3 below, we test for any star effects for our main characterization of stars, following our three empirical classifications, essentially testing Hypotheses 1 and 2 within a regression framework.

The left panel in Table 3 shows that transitions from "theater nonstars" to theater stars (theater stars are performers who had earned at least two Tony nominations by the time of the transition) significantly improve the economic performance of a show relative to other transitions. Both capacity and ticket prices increase significantly, as do revenues. When we examine the data, we see that not only the means, but the medians reflect the superior performance of theater stars, where median capacity and revenue increase as a theater star enters and drop as they exit. These findings seem to support Hypothesis 2 and suggest that even for the successful shows in our sample, adding vetted theater stars can make a difference. Specifically, Table 3 seems to be consistent with the MacDonald version of the star phenomenon (H2c)—it is the most talented people, vetted through an external validation process (Tonys) who generate financial rewards. We should note that some people appear as "nonstars" in earlier years and as "stars" later on in the sample as their career evolves. Given that there are personal fixed effects, which are hard to capture, we are encouraged by the fact that the classifications we formed are empirically meaningful.

We cannot say whether the actors who add value capture all the rent available, but this is not critical to the argument (although it is important for the actors). The economic magnitudes of the changes associated with star inclusion are large—shows average about $750,000 per week in overall revenue, so the addition of a theater star can increase the weekly revenue by about 18%.

There are indications that teams matter—breaking up a team is costly, and cast changes seem to have a negative effect on show performance. It also seems that the time from the opening has an effect, but this effect is not easy to interpret. Seasonal effects matter, as expected. The before-peak dummy has a strong positive effect; the after-peak dummy has a strong negative effect because the seasonal effect works against the change in this case.

In the middle panel, we consider transitions involving movie stars (movie stars are performers who had earned at least one Oscar nomination by the time of the transition). Here, both types of transitions (from star to nonstar and from nonstar to star) have no significant effect on show performance. This again supports the MacDonald (1988) view of stars. It is the theater-specific talent or training that counts.[23] Interestingly, again, the cast change and team variables are significant in the same direction—that is, breaking

Table 3. Effects of Different Types of Star Transitions on Performance: Fixed Effects Models

	Theater star			Movie star			Visibility star		
	Gross change (1)	Ticket price change (2)	Capacity change (3)	Gross change (4)	Ticket price change (5)	Capacity change (6)	Gross change (7)	Ticket price change (8)	Capacity change (9)
Star to nonstar	31.572	3.146+	1.204	–67.141	–2.784	–3.378	–10.059	–1.494	2.103
	(37.412)	(1.806)	(2.474)	(73.875)	(3.558)	(4.898)	(39.116)	(1.883)	(2.541)
Nonstar to star	134.618**	5.997**	9.819**	29.225	2.968	4.648	9.547	–0.805	2.760
	(47.536)	(2.295)	(3.143)	(63.472)	(3.057)	(4.209)	(38.886)	(1.872)	(2.526)
Cast change	–56.796*	–3.055*	–4.614**	–41.968+	–2.362*	–3.832*	–41.320+	–1.989+	–3.930*
	(24.656)	(1.190)	(1.630)	(24.501)	(1.180)	(1.625)	(24.522)	(1.180)	(1.593)
Time of transition	62.582+	6.262***	–4.088+	57.614	5.881**	–4.354+	71.076+	6.650***	–3.756
	(36.279)	(1.752)	(2.399)	(36.653)	(1.765)	(2.430)	(37.073)	(1.784)	(2.408)
Old team	–262.613**	–13.242**	–11.058+	–265.312**	–12.971**	–11.419+	–274.876**	–13.045**	–12.875*
	(95.362)	(4.604)	(6.306)	(96.537)	(4.650)	(6.401)	(97.163)	(4.677)	(6.312)
New team	38.605	–1.796	2.377	31.852	–2.036	1.966	34.825	–2.172	2.469
	(76.785)	(3.707)	(5.077)	(77.945)	(3.754)	(5.168)	(77.918)	(3.750)	(5.061)
Before peak week	95.935*	1.449	8.894**	107.270*	1.603	9.800***	102.375*	1.762	7.848**
	(42.750)	(2.064)	(2.827)	(42.880)	(2.065)	(2.843)	(43.881)	(2.112)	(2.850)
After peak week	–226.298***	–11.821***	–12.704***	–226.586***	–11.822***	–12.699***	–229.800***	–11.903***	–13.132***
	(36.521)	(1.763)	(2.415)	(37.404)	(1.802)	(2.480)	(37.089)	(1.785)	(2.409)
Observations	332	331	331	332	331	331	328	327	327
R^2	0.324	0.385	0.256	0.304	0.369	0.229	0.308	0.377	0.228
Number of shows	82	82	82	82	82	82	82	82	82

Notes. This table shows show fixed effects regressions. Columns (1)–(3) show the regression results when stars are defined as theater stars. Columns (4)–(6) show the regression results when stars are defined as movie stars. Columns (7)–(9) show the regression results when stars are defined as visibility stars. Star definitions: theater stars, At least two Tony nominations; movie stars, at least one Oscar nomination; visibility stars, at least 50 screen and theater appearances. Star to nonstar equals 1 if the transition is from a star to nonstar. Nonstar to star equals 1 if the transition is from a nonstar to star. Gross change: change in average weekly gross revenues from three weeks before the transition to three weeks after the transition, in thousands of 2013 constant dollars. Ticket change: change in the average ticket price from three weeks before the transition to three weeks after the transition, in 2013 constant dollars. Capacity change: Change in average capacity used (percentage of seats sold) from three weeks before the transition to three weeks after the transition. Cast change equals 1 if the transition involves changing multiple performers on the same day. Before peak equals1 if the transition occurs within a three-week window before the peak week. After peak equals 1 if the transition occurs within a three-week window after the peak week. Time of transition: years between the opening night and the transition. New team equals 1 if the new performers have worked with the director before. Old team equals 1 if the old performers have worked with the director before. Time of transition is years between the opening night and the transition. All models include show fixed effects and year fixed effects. Standard errors are in brackets.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; $^+p < 0.10$.

up or a departure of a "team" are detrimental to the economic performance of a show.

Finally, we run an analysis with visibility stars visibility stars are performers who are at the top 10% in terms of the total number appearances in movies, TV shows, and Broadway shows (at least 50 appearances). As we see in the rightmost panel, neither type of transition has a significant effect on performance changes, suggesting that visibility stars do not affect the economic value of Broadway shows. This does not provide support to the Adler (1985) view of stars. As noted before, some of our theater and movie stars are included in the set of visibility stars. However, it is clear that the addition of the other actors to the list just creates noise that dampens the significant effects found for theater stars. Again, the team variables and seasonal effects matter.

Our analysis so far identifies theater stars as the value drivers in the industry, confirming the MacDonald (1988) characterization of stars (Hypothesis H2c). We also seem to show that other types of stars do not matter. We ran numerous other specifications of theater stars and results remained qualitatively similar.

The results make sense in the institutional context. Theater acting requires a different set of skills from movie or TV acting. First, the training is different. For example, New York University Tisch School of the Arts, with one of the most prestigious theater schools and a very good film department, has a very different curriculum for theater actors and professionals and for film students.

The blog Theatrefolk (Hishon 2016) provides perhaps one of the clearest descriptions of the difference between theater acting and movie acting: "Theater is all about exaggerated body and facial gestures vs. subtle facial expressions which can be captured in a close up on film. Theater requires actors to project, speak in unnaturally loud voice with flawless diction and of course, there is no second take. In movies you can always re-record and microphones allow for much less clear annunciation. Theater performance requires a connection with the audience and ability to improvise should it be needed. In movies, you can always re-take the scene. This makes it clear why it is that movie actors, trained on subtle expressions, low voices and the ability to perfect a scene, may not do well in theater."

5.3. Theater Stars Once Again

One concern with the foregoing analysis may be the way we classify nonstars. For example, in the analysis of movie stars, theater stars, and visibility stars (who are not also movie stars) are considered nonstars. This may confound the results, as we know now that theater stars matter. Hence, in Table 4, we remove all the transitions from one type of star to another. For example, in the left panel (theater stars), we remove all the transitions from a theater star to a movie or a visibility star. We similarly reduce the number of observations in the other panels. The results are consistent with the results in Table 3. Revenues increase more than in Table 3 when a theater star joins the show, which strengthens the conclusion that theater stars make a difference. If we compare the two specifications, it seems that transitioning from other stars to a theater star is not as beneficial as transitioning from an unknown actor to a theater star, which makes sense. However, it is still dramatically better to put a theater star in the show than any other star, and removing any other star and including a theater star instead is still a very profitable proposition. The visibility stars and movie stars results are insignificant, as they were in Table 3, so that the lack of impact is not driven by a transition to or from a "more prominent star" (a theater star) but apparently by lack of interest on the part of the audience in movie and visibility stars as theater actors. In all cases, the team and seasonal variables are significant, as they were before.

As a final concept check, we try to narrow the definition of a theater star to people with three Tony nominations. There are two Tony categories for actors (a leading actor and a supporting actor) in musicals

Table 4. Pure Stars: Effects of Different Types of Star Transitions on Performance—Removing All Transitions Involving Other Types of Stars (Fixed Effects)

	Theater star			Movie star			Visibility star		
	Gross change	Ticket price change	Capacity change	Gross change	Ticket price change	Capacity change	Gross change	Ticket price change	Capacity change
Star to nonstar	25.470	1.926	2.711	–139.930	–9.823	–3.069	–9.562	–1.536	3.278
	(48.162)	(2.254)	(2.929)	(156.749)	(7.660)	(9.717)	(57.324)	(2.897)	(3.561)
Nonstar to star	151.055*	5.733*	9.714*	128.904	8.171	8.418	3.408	–1.152	1.458
	(61.782)	(2.891)	(3.758)	(149.052)	(7.284)	(9.239)	(47.993)	(2.425)	(2.981)
Cast change	–58.991*	–3.325*	–4.587**	–32.573	–1.809	–3.337$^+$	–45.935	–2.638	–4.177*
	(27.636)	(1.293)	(1.681)	(31.105)	(1.520)	(1.928)	(32.151)	(1.625)	(1.997)
Time elapsed	89.610*	8.161***	–2.935	75.580$^+$	8.286***	–3.282	57.293	6.429**	–3.955
	(40.739)	(1.906)	(2.478)	(40.108)	(1.960)	(2.486)	(39.855)	(2.014)	(2.475)
Old team	–383.549**	–20.671***	–15.507*	–788.558***	–39.592***	–32.591**	–421.063***	–19.603**	–19.704**
	(127.220)	(5.953)	(7.737)	(163.308)	(7.980)	(10.123)	(117.225)	(5.924)	(7.281)
New team	78.132	–0.759	4.386	104.747	1.414	7.544	100.667	1.081	7.710
	(89.500)	(4.188)	(5.443)	(102.196)	(4.994)	(6.335)	(106.278)	(5.371)	(6.601)
Before peak week	76.419	0.458	6.774*	85.233	0.704	7.262*	98.220*	1.617	7.938*
	(49.257)	(2.305)	(2.996)	(51.855)	(2.534)	(3.214)	(49.710)	(2.512)	(3.088)
After peak week	–210.871***	–11.736***	–10.273***	–198.241***	–11.606***	–7.753**	–208.546***	–11.627***	–10.105***
	(40.407)	(1.891)	(2.458)	(42.519)	(2.078)	(2.636)	(43.251)	(2.186)	(2.686)
Observations	276	275	275	239	238	238	259	258	258
R^2	0.330	0.430	0.243	0.356	0.458	0.234	0.295	0.355	0.226
Number of shows	71	71	71	64	64	64	66	66	66

Notes. Star definitions: theater stars: at least two Tony nominations; movie stars: at least one Oscar nomination; visibility stars: at least 50 screen and theater appearances. Star to nonstar equals 1 if the transition is from a star to nonstar. Nonstar to star equals 1 if the transition is from a nonstar to star. Gross change: change in average weekly gross revenues from three weeks before the transition to three weeks after the transition, in thousands of 2013 constant dollars. Ticket change: change in the average ticket price from three weeks before the transition to three weeks after the transition, in 2013 constant dollars. Capacity change: change in average capacity used (percentage of seats sold) from three weeks before the transition to three weeks after the transition. Cast change equals 1 if the transition involves changing multiple performers on the same day. Before peak equals 1 if the transition occurs within a three-week window before the peak week. After peak equals 1 if the transition occurs within a three-week window after the peak week. Time of transition: years between the opening night and the transition. New team equals 1 if the new performers have worked with the director before. Old team equals 1 if the old performers have worked with the director before. Time of transition are years between the opening night and the transition. All models include show fixed effects and year fixed effects. Standard errors are in brackets.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; $^+p < 0.10$.

and, similarly, two Tony categories for actors in plays. There are also the same four categories for actresses. The Tonys separate between musicals and plays, but because 91% of our transitions are in musicals, we are basically looking at the musicals category. To get a sense for the nominations cutoffs, consider the "Best Actor in a Musical" category. Out of 251 nominations between 1948 and 2017, 147 performers had only one nomination, and 27 actors had two nominations. Only 14 performers had three nominations, and only two nominees had four nominations. Therefore, only 16 men had three nominations or more in this category over a 70-year period (as discussed, there is a parallel process for women). Thus, the threshold of three nominations identifies a very prestigious class of actors. In our sample, we have 25 women and men with at least three Tony nominations (34 performer years).

Table 5 shows the results when theater stars are defined as actors with at least three Tony nominations. The left panel is similar to previous results in magnitudes and significance levels. The ticket price changes for adding a star are in the right direction and magnitude, but the coefficient is insignificant. This may be the result of fewer stars in the sample. However, when we have "pure" transitions (constructed in a similar fashion to the transitions in Table 4), the magnitudes shoot up. The main change is in capacity—more people come when an unknown actor is replaced by a theater luminary. The increase in revenues is most dramatic. As described previously, the average show takes in about $750,000 per week, so the change in revenues we document is about 50% of the average total revenue per week.

5.4. Robustness Checks—Regressions with Show Characteristics

As a robustness check, we reran all regressions in the paper using OLS with standard errors clustered by shows. In these analyses, we are able to see the effect of show characteristics (they are dropped in the show

Table 5. Effects of Different Types of Star Transitions on Performance—Theater Stars Are Performers with at Least Three Tony Nominations (Fixed Effects)

	All transitions			Removing transitions involving movie and visibility stars		
	Gross change (1)	Ticket price change (2)	Capacity change (3)	Gross change (4)	Ticket price change (5)	Capacity change (6)
Star to nonstar	–47.279	–0.146	–1.738	–80.804	–0.594	–1.411
	(46.606)	(2.267)	(3.078)	(67.838)	(3.208)	(4.194)
Nonstar to star	125.342$^+$	4.263	11.613**	366.644**	11.963*	16.584*
	(66.264)	(3.223)	(4.376)	(125.202)	(5.92)	(7.741)
Cast change	–43.915$^+$	–2.354*	–4.005*	–56.604*	–3.234*	–4.295*
	(24.245)	(1.179)	(1.601)	(27.376)	(1.294)	(1.693)
Time of transition	50.987	5.751**	–4.822*	71.783$^+$	7.655***	–3.635
	(36.44)	(1.772)	(2.406)	(40.715)	(1.925)	(2.517)
Old team	–252.505**	–12.907**	–10.969$^+$	–339.024**	–19.637**	–13.856$^+$
	(96.27)	(4.682)	(6.357)	(127.48)	(6.028)	(7.881)
New team	26.233	–2.111	1.636	73.575	–0.553	4.596
	(77.331)	(3.761)	(5.107)	(87.291)	(4.128)	(5.397)
Before peak week	102.025*	1.601	9.585***	94.077$^+$	1.022	7.696*
	(42.529)	(2.068)	(2.808)	(48.388)	(2.288)	(2.992)
After peak week	–236.452***	–12.332***	–13.587***	–214.392***	–11.890***	–10.497***
	(36.814)	(1.79)	(2.431)	(40.017)	(1.892)	(2.474)
Observations	332	331	331	276	275	275
R^2	0.317	0.369	0.25	0.345	0.431	0.235
Number of shows	82	82	82	71	71	71

Notes. This table used an alternative definition of a theater star: people with 3 Tony nominations. Columns (1)–(3) show the regression results all transitions, and columns (4)–(6) shows regressions results after removing all transitions involving movie or visibility stars. Star definitions: theater stars: at least three Tony nominations; movie stars: at least one Oscar nomination; visibility stars: at least 50 screen and theater appearances. Star to nonstar equals 1 if the transition is from a star to nonstar. Nonstar to star equals 1 if the transition is from a nonstar to star. Gross change: change in average weekly gross revenues from three weeks before the transition to three weeks after the transition, in thousands of 2013 constant dollars. Ticket change: change in the average ticket price from three weeks before the transition to three weeks after the transition, in 2013 constant dollars. Capacity change: change in average capacity used (percentage of seats sold) from three weeks before the transition to three weeks after the transition. Cast change equals 1 if the transition involves changing multiple performers on the same day. Before peak equals 1 if the transition occurs within a three-week window before the peak week. After peak equals 1 if the transition occurs within a three-week window after the peak week. Time of transition: years between the opening night and the transition. New team equals 1 if the new performers have worked with the director before. Old team equals 1 if the old performers have worked with the director before. Time of transition are years between the opening night and the transition. All models include show fixed effects and year fixed effects. Standard errors are in brackets.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; $^+p < 0.10$.

fixed effects analysis). The results shown in Table 6 confirm our previous analysis and suggest that theater stars affect performance in a very clear fashion. The only additional result is that revenues seem to drop if movie stars leave the show as well. We looked at these transitions in detail—this somewhat different result may be due to show characteristics captured by fixed effects, but not by the control variables we have here as well as to seasonal effects (the specific timing of these transitions).

The coefficient of cast changes is negative as it was in the previous regressions, and usually significant. The old team variable is negative, but the significance is generally in regressions where capacity is the dependent variable. There are more cast changes than people who had worked with the same director before, and this may account for these outcomes. Similarly, musicals seem to be somewhat less affected by changes than other types of shows.[24] Interestingly, show-related awards (show quality) do not seem to make a difference. Possibly musicals (or not) and revivals (or not) are more important in determining how a transition would fare. Also, we should keep in mind that we are looking at the effect of the control variables on transitions—it may well be that awards do affect the fortunes of the show, but do not affect transitions.

To address the potential concern that our results may be driven by a few outliers, we ran four (unreported) robustness checks. First, we removed all transitions with extremely high gross change (top 5 and top 10 percentiles of gross change, respectively). Then, we removed the transitions with extremely low

Table 6. Effects of Different Types of Star Transitions on Performance—Ordinary Least Squares Models

	Theater star			Movie star			Visibility star		
	Gross change	Ticket price change	Capacity change	Gross change	Ticket price change	Capacity change	Gross change	Ticket price change	Capacity change
Star to nonstar	−17.532	−0.917	−0.939	−97.850*	−3.739	−6.973	−22.935	−0.753	−0.441
	(29.591)	(1.559)	(2.153)	(43.215)	(2.298)	(5.639)	(28.244)	(1.339)	(2.966)
Nonstar to star	72.078***	2.495**	6.107**	−24.811	−2.820	−2.239	11.704	−0.264	3.201
	(20.371)	(0.833)	(2.071)	(42.495)	(4.162)	(5.458)	(26.352)	(0.987)	(2.729)
Cast change	−45.500⁺	−3.109*	−3.567*	−38.720	−2.754*	−2.923*	−41.533⁺	−2.932*	−3.629*
	(24.960)	(1.352)	(1.512)	(23.302)	(1.276)	(1.314)	(23.608)	(1.316)	(1.380)
Time of transition	1.764	0.092	0.104	1.711	0.093	0.102	1.995	0.104	0.093
	(1.827)	(0.119)	(0.146)	(1.859)	(0.121)	(0.140)	(1.867)	(0.122)	(0.148)
Old team	−130.939	−4.318	−9.206*	−148.830	−5.166	−10.492*	−144.794	−4.821	−10.282*
	(128.646)	(7.403)	(4.347)	(122.634)	(7.130)	(4.144)	(124.473)	(7.209)	(4.157)
New team	11.254	0.351	−0.305	6.882	0.141	−0.628	10.029	0.224	−0.199
	(34.539)	(2.264)	(1.958)	(34.153)	(2.305)	(1.819)	(34.117)	(2.358)	(1.735)
Before peak week	81.231*	1.447	6.401*	91.875*	1.916	7.296*	90.438*	1.902	5.501⁺
	(39.695)	(1.948)	(3.131)	(37.964)	(1.692)	(3.272)	(39.291)	(1.836)	(2.840)
After peak week	−224.800***	−13.254***	−9.762*	−225.194***	−13.270***	−9.860*	−231.381***	−13.455***	−10.273*
	(29.996)	(1.517)	(4.254)	(28.497)	(1.450)	(4.184)	(30.754)	(1.525)	(4.267)
Award	−9.602	0.527	−0.654	−2.956	0.769	−0.161	−6.887	0.626	−0.195
	(17.198)	(1.113)	(1.251)	(15.947)	(1.068)	(1.157)	(16.219)	(1.090)	(1.233)
Musical	35.339	4.912*	5.579*	23.379	4.232*	4.604*	33.024	4.765*	6.509**
	(24.483)	(1.934)	(2.297)	(26.334)	(1.881)	(1.942)	(26.247)	(2.081)	(2.299)
Revival	−2.102	−0.815	−0.569	1.166	−0.598	−0.354	−1.844	−0.732	−0.931
	(15.440)	(0.848)	(1.278)	(14.884)	(0.825)	(1.187)	(14.831)	(0.842)	(1.224)
Observations	332	331	331	332	331	331	331	330	330
R^2	0.273	0.284	0.238	0.270	0.284	0.232	0.263	0.279	0.233

Notes. In this table, we reran the regressions in Table 3 using OLS with standard errors clustered by shows. Star definitions: theater stars: at least two Tony nominations; movie stars: At least one Oscar nomination; visibility stars: at least 50 screen and theater appearances. Star to nonstar equals 1 if the transition is from a star to nonstar. Nonstar to star equals 1 if the transition is from a nonstar to star. Gross change: Change in average weekly gross revenues from three weeks before the transition to three weeks after the transition, in thousands of 2013 constant dollars. Ticket change: Change in the average ticket price from three weeks before the transition to three weeks after the transition, in 2013 constant dollars. Capacity change: Change in average capacity used (percentage of seats sold) from three weeks before the transition to three weeks after the transition. Cast change equals 1 if the transition involves changing multiple performers on the same day. Before peak equals1 if the transition occurs within a three-week window before the peak week. After peak equals 1 if the transition occurs within a three-week window after the peak week. Time of transition: years between the opening night and the transition. New team equals 1 if the new performers have worked with the director before. Old team equals 1 if the old performers have worked with the director before. Time of transition are years between the opening night and the transition. Musical equals to 1 if the show is a musical and 0 if the show is a straight play. Revival equals to 1 if the show is a revival of a previous show and 0 if it is a new production. Award equals to 1 if the show has won any award. Standard errors are clustered by shows and are shown in brackets. Year dummies are included.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; $^+p < 0.10$.

gross changes (bottom 5 and 10 percentiles of gross change, respectively). The results of these four regressions remain similar to our main results.

5.5. Are Stars Overpaid?

We can now provide a partial answer to this question. According to Tables 3–6, theater stars, who are the stars that seem to matter most in this exercise, increase show revenues by at least $72,000 a week on average. Three-time Tony nominees may bring the revenue bump to over $360,000 (consider the coefficients of nonstar to star variable in Tables 3–6, respectively). The lower bound comes from Table 6, when we ran an OLS regression. The coefficients indicate a star value of at least $125,000 per week in all fixe-effects models, which we believe may be more robust.[25]

We note that part of the increase comes from increased attendance, and the other part comes from a significant increase in the average ticket price.

Because, as discussed, the show continues exactly as it had run before, except for the change in cast, the entire surplus must be due to the star's presence.

Even $72,000 a week is more than most theater stars get paid (the union (Equity) mandated minimum pay for a principal actor in a play or a musical was $1,861 per week as of September 2015). However, as early as 2002, the *New York Times*, in discussing cost components of Broadway shows, said "and stars like Nathan Lane can make more than $50,000 a week" (McKinley 2002). Lane is a theater star in our sample. Most salaries on Broadway are not released to the public (for one of the very few studies of movie star salaries, see Chisholm 1997), but this bit of casual evidence seems to show that theater stars may actually capture much of their value. However, our work also suggests that it is important to pay the right people. If theaters pay outsized salaries to movie stars or celebrities, they may be wasting their money, at least according to our analysis.

5.6. Alternative Definitions

As discussed earlier, we ran a few alternative definitions of various star categories. Appendix B contains a few of the more interesting runs.

One may worry that visibility stars are too broadly defined in the previous analysis, adding noise and leading to insignificant results. To address this concern, we ran an analysis with a narrower definition for visibility stars—namely, a performer in the top 5% of total credits. The results are listed in Appendix B. There are still no significant coefficients. Thus, it seems that our conclusion that visibility stars do not matter is robust.

As another robustness check, we run an (unreported) analysis that only included transitions occurring at least two years after the start of the show. These transitions are unlikely to reflect managerial decisions and are most likely to be motivated by contract issues. The results were similar.

We also tried to see whether "multitalented" stars matter—does movie fame add economic value to theater skills? This analysis is also presented in Appendix B. The number of multitalented people is rather small (20 unique performers for the narrower definition and 29 for the broader one), but the results are similar to the previous results. However, here sometimes the departure of a multitalented star is significant as well. For the broader definition, weekly revenues increase by more than $167,000 if a multitalented star replaces a nonstar. This evidence provides some support to the view that theater stars who are also known through their movie career may be more attractive to audiences.

Finally, although it seems evident that star transitions matter more for leading roles, we collected information about transitions in other random roles in shows. There were less star-related transitions in this sample, both in absolute number and in relative terms (for example, we could find no cases of nonstars in minor roles who were replaced by stars, which is possibly not a surprising finding). In unreported regressions, we found that transitions from star to nonstar were insignificant, although team and seasonal variables were significant. We believe that this supports our strategy of focusing on transitions for featured leading roles. Possibly another conclusion from this exercise is that, unless you have a very clean experiment, it is difficult to disentangle the influence of teamwork from the value of individual participants in a creative enterprise.

6. Conclusions

We find that theater stars—that is, exceptionally talented theater actors, as opposed to movie stars or celebrities, matter to the success of theater shows. Our experiment has more power than previous studies in other spaces to identify such effects and thus may not be inconsistent with work that found little or no effect of stars on the success of movies (DeVany and Walls 1999, Ravid, 1999, Elberse 2007), as well as inconsistent evidence on the value of music stars and CEOs.

Our main contribution is in using a tightly controlled experiment to measure the contribution of key players in an organization and characterize these key players. Although theater is a specific setting, one may surmise that if such experiments were possible in other areas of human enterprise, the results would probably be amplified, because individuals are freer to express more aspects of their personality and creativity in many other professions, whereas in theater they follow a scripted process.

This paper also adds to a long list of studies that find some support for the value of teams.

We also identify significant seasonal effects in all regressions, and to some extent, we see that musicals are helpful in sustaining a show momentum.

Our conclusion that theater stars matter can be interpreted as supporting theoretical papers such as MacDonald (1988) and Rosen (1981) and less supportive of models such as Adler (1985).

Our experiment also seems to suggest that if MacDonald (1988)-type stars can be correctly identified, they deserve a pay far outstripping union wages.

Movie stars and celebrities, however, do not seem to have the same effect on the success of theater shows, except that screen credentials can enhance the value of theater stars.

Using our approach, we are able to attenuate both time-varying and time-invariant omitted variable bias, which have been concerns in the CEO and movie literature. Various relevant variables may change contemporaneously with CEO transitions (such as firm strategy, the competitive environment, or support from the board). Failure to control for these time-varying variables can bias the results. In our setting, all other aspects of the show (including the script, the director, the other performers, the stage design, etc.) stay the same after the transition. Thus, we are able to minimize the concern of time-varying omitted variables. The movie literature compares the performance of two movies, one with a star and the other without a star. It is difficult to control for all the other factors that contribute to the success of a movie (such as performance of other performers, the script, the director, etc.). Thus, these time-invariant omitted variables create a concern. In our setting, we are comparing transitions within a show, thus eliminating the concerns of time-invariant omitted variables as well.

Our main conclusion—that it is theater stars that support long running shows rather than other types of stars—is echoed in the review of the show *Finding Neverland* by *New York Times* critic Ben Brantley. The review laments the replacement (from the previous sold-out Cambridge, MA, production of the musical) of Jeremy Jordan, "who exuded a sweetness thinning anguish that seems to be about something other than an actor's being stuck in an uncomfortable production" with TV star Matthew Morisson and the replacement of the "very good" Michael McGrath with TV star Kelsey Grammer (Brantley 2015). Mr. McGrath (two Tony awards and several other accolades) would be classified as a theater star in our paper, and Mr. Jordan, who had only one Tony nomination, but had also won the award, could arguably be included as well.

To be fair, both Mr. Grammer and Mr. Morisson have one Tony nomination each (and a storied TV career).

Acknowledgments

The authors thank seminar participants at the 16th annual Mallen Movie Economics Conference at Yale University; participants in seminars at Harvard Business School, Yeshiva University, University of Nebraska, and Lund University, as well as at New York University (NYU), in particular, David Yermack and Yakov Amihud; participants in the Financial Institutions, Regulation and Corporate Governance conference in Melbourne, 2017, especially the discussant, Michael Smith; and participants in the creative industries conference at NYU, 2017 and Financial Management Association 2017, especially the discussant Lorenzo Casaveccia. The authors also thank participants at the International Conference on Arts and Management in France, 2015, in particular, Allegre Hadida and Pier Mannucci, for useful comments and suggestions on an earlier version of the paper; Lauren Cohen, Liran Einav, Kose John, Raghu Rau, Stephen Brown, and Olav Sorenson for useful comments and conversations, as well as Sara Ravid for suggestions; Carolee Carmello and Gregg Edelman for many useful discussions based on their decorated Broadway career; Charlotte St. Martin, President of the Broadway League, and the League's research staff for helpful discussions; and Ethan Applebaum, Avi Goldstein, Raff Hizami, Sara Ravid, Orren Ravid, and Avi Skidelsky for dedicated research assistance. The authors are grateful to the editor, Renee Adams, for guidance and for many useful comments and suggestions.

Appendix A

Figure A.1. The Opening Night *Playbill* for the Show *Mamma Mia*

WHO'S WHO IN THE CAST

LOUISE PITRE (*Donna Sheridan*). Original Donna (North America), for which she was awarded the Dora Mavor Moore Award (Toronto), San Francisco Critics Circle Award and the U.S. National Broadway Award; Piaf* (*Piaf*); Mrs Johnstone* (*Blood Brothers*); Fantine (*Les Misérables*, Paris cast recording); *The World Goes 'Round; I Love You, You're Perfect, Now Change; Jacques Brel Is Alive and Well...; Who's Afraid of Virginia Woolf?* (Martha). Her CD "All of My Life Has Led to This" (containing two songs from *Mamma Mia!*) is in stores or at www.louisepitre.com. Oh, and she's French, so it's "Pee-trah" - not Petrie. *Dora Mavor Moore Award (Toronto).

DAVID W. KEELEY (*Sam Carmichael*). Broadway: *The Mikado*. Royal Alex: *Mamma Mia!* Stratford Festival of Canada: *Hamlet*, *The Three Musketeers*, *Richard III*, *Coriolanus*, *Love's Labour's Lost*, *The Changeling*. Citadel Theatre: *As You Like It*, *Oedipus*, *Oliver*, *Romeo and Juliet*, *Robin Hood*. Other theatre: *The Rocky Horror Show*, *Born Yesterday*, *Napoleon*. Film & TV: *Sugartime*, *A Saintly Switch*, *Forever Knight*, *The Dan Jansen Story*. David has two independent CDs released with "Due South" star Paul Gross, titled *Two Houses* and *Love and Carnage*.

TINA MADDIGAN (*Sophie Sheridan*). Broadway debut. Originated role of Sophie in Toronto and was nominated for National Star Award in North American tour of *Mamma Mia!* From the rocky shores of Newfoundland, Canada, Tina studied musical theatre at Sheridan College (Toronto). Regional credits: Sally (*Me & My Girl*), Sister Amnesia (*Nunsense*) and Cinderella in *Cinderella*. Tina thanks her high school teacher Jacinta for instilling the dream and her devoted mother for supporting the dream. Love to family, Darren and D.C.! www.tinamaddigan.com

JOE MACHOTA (*Sky*). Broadway debut. Recently created the role of Laurie in the pre-Broadway workshop of *Little Women*. National tours include *Footloose* (Ren McCormack), *Joseph...* (Joseph). Regional: *Gypsy* w/Betty Buckley (Tulsa), *Starlight Express* (Rusty) and played the lead role in *EFX!* for the vacationing Michael Crawford. New York workshops: *Romeo & Juliet* (Romeo), *Go Go Beach* (Woody). A graduate of the Boston Conservatory, Joe would like to thank all of his teachers, especially Fran, Lynne and Kerry.

JUDY KAYE (*Rosie*). Broadway: Carlotta, *The Phantom of the Opera* (Tony Award); Lily Garland, *On the Twentieth Century* (Theatre World Award, Drama Desk nomination, L.A. Drama Critics Circle Award); Emma Goldman, *Ragtime* (Theatre L.A. Ovation Award). Other roles: Musetta, *La Boheme;* Shirley Valentine; Mama Rose, *Gypsy;* Sally, *Follies;* Nellie Lovett, *Sweeney Todd;* Penny, *You Can't Take It With You;* Kitty, *The Royal Family*. Cabaret and concert performances, including the White House. Numerous recordings include solo disks *Diva by Diva* and *Songs From the Silver Screen*. She is the voice of Kinsey Millhone on the Sue Grafton "Alphabet Mysteries" recordings. For more, please visit: www.JudyKaye.com.

KAREN MASON (*Tanya*). Broadway: *Sunset Boulevard, Jerome Robbins' Broadway, Torch Song Trilogy*. Off-Broadway: *And the World Goes 'Round, Carnival*. TV/film:"Law & Order," "As the World Turns," *Sleeping Dogs Lie*. Concert/cabaret: four-time MAC Award winner, Carnegie Hall (w/NY Pops), Rainbow & Stars, Arci's, Davenport's (Chicago), Cinegrill (L.A.). CDs: *And the World Goes 'Round* (RCA); *Wonderful Town* (JAY); *Better Days* (including 1998 Emmy Award-winning song "Hold Me"); *Christmas! Christmas! Christmas!; Not So Simply Broadway* (Zevely Records); and her newest release *When the Sun Comes Out* (Jerome Records). Please visit www.KarenMason.com

KEN MARKS (*Bill Austin*). Broadway credits: *Present Laughter*, *Dancing at Lughnasa*. Off-Broadway: More than 50 productions including *Blur* (MTC), *When They Speak of Rita* (Primary Stages), *Henry V* (NYSF), *Birdseed Bundles* (DTW) as well as the Drama Dept., NYTW, MCC and Naked Angels. Regional: the Guthrie, Mark Taper Forum, ACT, Long Wharf, Seattle Rep. and ATL. Film/TV: *Bad Bride*, *The Confession*, "Law & Order," "Law & Order: SVU," "Trinity." Ken is a graduate of

Note. We use the first three featured actors.

Appendix B

Table B.1. Additional Robustness Checks: Effects of Visibility Star Transitions (Alternative Definition) and of Multi-Talented Stars Transitions on Performance (Fixed Effects Models)

				Multitalented star definition					
	Alternative visibility star definition (at least 68 credits)			At least two screen awards and two Tony nominations			At least two screen awards and one Tony nomination		
	Gross change (1)	Ticket price change (2)	Capacity change (3)	Gross change (4)	Ticket price change (5)	Capacity change (6)	Gross change (7)	Ticket price change (8)	Capacity change (9)
Star to nonstar	1.365	−0.978	3.667	−137.191$^+$	1.573	−14.727**	−69.526	2.603	−5.835$^+$
	(45.409)	(2.188)	(3.002)	(74.329)	(3.646)	(4.806)	(51.042)	(2.499)	(3.327)
Nonstar to star	6.128	1.112	2.854	117.649$^+$	3.298	11.195*	167.673**	5.657$^+$	15.063***
	(43.985)	(2.119)	(2.908)	(67.233)	(3.298)	(4.348)	(63.017)	(3.086)	(4.107)
Cast change	−40.216	−2.246$^+$	−3.684*	−40.159$^+$	−2.290$^+$	−3.468*	−42.733$^+$	−2.435*	−3.759*
	(24.397)	(1.175)	(1.613)	(23.862)	(1.171)	(1.543)	(23.730)	(1.162)	(1.547)
Time of transition	58.084	6.001***	−4.551$^+$	55.480	5.914***	−4.591$^+$	57.942	6.120***	−4.313$^+$
	(36.911)	(1.778)	(2.440)	(36.069)	(1.769)	(2.332)	(35.994)	(1.762)	(2.346)
Old team	−266.497**	−13.396**	−12.424$^+$	−263.301**	−12.862**	−11.339$^+$	−263.784**	−12.878**	−11.364$^+$
	(98.238)	(4.733)	(6.494)	(94.962)	(4.658)	(6.141)	(94.529)	(4.628)	(6.161)
New team	32.626	−2.011	2.163	31.256	−2.010	1.786	32.907	−1.944	1.973
	(78.192)	(3.767)	(5.169)	(76.660)	(3.760)	(4.957)	(76.320)	(3.737)	(4.974)
Before peak week	107.766*	1.610	9.870***	99.629*	1.623	9.107***	104.364*	1.298	9.603***
	(43.021)	(2.073)	(2.844)	(42.212)	(2.071)	(2.730)	(42.163)	(2.064)	(2.748)
After peak week	−232.903***	−12.208***	−13.180***	−239.856***	−12.207***	−13.868***	−238.948***	−12.177***	−13.688***
	(37.125)	(1.789)	(2.454)	(36.468)	(1.789)	(2.358)	(36.288)	(1.777)	(2.365)
Observations	332	331	331	332	331	331	332	331	331
R^2	0.300	0.365	0.230	0.326	0.367	0.291	0.332	0.375	0.286
Number of shows	82	82	82	82	82	82	82	82	82

Notes. This table shows results of several robustness checks. Columns (1)–(3) show regression results using an alternative definition of visibility stars: at least 68 credits. Columns (4)–(9) show the regression results using two different alternative definitions of multitalented stars. In columns (4)–(6) multitalented stars are defined as performers who have won at least two screen awards and two Tony nominations by the time they join the show, and in columns (7)–(9) as performers who have won at least two screen awards and one Tony nomination. Star to nonstar equals 1 if the transition is from a star to nonstar. Nonstar to star equals 1 if the transition is from a nonstar to star. Gross change, change in average weekly gross revenues from three weeks before the transition to three weeks after the transition, in thousands of 2013 constant dollars; ticket change, change in the average ticket price from three weeks before the transition to three weeks after the transition, in 2013 constant dollars; capacity change, hange in average capacity used (percentage of seats sold) from three weeks before the transition to three weeks after the transition. Cast change equals 1 if the transition involves changing multiple performers on the same day. Before peak equals 1 if the transition occurs within a three-week window before the peak week. After peak equals 1 if the transition occurs within a three-week window after the peak week. Time of transition, years between the opening night and the transition. New team equals 1 if the new performers have worked with the director before. Old team equals 1 if the old performers have worked with the director before. Time of transition is years between the opening night and the transition. All models include show fixed effects and year fixed effects. Standard errors are in brackets.

$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; $^+p < 0.10$.

Appendix C

Table C.1. Definition of Variables

Variables	Definition
Star to nonstar	1 if the transition is from a star to nonstar.
Nonstar to star	1 if the transition is from a nonstar to star.
Gross change	Change in average weekly gross revenues from three weeks before the show to three weeks after the show, in thousands of 2013 constant dollars.
Ticket change	Change in the average ticket price from three weeks before the show to three weeks after the show, in 2013 constant dollars.
Capacity change	Change in average capacity used (percentage of seats sold) from three weeks before the show to three weeks after the show.
Award	1 if the show has won any award.
Cast change	1 if the transition involves changing multiple performers on the same day.
Before peak	1 if the transition occurs within a three-week window before the peak week.
After peak	1 if the transition occurs within a three-week window after the peak week.
Time of transition	Years between the opening night and the transition.
Musical	1 if the show is a musical; 0 for play.
Revival	1 if the show is a revival of a previous show.
New team	1 if the new performers have worked with the director before.
Old team	1 if the old performers have worked with the director before.

Endnotes

[1] John et al. (2017) document such a process in the market for film directors.

[2] One show in our sample, *Wicked*, is sold out before and after some transitions. We ran the analysis with or without that show, and the results did not change. In principle, one can analyze sold out shows if there is available data on resales. However, data on resales is spotty and it is not available for a large sample of shows or for a long period of time (not too many shows are sold out for long periods of time in the first place). Also, resales do not affect producers' or actors' revenues. Nevertheless, there seems to be anecdotal support to the idea that a theater star departure can lead to a drop in resale prices of sold out shows (see Fehr 2016).

[3] See, for example, Tamny 2015. See Tervio (2009) for a different perspective on the evolution of superstar pay.

[4] For 60 shows, we did not find any transitions, leaving us with 155 shows. We then eliminated all transitions that we could not date, which left us with 94 shows. After eliminating transitions that were within three weeks of each other we were left with 82 shows.

[5] As discussed later, we also tried transitions involving other members of the cast.

[6] Matching transitions is a tedious mostly manual job since the website does not have replacement chains but rather lists actors in different roles in different time periods.

[7] While "list" ticket prices do not change often, the mix of regularly priced seats and "premium seats" (well above list price) as well various discount seats sold through organizations such as playbill .com and tdf.org or for specific groups such as students or "30 under 30" may change rather dramatically throughout the run. This type of adjustment as well as changes in the mix of cheaper and more expensive seats sold, changes the average ticket price of shows.

[8] Three weeks seem reasonable for the impact of a change to be felt, and also to identify any pretransition trends. We also tried 1 week before and 1 week after the event.

[9] We include as credits also appearances as understudies, standbys, or swings.

[10] Razzies are awards by an "alternative" group for the worst movies, screenplays, actors, and directors of the year.

[11] More runs and results are available from the authors upon request.

[12] There is a difference between an assistant director and assistant to the director. The latter is not usually involved in the creative part of the job, but helps the director in various administrative tasks.

[13] Because some of the shows are long-running, a director may be directing a few shows simultaneously. For example, if a show started its run in 2002 and we are looking at a 2010 transition, it may be that the incoming actors might have worked with the current director on a different show in, say, 2005.

[14] This is similar to seasonal effects documented in movies; see Ravid (1999) and Einav (2007).

[15] Examples of theater stars include Alan Alda, Bebe Neuwirth, Brian d'Arcy James, Carolee Carmello, Harvey Fierstein, Idina Menzel, Judd Hirsch, Mercedes Ruehl, Nathan Lane, and Victor Garber.

[16] Movie stars include, among others, Jeff Goldblum, John Lithgow, Sally Field, and Kathleen Turner.

[17] All our movie stars (by definition) have acting nominations (or wins) for Oscars. One theater performer who is a well-known singer has an Oscar nomination for music. We ran all the relevant tables with and without this performer and the results do not change. In order to be fully transparent, the results reported display the analysis with this performer identified as a movie star.

[18] Almost by definition, some visibility stars are also movie stars or theater stars. If the power of the tests were to come from the visibility rather than the talent, then we would expect significant results for the visibility stars and possibly less significant results for the other types. However, as we will see below, we find no significant results for the visibility stars. We also tried the top 5% of performers, and the results were similar (see Appendix B). We present the 10% results in the table because the numbers of performers if we choose this characterization is of the same order of magnitude as the number of stars in other categories. Visibility stars (who are not also theater or movie stars) include for example, Brooke Shields and Tom Bosley.

[19] A discussant suggested that we try Grammy winners (the most celebrated music awards) on the theory that, in musicals (which are most of our sample), Grammy winning would also indicate a star. However, only two performers in our sample had won a Grammy prior to their appearance in our database (Julie Andrews and Huey Lewis). A handful won after the appearance in our shows. There were two nominees (who did not win) Keith Carradine and Ricky Martin. This does not allow us to establish an independent class of "music stars" and more importantly, this shows that there is not a clear overlap of skills between music stars and Broadway performers. Carradine and Andrews are classified as a movie stars in our paper (and otherwise). Lewis was nominated for an Oscar for the best original song.

[20] Following a discussant's suggestion, we ran all regressions with random effects as well. The results were qualitatively similar. In the models where show fixed effects are used, we charted rvf and rvp plots and ran a Breusch–Pagan test for heteroscedasticity. We did not find heteroskedasticity to be a serious concern. Since tests are never totally conclusive, we also ran, for our own benefit, tests with heteroscedasticity adjusted standard errors. Our main conclusions stay

the same. The team dummy variable (which is not significant in the OLS regressions), changed in significance—the cast change variable, also measuring team value, which is more often significant, stayed significant.

[21] The average number of transitions per show is 4.1, with the minimum of 1 per show and a maximum of 63 (the next one down is 28). We ran a robustness test removing the show with the 63 transitions, and the results remain similar.

[22] For example, Carolee Carmello opened the show *Tuck Everlasting* in Atlanta in February 2015 but had a previous commitment on Broadway and, thus, regardless of the success of the show, had to leave Atlanta at a prespecified time. Another example is the departure in 2018 of Tony Shalhoub from the lead role in the show *The Band's Visit*, because of prior commitments, even though he won the 2018 Tony for the best actor for this show (and the show itself also won the 2018 Tony for the best show).

[23] There are only two cases where a movie star replaces a theater star. In both of these cases, there was a very large drop in ticket prices, capacity, and revenues. Obviously, we cannot draw statistical inferences, but these cases are indicative.

[24] These results are consistent with survival analysis by Kulmatitskiy et al. (2015), which finds that musicals survive longer and revivals are less likely to have long runs.

[25] An indication that we are in the ball park for these effects can be found in an interesting article regarding the show *Love Letters*. The show features two actors, a man and a woman. Gerard (2014) wrote: "Hawkeye Pierce and Murphy Brown—who knew? In a somewhat slumpy mood last week, the Broadway box office had a bit of good news for the latest *Love Letters* pairing of Alan Alda and Candice Bergen, lifting the revival almost $90,000 to $483,280 at the Brooks Atkinson." Alda is a theater star in our listing.

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