Revenue implications of celebrities on Broadway theatre

Kyle D. S. Maclean1 · Fredrik Ødegaard1

Abstract

Live entertainment revenue management practices depend upon understanding the most salient drivers of shifts in demand. Motivated by the increasing usage of dynamic pricing on Broadway, we explore factors that impact revenue in live theatre. Based on a fixed effects model and a novel dataset of revenues and actor usage, we estimate the revenue impact that celebrity actors have on Broadway shows. We find that weeks that have a celebrity are associated with an increase in revenue of approximately $250 k. The two major acting awards—Tony and Academy (the Oscars)—were found to have a non-significant impact on weekly revenue. We discuss implications on Revenue Management practices.

Keywords  Revenue management · Live entertainment · Empirical analysis · Broadway actors · Theater revenue analytics

Introduction

Live entertainment, including sporting, theatrical, and concert events is a multi-billion dollar industry. The industry fulfills the characteristics of traditional Revenue Management (RM) industries, including having fixed capacity (limited seating), low marginal costs, uncertain but forecastable demand, and fences to segment customers. In part due to this commonality, the usage of RM techniques in live entertainment has increased. For instance, it is common to see professional sports teams dynamically price tickets depending on the opponent they face (Dunne 2012).

In other live entertainment sectors, the uptake of RM tactics and strategies is still ongoing. For instance, in commercial theatre, sophisticated RM tactics are implemented differently by each show. To illustrate this, in Fig. 1, we show five long-running shows and their potential gross in USD over the 2017–2020 period. The potential gross shows the total revenue possible if a show sold all tickets at their posted prices. Changes in potential gross, thus, reflect changes in week-to-week prices.

Figure 1 shows that while the two Disney shows The Lion King and Aladdin adjusted prices weekly, The Book of Mormon and Wicked almost never adjust them. This occurs even though the latter two shows are qualitatively as successful. The show Hamilton seems to take an “in-between” stance and jumps between set price points. Thus, there exists a wide range of RM practices and sophistication occurring on Broadway that may at least partially be explained by a relative lack of attention paid to it in the RM literature.

A key component of a successful RM implementation is the ability to forecast demand, since many pricing or quantity allocation models assume known or estimated demand functions. While recent literature (Lin 2006; Cooper et al. 2015; den Boer 2015) has started to incorporate unknown demand functions with learning, the literature still generally assumes stationary demand processes, or demand processes that depend solely on price. In reality of course, particularly in entertainment, other factors also impact demand.

To encourage the application of RM tactics to live entertainment industries such as commercial theatre, we first seek to understand how product features influence demand. For live entertainment, perhaps one of the most important product features are the people involved. In sports, athletes are the critical variable in determining team success, which in turn are predictors of attendance in many leagues (Baade and Tiehen 1990). At a concert, the singer or band involved is naturally the driver of demand. For commercial live theatre, the actors involved are one of the critical product features. As such, in this paper, we study a specific key decision of an illustrative live entertainment business: the decision of whether to hire a well-known actor (i.e. a celebrity) to act in a Broadway show. Broadway is unique in entertainment products in that the product is re-created nightly. Thus, unlike in films or
novels or other cultural products, one can more cleanly “test” how various versions of the show perform, holding script, budget, songs, and other creative elements identical.

We show that the inclusion of a celebrity in a given week improves revenue on average by the order of $250k, through both quantity (increases in attendance) and pricing changes. On the other hand, we find no statistical evidence that, independent of celebrity status, actors who achieve artistic recognition via Tony or Academy Award nominations increase revenue. We provide implications for RM system design and team organization.

**Literature review**

RM for live entertainment has focused on theoretical and empirical studies. Phumchusri and Swann (2014) examined the process of “scaling the house”, or sectioning a seating map into various zones. They derived closed form solutions for the number of rows to offer at a premium price and suggested that distance from the stage mattered more than distance from the centre for buyers. Maclean and Ødegaard (2020) investigated the process of “stacking the house” or the dynamic process of offering seats to incoming seat requests. They provided dynamic seat allocation strategies to avoid leaving single seats which can be difficult to sell. The authors proposed a heuristic algorithm which generates revenue enhancement over ignoring the single seat issue.

Previous empirical research has examined the revenue gain from variable and dynamic pricing approaches in live entertainment. Two papers explored this area using data from Major League Baseball. Using a single team’s season data, where half the season was an experimental dynamic pricing regime, Xu et al. (2016) found that the dynamic pricing did not meaningfully affect revenue. However, they proposed that it is possible to increase revenue by as much as 17% through daily price reoptimization. Courty and Davey (2020), using two decades worth of data, found that variable pricing increases revenues by approximately 4%, but that perhaps counter-intuitively, dynamic pricing is not associated with changes in revenue.

Our research also intersects with work that has been done on the success of commercial theatre productions or even entertainment in general. Reddy et al. (1998) examined factors that impact the success of a Broadway show. They found that critic reviews both predict and influence the likelihood of a show being successful. Relevant to this study, Reddy et al. (1998) also investigated how opening night actors impact lifetime revenue on Broadway. They found no significant impact. However, their analysis was limited by considering only the opening night cast and did not test what happened when these lead actors left the show.

Han and Abraham Ravid (2020) looked at the theatre casting issue to find insights into general super-star compensation, such as CEO pay, and found that among three types of actors (theatre stars, movie stars, and visibility stars), only theatre stars impact Broadway show revenues and ticket prices; a commentary on their methodology and results is provided in Maclean and Fredrik (2021). Our study is similar but has a slightly more recent dataset and uses a different operationalization of what a star or celebrity is.

![Figure 1: Potential weekly Gross (USD) of five Broadway shows](image-url)
Finally, Maclean (2021) used a synthetic control method to test the inclusion of one celebrity in a case-study analysis, and found that revenue of the show was positively impacted by the celebrity. However, after accounting for costs and inter-temporal purchasing substitutions, the profit impact of the celebrity hiring was deemed non-significant.

**Data and variable definitions**

We collected data from the Internet Broadway Database IBDB.com, for all shows that ran during the period 31st May 2009–1st August 2015. In total, there were 290 shows over this period. The 2009 starting date was chosen due to a change in the data definitions prior to that date. These data included the gross revenue (in USD) of each Broadway show in each week that it was playing. Thus, in the ensuing analysis, each observation is at the show-week level (N = 9420). The gross revenue is composed of the ticket revenue for a show prior to transaction fees or group sales commissions. It does not include ancillary revenue, e.g. merchandising or soundtrack revenues. The primary-dependent variable for our analysis is an adjusted measure of revenue for each show-week combination. Weekly Gross was inflation adjusted to 2015 values using monthly CPI data and subsequently standardized to an eight performance week. We refer to this variable as Gross.

We also included as secondary-dependent variables in our analysis the average ticket price per week, as well as the capacity-filled percentage. The average ticket price is defined as the gross revenue divided by that week’s total attendance (including complimentary tickets, if any). The capacity-filled percentage is defined as the proportion of total attendance to total seating capacity. Seating capacity, in turn, is constant per performance but can vary by week depending on how many performances a show does in that week. Capacity-filled percentage can, in rare cases, be greater than 100% when a show sells standing room tickets.

From the same site, we obtained information on which actor played which characters for all shows within the sample period. We refer to the character–actor combination as “Roles”. Role information included the actor’s name, the character(s) they played in the show, and the dates they joined and left the show. Since a role is both a character and actor combination, some actors are included in the dataset in multiple roles.

We made significant efforts to ensure that the data were cleansed and precise. Role information was removed due to a lack of either a start date, ending date, or imprecise start/ending dates. Generally speaking, roles that were removed were either less important characters (aka “ensemble” members) or non-notable actors. We also ensured that no roles conflicted with each other, e.g. data that specified two actors playing the same character in the same week. For those weeks that showed two actors overlapping the same part, we assumed that the actor with the shorter overall time period was actually in the show. This tended to occur for short vacation periods of the main actor. After this data-cleansing process, we had 4,860 unique roles and unique actors.

**Defining celebrity actors**

To determine the impact that celebrities have on Broadway show revenue, we must operationalize the concept of celebrity or star power. There are many researcher degrees of freedom on this issue, and the literature has not coalesced on a single method. For one, there is the issue of whether being a celebrity should be conceptualized as a binary condition, or as a continuous measure of stardom. While binary variables are easier to interpret than a potentially multi-dimensional measure of stardom, they have been criticized as not capturing the granularity that exists between different celebrities (Nelson and Glotfelty 2012).

The definition of “celebrity variables” has also been based on different underlying data sources. For instance, some papers have used pre-existing trade lists to define who celebrities are (De Vany and Walls 1999; Liu et al. 2014). Others use online fan predictive markets lists of well-known film actors (Elberse 2007). The other approach is to define a celebrity from the bottom up, using the number of films or television shows an actor has appeared in (Han and Abraham Ravid 2020), the number of awards an actor has won (Ravid 1999), or the revenue of previous shows the actor was in. In some situations, even the author’s own judgement has been used to define a star (Prag and Casavant 1994).

Most of these data sources are inappropriate for Broadway because Broadway actors come from many industries. They may be successful movie actors (Daniel Radcliffe), well-known singers (Billie Joe Armstrong, Nick Jonas), television series actors (Matthew Morrison, Sean Hayes), or even well known specifically for their work on Broadway (Kristen Chenoweth, Sutton Foster). Using box office revenue, or any specific award types do not allow us to establish celebrities across entertainment industries.

We instead combine these approaches using a publicly available data source to measure any actor’s awareness in the general public. Specifically, we use the Internet Movie

---

1 For example, some data points only indicated a general month of when an actor started with a show.
Database IMDb.com to quantify how often each actor is searched. IMDb provides a proprietary metric “STARmeter” that is based on the volume of searches on the website. This measurement was previously used and recommended by Nelson and Glotfelty (2012). On IMDb, STARmeter is a rank system such that the top actor with the most searches has a ranking of one and increases in rank value reflect fewer searches (and arguably less popularity and public recognition).

For each performer in each show, we collected the average STARmeter rank of the performer in the six months prior to starting their role. About 3% of the roles had actors without IMDb profile, which by manual check were confirmed as unknown actors. We define a celebrity as anyone with a STARmeter ranking below 1,000 at the time they joined the show. Table 1 displays an illustrative list of twenty celebrities in our dataset, along with their six-month average IMDb Starmeter rank at the time they joined a show. We note that several blockbuster Hollywood stars are present, including Scarlett Johansson, Hugh Jackman, and Samuel L. Jackson, as well as other very famous actors, such as Al Pacino, Christopher Walken, and Sigourney Weaver.

One reservation of the employed method may be that the IMDb measurements are generated from underlying user actions. If users of IMDb are statistically different from the population of Broadway theatre-goers, we might expect there to be a bias in the celebrity variable. This is a reasonable conjecture. The average age of a Broadway theatre-goer is 44 years compared to a United States median age of 39 (Broadway 2015; The World Factbook 2022). It is reasonable to assume that the median age of an online platform such as IMDb is younger than this. To the extent, this is an issue though, it would attenuate the coefficients we find.

Overall though, operationalizing star power using IMDb STARmeter rankings is attractive because IMDb maintains a history of the measurement. Contrast this with social media outlets (e.g. Instagram, Twitter) which do not maintain a history of “followers” or “likes”. A history is necessary to rule out an alternative form of reverse causality – actors becoming famous because of the success of their show. For example, prior to the television show Glee, Lea Michele was on Broadway in the musical Spring Awakening. Another potential approach is to considered using Google Trends, which is a public information source about the relative popularity of search topics. However, since they return a relative measure, it does not as easily allow one to assess actors’ stardom. On the other hand, the proposed IMDb-based measurement does not measure the general public sentiment of a specific

Table 1  Selected list of celebrities in our data

| Actor                                | IMDb StarMeter | Show                                      | Start date   | End date   |
|---------------------------------------|----------------|-------------------------------------------|--------------|------------|
| Scarlett Johansson                    | 34             | Cat on a Hot Tin Roof                     | 2012-12-11   | 2013-04-06 |
| Denzel Washington                     | 106            | Fences                                    | 2010-04-07   | 2010-07-18 |
| Hugh Jackman                          | 107            | The River                                 | 2014-10-24   | 2015-02-15 |
| Al Pacino                             | 112            | The Merchant of Venice                     | 2010-10-12   | 2011-02-27 |
| Daniel Craig                          | 133            | A Steady Rain                             | 2009-09-03   | 2009-12-13 |
| Rose Byrne                            | 135            | You Can’t Take It With You                | 2014-08-19   | 2015-01-04 |
| Daniel Radcliffe                      | 160            | How to Succeed in Business Without Really Trying | 2011-02-19   | 2012-01-01 |
| Samuel L. Jackson                     | 204            | The Mountaintop                           | 2011-09-15   | 2012-01-29 |
| Andrew Garfield                       | 273            | Death of a Salesman                       | 2012-02-07   | 2012-06-09 |
| Catherine Zeta-Jones                  | 301            | A Little Night Music                      | 2009-11-17   | 2010-06-20 |
| Michael C. Hall                       | 389            | Hedwig and the Angry Inch                 | 2014-10-16   | 2015-01-18 |
| Sigourney Weaver                      | 442            | Vanya and Sonia and Masha and Spike       | 2013-02-26   | 2013-07-28 |
| Judy Greer                            | 450            | Dead Accounts                             | 2012-10-29   | 2013-01-13 |
| Christopher Walken                    | 455            | A Behanding in Spokane                    | 2010-02-08   | 2010-06-13 |
| Matthew Broderick                     | 498            | The Philanthropist                        | 2009-04-03   | 2009-07-05 |
| Philip Seymour Hoffman                | 516            | Death of a Salesman                       | 2012-02-07   | 2012-06-09 |
| Neil Patrick Harris                   | 536            | Hedwig and the Angry Inch                 | 2014-03-22   | 2014-08-17 |
| Rupert Grint                          | 761            | It’s Only a Play                          | 2014-08-21   | 2015-01-04 |
| Jane Lynch                            | 865            | Annie                                     | 2013-05-14   | 2013-07-14 |
| James Spader                          | 867            | Race                                      | 2009-11-10   | 2010-06-20 |

Results for considering only top 100 ranked actors were similar but with much smaller sample size.
Revenue implications of celebrities on Broadway theatre

actor (e.g. likeability). We leave this aspect of the research to future studies.

**Descriptive analysis**

It is informative to first look at the data and see what insight, if any, might be visible. We provide summary statistics of the dependent variables conditional on celebrity presence in Table 2. From the table, we note that at the aggregate the distributions across the two show-type categories are roughly the same but with shows without celebrities to financially be slightly better. This insight is further supported by Figure 2 which displays the empirical distributions of weekly Gross conditional on shows having (“With Celebrity”) and not having (“Without Celebrity”) a celebrity. The two distributions appear similar but with weeks with a celebrity have a mass that is shifted slightly to the left. That is, it appears the higher revenue right-tail outcomes are disproportionately for shows without celebrities.

That favourable outcomes are primarily associated with weeks that did not have a celebrity may seem counter-intuitive. This, however, may be due to the fact that show fixed effects are not accounted for. That is, the right-tail outcomes may be successful individual shows that never had a celebrity. We note that shows that never had a celebrity ran, on average for 63 weeks before closing, but that shows that had a celebrity were open, on average, for 17 weeks. This is evidence that there are systemic differences between shows that hire a celebrity at some point and those that do not. To discover if this is occurring, we can look at how a given show performed with and without a celebrity.

Figure 3 displays illustrative boxplots of the weekly Gross (a), Average Ticket Price (b), and Capacity-Filled (c) conditional on having a celebrity. For each show, the

| Table 2 Summary statistics of dependent variables |
|-----------------------------------------------|
| Show type          | Statistic       | Mean  | SD   | Min  | Max   |
|--------------------|-----------------|-------|------|------|-------|
| Without celebrity  | Average ticket price | $94.7 | $29.0 | $17.6 | $248.1 |
| $N = 7967          | Capacity-filled percentage | 83.0% | 14.7% | 29.0% | 110%  |
|                    | Gross (in ‘000)  | $846  | $465 | $81  | $2,880 |
| With celebrity     | Average ticket price | $93.3 | $30.4 | $23.8 | $186.2 |
| $N = 1453          | Capacity-filled percentage | 82.3% | 16.1% | 32.0% | 110%  |
|                    | Gross (in ‘000)  | $666  | $343 | $128 | $1,771 |

![Fig. 2 Histogram of weekly gross conditional on celebrity present in a week (with celebrity) or not present (without Celebrity)](image-url)
right ("WO") and left ("W") box plots represent the weekly Gross without and with a celebrity, respectively. By visual inspection, and focusing on panel (a), it seems celebrity inclusion has an impact on the weekly revenue since the left box plots are predominately shifted up compared to the right box plots. 8 of the 10 shows display a drastic gain with the star, while only a single show had an obvious decrease (The Trip to Bountiful). Furthermore, some shows exhibit very large positive shifts in the distribution.

---

3 In the Appendix, Figure 5 displays for the same set of shows the average weekly metrics as bar charts. The features and insights of the bar charts are consistent to the box plots.
of Gross, e.g. *A little Night Music* and *It’s only a Play*. Taken together, there is suggestive evidence to indicate that celebrities are associated with an increase weekly revenue.

By furthermore considering panels (b) and (c), we see that for the shows where there was a revenue increase, the increase effect was a combination of both price and quantity sold changes. Notably, no show without a celebrity has a binding capacity constraint, though some do end up at the limit with the celebrity.

Another reasonable driver of demand would be time. Like many other live entertainment business, Broadway also exhibits great seasonality effects. In Figure 4, we provide the average weekly Gross of all shows that spanned our sample. The clear peaks at the end of each year reflect the predictable boost from the Christmas and New Year holidays. However, there are additional holiday impacts (e.g. July 4th, Thanksgiving, Easter), some seasonal trends, and some idiosyncratic weekly effects (e.g. snowstorm effects).

**Model formulation and analysis**

Let $Y_{ij}$ be the dependent variable for show $i$ in week $t$, the fixed effects model is then defined as follows:

$$Y_{ij} = \alpha_i + \delta_t + \beta Z_{ij},$$

(1)

where $\alpha_i$ are show $i$ fixed effects, $\delta_t$ are weekly $t$ fixed effects to account for seasonality or time trends, and $\beta$ the coefficient vector for covariates $Z_{ij}$. As included in these other covariates, there is a dummy variable *CelebrityPresence* defined as one, if at least one celebrity was in the show in the given week. This model does not differentiate between a celebrity leaving and a celebrity joining, and this is intentional to ensure that celebrity effects are easy to interpret. We also included three dummy variables *FirstMonth*, *FirstYear*, and *ClosingWeek* to control for potential life-cycle effects, i.e. closing. We conduct three separate analyses for each of the three dependent variables: Gross revenue, *Average Ticket Price*, and *Capacity-filled percentage*. Standard errors are clustered by show to control for the presence of heteroskedasticity and serial correlation (cf. Cameron et al. 2015; Millo 2017).

The inclusion of show and week-fixed effects make both economic and statistical sense. It has been shown that some cultural product revenues follow power law-type distributions but that predicting which ones will succeed and which will fail is essentially a crapshoot (De Vany and Walls 1999). As such, accounting for time-invariant fixed effects of the show (e.g. script quality, production effects, etc.) is essential; see Fig. 1 and 3a. Weekly fixed effects are to control non-parametrically for any seasonality or year over year trends that may occur. Thus, while our model seems simplistic in some ways, it controls for the most salient factors impacting Broadway show revenues.

One consequence of including show fixed effects, however, is the inability to estimate time-invariant factors, since their impact would be included under the show fixed effect. That is why, for instance, our model does not include a variable for whether a show is a musical or play, i.e. it is impossible to separate the type of show from the show. Another consequence of this is that the coefficient for *CelebrityPresence* is estimated only using shows where celebrities either left or joined, and where the *CelebrityPresence* variable changed throughout the show run. For shows where *CelebrityPresence* was unchanged, the “celebrity effect” would

---

4 Alternative model formulations could be to consider log transforms of Gross revenue, *Avg Ticket Price*. The results from these analysis are provided in the Appendix and are consistent with the main findings.
again be another time-invariant factor included in the show fixed effect.

In Table 3, we present the coefficient estimates from this model. The coefficient on CelebrityPresence indicates that a celebrity performing in a week is associated with an increase in weekly Gross of approximately $250,000. The effect is both statistically significant (p < .01) as well as managerially relevant. This increase appears to be caused by both increased attendance and increased ticket prices on average. Specifically, ticket prices are higher by $22 and attendance increases by 12%.

Han and Abraham Ravid (2020) bring up the idea that different types of actors may have different impact on revenues. For instance, actors who are artistically successful in movies versus actors who are artistically successful in theatre. Our data can also lend insights into this. We define
a *TonyNominee* week as one where an actor was employed who had previously been nominated for at least *two* individual Tony awards, the primary and most prestigious awards for Broadway shows. Likewise, we define an *OscarNominee* week as weeks with actors who had previously been nominated for at least *one* Academy award (i.e. the Oscars). These variables are not mutually exclusive as potentially an actor can fit multiple definitions, or a show can have one of each kind of actor. In our dataset, three actors (who had four roles total) fit both definitions. Both variables are indicator variables indicating the presence, and not the quantity, of actors who fit these definitions.

In Table 4, we present the results from this model. Our conclusion for celebrities is not impacted, as they are still associated with an increase in revenue, ticket prices, and attendance. Performers who have been nominated for Oscars do not have a statistically significant impact on revenue, ticket prices, or capacity filled. Similarly, we cannot rule out zero impact from performers who have at least two Tony award nominations. This interpretation would be consistent with consumer interest in a performer being more related to celebrity awareness rather than artistic talent or ability.

### Discussion and conclusion

In this paper, we studied the impact that celebrity hiring and presence have on Broadway weekly revenue, and decompose this impact into quantity and pricing effects. We find that weeks that celebrities are in a Broadway show are associated with increased revenues for Broadway shows. This impact is achieved through both increasing the average ticket price, and by increasing the quantity of tickets sold.

The estimated revenue gain is statistically significant and managerial relevant. It has been reported that some celebrities can earn anywhere from $100–150 k per week in a Broadway show (Simonson 2010). Our estimate is higher than this which would seem to suggest that celebrities are a profitable opportunity for shows. However, other costs may also be associated with celebrity hiring. For instance, we conjecture that marketing costs would increase as a result of hiring a celebrity. Maclean (2021) estimated through a case analysis that a star cost $120 k in total increased expenses. Either estimate would still suggest hiring a celebrity is a profitable opportunity, which perhaps is an explanation for why the trend continues to occur on Broadway.

One might conjecture that the impact of a celebrity may depend on how long a show has been running. For instance, celebrities who join a show three years into its run versus a celebrity who opens a show. This question is difficult to empirically estimate in our data due to how Broadway currently uses celebrities. In our dataset, 99% of celebrity weeks occur within the first year that a show is running. Thus, a question outside of this period is too far outside of what currently occurs on Broadway. However, in statistical tests, we did not observe statistically significant differences between celebrity weeks in the first six months and celebrity weeks after six months.

We can also interpret these results in the context of current RM practices. First, these research results reinforce the value of measuring historical factors that influence demand. The impact of a star, or any product decision, is not an idiosyncratic error, but something that should be explicitly considered when forecasting future demand. Using historical data without controlling for the most salient impacts will, at best, lead to high uncertainty, and at worst, may bias estimates. This also suggests that domain-level knowledge is still critical for effective RM implementation, and that partnerships with domain experts is likely to be fruitful. We echo the call of Currie (2015) for industry-focused RM models.

Secondly, RM techniques should be decided in tandem with product decisions, not subsequent to them. Decision makers in a firm that are deciding product attributes (such as actors in a Broadway show) should involve tactical RM teams to inform them, and help understand the impact that different attributes may have on the RM decisions. When a star is brought on, the economic consequences can likely be better estimated by including the RM decision makers in the discussion.

Future research in this area could more narrowly focus on the predictors of dynamic pricing practices on Broadway, and how they interact with features of a show, e.g. the organizational capabilities of a show or the inclusion of a celebrity. Empirically testing what features are more likely to lead to modern dynamic pricing practices would assist practitioners in this field. In addition, empirically testing the effectiveness of dynamic pricing practices across shows would contribute to the literature on RM implementation issues.

Another extension to this work could involve research on how performer characteristics and performer history interact with show-specific characteristics. For instance, if a comedic performer is called upon to perform in a dramatic play, the research could also focus not just on how aware the public is of the performer, but the underlying valence of emotion.

---

5 The awards comprise both actor performances (e.g. Best Performance by a Leading Actor in a Play, Best Performance by a Leading Actress in a Musical), creative team contributions (e.g. Best Costume Design in a Musical, Best Sound Design of a Play), and the coveted overall show awards (e.g. Best Musical, Best Play). Nominations are done by a committee and then voted on by a few hundreds designated voters.

6 In a robustness test, we do, however, find a statistically significant and positive impact from performers who have at least three Tony nominations, with a gain of approximately $113k.
towards them. This would differentiate performers who are well known, but disliked from well known and loved performers.

Finally, we note that as Broadway and other live entertainment industries have started to re-open from the Covid-19 pandemic, and as these industries do so amidst record levels of structural uncertainty, that understanding drivers of demand and revenue is more important than ever. We hope that our paper contributes to this discussion and helps support sound decision making, in particular regarding the effectiveness of specific hiring practices.

Appendix

See Fig. 5 and Tables 5 and 6.

---

**Fig. 5** Bar graph of mean weekly outcomes conditional on without a celebrity (right, “WO”) and with a celebrity (left, “W”) celebrity; a gross, b average ticket price, c capacity-filled percentage
Table 5 Logged-dependent variables

| Dependent variable | LOG [Gross (in thousands)] | LOG (average ticket price) |
|--------------------|-----------------------------|-----------------------------|
| CelebrityPresence  | 0.3619*** (0.0755)          | 0.2056*** (0.0492)          |
| FirstYear          | 0.1652*** (0.0445)          | 0.0841*** (0.0296)          |
| FirstMonth         | −0.0848*** (0.0188)         | −0.1791*** (0.0131)         |
| ClosingWeek        | 0.0396** (0.0160)           | −0.0222* (0.0111)           |
| Observations       | 9,420                       | 9,420                       |
| R²                 | 0.9018                      | 0.8482                      |
| Residual Std. Error (df = 8825) | 0.1922 | 0.1260 |

*p < 0.1; **p < 0.05; ***p < 0.01
Clustered (by show) standard errors shown in parentheses

Table 6 Logged-dependent variables—other award variables

| Dependent variable | LOG [Gross (in thousands)] | LOG (average ticket price) |
|--------------------|-----------------------------|-----------------------------|
| CelebrityPresence  | 0.3303*** (0.0805)          | 0.1901*** (0.0485)          |
| FirstYear          | 0.1656*** (0.0445)          | 0.0845*** (0.0298)          |
| FirstMonth         | −0.0872*** (0.0188)         | −0.1803*** (0.0131)         |
| ClosingWeek        | 0.0434*** (0.0158)          | −0.0202* (0.0110)           |
| TonyNominee        | 0.0725                      | 0.0399                      |
| OscarNominee       | 0.1370                      | 0.0675                      |
| Observations       | 9,420                       | 9,420                       |
| R²                 | 0.9027                      | 0.8491                      |
| Residual Std. Error (df = 8825) | 0.1914 | 0.1257 |

*p < 0.1; **p < 0.05; ***p < 0.01
Clustered (by show) standard errors shown in parentheses

References

Baade, Robert A., and Laura J. Tiehen. 1990. An analysis of major league baseball attendance, 1969–1987. *Journal of Sport and Social Issues* 14 (1): 14–32.

Broadway League. 2015. *The demographics of the Broadway audience 2014-2015*.

Cameron, A. Colin., and Douglas L. Miller. 2015. A practitioner’s guide to cluster-robust inference. *Journal of Human Resources* 50 (2): 317–372.

Cooper, William L., Tito Homem-de-Mello, and Anton J. Kleywegt. 2015. Learning and pricing with models that do not explicitly incorporate competition. *Operations Research* 63 (1): 86–103.

Courty, Pascal, and Luke Davye. 2020. The impact of variable pricing, dynamic pricing, and sponsored secondary markets in major league baseball. *Journal of Sports Economics* 21 (2): 115–138.

Currie, Christine S. M. 2015. How far will the airline model stretch? *Journal of Revenue and Pricing Management* 14 (2): 120–122.

De Vany, Arthur and Walls David W. 1999. Uncertainty in the movie industry: Does star power reduce the terror of the box office? *Journal of Cultural Economics* 285–318.

den Boer, Arnoud V. 2015. Dynamic pricing and learning: Historical origins, current research, and new directions. *Surveys in Opera- tions Research and Management Science* 20 (1): 1–18.

Dunne, Patrick. 2012. Dynamic pricing trend sweeps across major league baseball. *TicketNews*.

Elberse, Anita. 2007. The power of stars: Do star actors drive the success of movies? *Journal of Marketing* 71 (4): 102–120.

Han, Shu, and S. Abraham Ravid. 2020. Star turnover and the value of human capital—Evidence from Broadway shows. *Management Science* 66 (2): 958–978.

Lin, Kyle Y. 2006. Dynamic pricing with real-time demand learning. *European Journal of Operational Research* 174 (1): 522–538.

Liu, Angela, Tridib Mazumdar Xia, and Bo Li. 2014. Counterfactual decomposition of movie star effects with star selection. *Management Science* 61 (7): 1704–1721.

Maclean, Kyle D. S., and Fredrik Ødegaard. 2021. A commentary note on ‘star turnover and the value of human capital—Evidence from Broadway shows. Han & Ravid, Management Science, 66 (2).

Maclean, Kyle D. S. 2021. Value of stars on Broadway: A case study. *Service Science* 13 (2): 77–87.

Maclean, Kyle D. S., and Fredrik Ødegaard. 2020. Dynamic capacity allocation for group bookings in live entertainment. *European Journal of Operational Research* 287 (3): 975–988.

Millo, Giovanni. 2017. Robust standard error estimators for panel models: A unifying approach. *Journal of Statistical Software* 82: 1–27.

Nelson, Randy A., and Robert Glotfelty. 2012. Movie stars and box office revenues: An empirical analysis. *Journal of Cultural Economics* 36 (2): 141–166.

Phunchusri, Naragin, and Julie L. Swann. 2014. Scaling the house: Optimal seating zones for entertainment venues when location of seats affects demand. *International Journal of Revenue Management* 8 (1): 56–98.

Prag, Jay, and James Casavant. 1994. An empirical study of the determinants of revenues and marketing expenditures in the motion picture industry. *Journal of Cultural Economics* 18 (3): 217–235.

Ravid, S. Abraham. 1999. Information, blockbusters, and stars: A study of the film industry. *The Journal of Business* 72 (4): 463–492.

Reddy, Srinivas K., Vanitha Swaminathan, and Carol M. Motley. 1998. Exploring the determinants of Broadway show success. *Journal of Marketing Research*.

Simonson, Robert. 2010. Actors’ salaries & the levels of stage management. http://www.playbill.com/article/ask-playbillcom-actors-salaries-the-levels-of-stage-management-com-170516.
The World Factbook. 2022. Technical report Central Intelligence Agency.

Xu, Joseph Jiaqi, Peter Fader, and Senthil K. Veeraraghavan. 2016. The revenue impact of dynamic pricing policies in major league baseball ticket sales. SSRN.

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Kyle D. S. Maclean is an Assistant Professor in Management Science at Ivey Business School, University of Western Ontario. He received his PhD degree in Management Science from the University of Western Ontario in 2017. His research interests include revenue management in live entertainment settings and applications of analytics to sports and entertainment settings.

Fredrik Ødegaard is an Associate Professor in Management Science at Ivey Business School, Western University. He received his BSc degree from Arizona State University, dual MSc degrees from Stanford University, and PhD degree from University of British Columbia. His research interests include theory and applications of revenue management and auction theory, stochastic processes, and applications of analytics to eCommerce, health care and sustainability.