“The Beyconomics of Ticket Buying”: A Data-Driven Guide to Navigating the Secondary Market

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June 10, 2025

1 Introduction

Many musicians have been urging audiences to return to live events post-pandemic, but sharply rising ticket prices have become a major barrier for concertgoers. Nearly half of consumers now attend fewer concerts than they did three years ago, largely due to these costs.[1] In 2024, average concert ticket prices reached a record $127.38 (up from $92.42 in 2019). For comparison, a Michael Jackson ticket at Wembley in 1997 was £28.50 (about £50 today), while a 2024 Taylor Swift ticket at the same venue started at £110, with resale prices exceeding £500.[2,3]

This surge is widely attributed to the ticketing industry’s monopolization, especially by Ticketmaster, which uses dynamic pricing: prices adjust in real-time based on demand (similar to airlines and hotels), often leading to even higher costs.[4] Limited competition and high initial prices could also inflate the resale market, making affordable tickets harder to find, especially after primary sales end and most availability shifts to secondary marketplaces (StubHub, SeatGeek, Ticketmaster resale), often with additional fees tacked on.

1.1 Artist Spotlight: Beyoncé

Beyoncé offers a rational case study of demand and affordability within the context of modern ticketing. As a global icon, her tours generate intense anticipation, with fans eager to find the best seats for the best price.

For her 2023 Renaissance World Tour, Ticketmaster’s Verified Fan program split buyers into three presale groups (A, B, and C) to manage demand, yet high prices and limited affordable seats persisted throughout.[5] Some fans chose not to participate, hoping for price drops closer to the event or to snag last-minute resale deals, while others joined presales for a shot at good seats, later turning to the secondary market if needed. Ultimately, ticket timing became nearly as important as willingness to pay (or even travel to another city), as fans weighed buying early against waiting for potential deals.

Given these challenges, this study aims to answer the following questions: **What is the relationship between purchase timing, seat section, market size, and the likelihood of getting the best value for resale tickets when buying Beyoncé concert tickets for future shows? At what point before a concert, and in which markets, can buyers most effectively maximize seat quality while minimizing price?**

2 Overview of Data

The data examined in this case study comes from SeatData.io, a platform that offers real-time and historical secondary market sales data for live events. Beyoncé’s 2023 Renaissance World Tour serves as the basis for this analysis. Only third-party resale data from the United States and Canada was available for this tour.

The dataset covered all of her North American tour dates in 25 locations:

Atlanta	Boston	Charlotte	Chicago
Dallas	Detroit	Houston	Kansas City
Las Vegas	Los Angeles	Louisville	Miami
Minneapolis	Nashville	New Orleans	New York City
Philadelphia	Phoenix	San Jose	Seattle
St Louis	Tampa	Toronto	Vancouver
Washington DC			

Each record represented an individual ticket listing. Incomplete or ambiguous listings were removed, leaving a total of 66,704 listings for observation.

The main variables derived from the dataset were **EventDate** (the concert date), **City** (the event location), **Zone** [(the general seating area) (e.g., "Upper Terrace")], **Section** [(the specific section within a zone (e.g., "225C")], **ActualPrice** (the listing price in USD), and **PriceDate** (the date of the listing and purchase).

Other features such as row and available quantity were also present in the dataset.

Additional variables were created for analysis. **Lowest_Price** was calculated for each section and event date to benchmark deals. **StandardizedZone** and **Section_Group** were introduced to ensure uniformity across venues with inconsistent naming; for the Renaissance World Tour, these groups included both premium sections (*from most premium to least:* VIP Pure Honey Risers, B-Hive, Club Renaissance, Floor) and regular sections, typically ranging from the 100s (Lower Bowl) up to the 300s (Upper Bowl), with some venues extending to the 700s, and the 200s corresponding to Club level.

Finally, **DaysBeforeEventDate** was added to capture how far in advance of the show a listing appeared.

Modeling Approach: LASSO Regression To estimate fair market value, I compared OLS, ridge, and LASSO regression on log-transformed ticket prices, using section group and city as predictors. The data was split 80/20 into training and test sets. Dummy variables were created for all predictors.

Model performance was evaluated using RMSE and R^2. The QQ plots and residual diagnostics indicated no major violations of model assumptions for any approach (Figure 11). However, LASSO regression was ultimately chosen as the seemingly best fit model. The RMSE and R^2 were the lowest and highest, respectively, in comparison to the other two models (Table 1). The final model's predicted log prices were exponentiated and clamped to a $10 minimum, which then created the **ExpectedPrice** variable.

Model	**R^2_log**	**RMSE_log**	**RMSE_original**
OLS	0.682	0.390	231.471
Ridge	0.679	0.392	233.203
Lasso	0.682	0.390	231.751

Table 1: Comparison of regression models.

Calculating Deal Score Each ticket's deal score quantified how much its price differs from expected value:

$$\textbf{Deal\_Score} = \frac{\text{ExpectedPrice} - \text{ActualPrice}}{\text{ExpectedPrice}}$$

Scores were clamped between 0 and 1 for interpretability. A deal score near 1 meant a strong bargain, while a score near 0 meant a weak bargain. A score of 0 meant the ticket was at or exceeded the typical value for its section and city/venue.

Although **Lowest_Price** was not directly used to calculate deal scores, it served as a practical benchmark. Tickets priced closer to the lowest observed price for their section, city, and event tended to have higher deal scores, signaling potentially strong bargains. Thus, **Lowest_Price** helped interpret and validate the deal score as an indicator of meaningful price advantage.

Quantifying Seat Quality Seat quality (**Seat_Quality_Score**) was determined using the median expected price for each section group (higher median = better/more desirable seat) and publicly observable trends when consumers select certain seats at concerts. This simplified approach was inspired by the proprietary formulas used by SeatGeek and StubHub, since their exact methods are not public. *(See appendix for more details and code.)*

Deal_Score and Seat_Quality_Score were then combined into a single metric that reflected the overall "all-in" goodness of a ticket purchase using the geometric mean. The given name for this variable was **Final_Deal_Score.**

3 Exploratory Data Analysis (EDA)

Analysis Using C and R To begin, I examined the overall distribution of ticket prices using a kernel density estimate (KDE) computed in both C (blue line) and R (red dashed line), as shown in Figure 1. Both methods show a strongly right-skewed distribution: while most tickets were sold at moderate prices, rare high-priced tickets still persisted.

Next, to assess the impact of market size on ticket price distribution, Figure 2 grouped cities as big (e.g., Los Angeles), medium (e.g., Dallas), or small (e.g., Kansas City) based on the total potential customers (population size), the demographics of the population in a particular city (which would influence purchasing behavior), and several other factors. Prices were generally higher in big markets, with most tickets falling in a moderate range; however, again, all market sizes exhibited right-skewed distributions driven by a minority of very expensive tickets.

Finally, the timing of purchases provided further insight into market dynamics and competition for tickets among concertgoers. According to Figure 3, most buyers purchased tickets either very early (at least 6 months out) or very late (last 1–2 weeks), with relatively few purchases occurring in the "middle window" (2–4 months before the event) and, for a brief moment, immediately following the duration of the presales and general onsale. The clustering of purchases at the start and end of the sales window suggests that buyer competition is highest when tickets first go on sale, then tapers off, and increases again as the event date approaches, possibly due to last-minute decisions or price drops by resellers.

What is a "Good Deal"? A "good deal" in this case study is defined by a ticket purchase that has a **Final_Deal_Score** that is within the ***top 20%*** of scores. Figure 4 shows the proportion of good deals by market size. There appears to be roughly similar proportions of "good deals" in big, medium, and small markets.

Figures 5 and 6 show the spread of prices for each section based on ticket price and final deal score, respectively. "B-Hive" and "Floor" sections appear to have had the highest median and spread of Final Deal Scores. Other sections had lower, more consistent deal scores. Regular sections (100s-700s) appear to be clustered at lower price points, but each section had a range.

4 Probability Modeling

4.1 Comparing Generalized Models

Earlier, the EDA implied that competition among buyers is not constant over time. This suggested that the timing of a ticket listing, whether it falls into a high or low competition window, could meaningfully impact the likelihood of finding a good deal.

To isolate the impact of different factors, I fit several logistic regression models:

Full model: `GoodDeal ~ MarketSize + Section_Group + DaysBeforeEventDate`

No Market Size: `GoodDeal ~ Section_Group + DaysBeforeEventDate`

No Section Group: `GoodDeal ~ MarketSize + DaysBeforeEventDate`

Timing Only: `GoodDeal ~ DaysBeforeEventDate`

A generalized additive model (GAM) was also fitted to allow the effect of days before the event to vary flexibly and capture potential non-linear relationships.

The GAM formula was:

`GoodDeal ~ MarketSize + Section_Group + s(DaysBeforeEventDate)`

The AIC and accuracy of each model is summarized in Table 2. The GAM seemed to have had by far the lowest AIC, indicating a much better fit than any of the linear models. All models achieved similar accuracy (about 80%), with the GAM performing marginally best, suggesting it has an ability to capture important non-linear effects of timing on deal probability.

Model	**AIC**	**Accuracy**
GAM (smooth timing)	52,652	0.8006
GLM (full model)	53,114	0.8001
GLM (no market)	53,153	0.8001
GLM (no section)	66,506	0.8000
GLM (timing only)	66,655	0.8000

Table 2: Model performance comparison by AIC and accuracy.

Using the GAM model, results (see Figure 7) give the impression that the effect of timing is both strong and complex. For MarketSize, "Big" is the reference point. For Section_Group, it is the "100s" section. The smooth term for **DaysBeforeEventDate** demonstrates high statistical significance, with an estimated degrees of freedom of 8.77 and an extremely low p-value. The plot shows that the "middle window" discussed earlier is especially promising: here, the probability of a good deal remained relatively high and declined only gradually.

Medium-sized markets were associated with a higher probability of good deals (estimate = 0.128, $p < 0.001$), while tickets in smaller markets are slightly less likely to be good deals (estimate = -0.079, $p = 0.015$).

Certain seat sections stand out: for example, B-Hive and Floor sections are significantly more likely to offer good deals, even after adjusting for timing and market size. In contrast, being in the 300s, 600s, or 700s sections is associated with a much lower chance of a good deal, all else equal. The model explains about 21% of the deviance in deal probability (adjusted $R^2 = 0.16$), which is substantial given the complexity and volatility of ticket resale markets.

4.2 How Section and Timing Shape Deal Probability

To explore which seat types offer the best chance of a good deal, Figures 8 and 9 show how seat section and purchase timing shape this likelihood. Figure 8 demonstrates that premium sections consistently provided the highest probability of a good deal, especially when tickets are bought well in advance; this probability declines as the event approaches. In contrast, upper and outer sections (300s–700s) had much lower, flatter probabilities, indicating that timing might matter less for these seats.

Figure 9, which controls for timing, reinforced the idea that premium sections stand out with the highest probabilities, while regular sections offer fewer bargains regardless of when tickets are purchased. Club (200s) and Lower Bowl (100s) sections generally occupy a middle ground: they offer better chances than the upper bowl and remain good options for buyers seeking a balance between value and location, particularly if purchased earlier. Taken together, these plots seem to reinforce that both *where* and *when* you buy matter, but the effect seemed strongest for premium sections, which effectively "carry" the good deal probabilities in the ticket market.

5 Conclusion

5.1 Discussion/Recommendations

Based on these findings, buyers seeking the best value on future Beyoncé concert tickets should focus primarily on timing and seat section, rather than market size, even if they are considering traveling to smaller markets in search of better deals. While big cities such as Los Angeles have higher average ticket prices (median around $350) than small markets (median around $220), the proportion of good deals remains nearly identical across market sizes (about 21–22%). Both early buyers (6+ months out) and last-minute shoppers (final 1–2 weeks) may enjoy increased chances of finding bargains, but the “middle window” (roughly 2–4 months before the event) also could offer a particularly high and stable probability of good deals, with the likelihood gradually declining as the concert date approaches.

Premium sections like B-Hive and VIP Pure Honey Risers appear to offer the best opportunities for strong deals (up to 54% probability in B-Hive if purchased early), while Club (200s) and Lower Bowl (100s) provide a balanced combination of value and view, yielding deal probabilities of 34–38% when bought several months in advance. Across all sections, tickets listed near the section’s lowest observed price are most likely to be top-value deals, so buyers should act quickly when such listings appear.

5.2 Limitations

This study’s findings are limited by their focus on Beyoncé’s 2023 Renaissance World Tour. Buyer behavior, pricing dynamics, and seat desirability may differ for other artists, genres, or regions if market conditions change. Only verified secondary market listings were analyzed, omitting primary sales and presales. One might be able to find a deal on a primary platform (if an artist chooses to release more tickets on Ticketmaster, for instance, should they do so closer to the start date of a specific show) or through Buy, Sell, Trade groups/word of mouth. Market volatility, local demand changes, and overall shifts in public sentiment of Beyoncé or of any other artist could affect future results.

The “good deal” definition (top 20% of scores) is also somewhat arbitrary. This threshold was chosen to provide a clear cutoff for analysis, but selecting a different percentile, such as the top 10% or 25%, would yield a different subset of listings labeled as “good deals.” Fans may have differing opinions on what constitutes a “good deal” (personal preference, budget, etc.). Therefore, while these insights are useful for Beyoncé fans, they should be applied cautiously to her case in addition to other situations.

5.3 Future Studies

For future studies, expanding the analysis to include concerts from a wide range of artists and genres would help determine whether the observed patterns hold across the broader live events market. I would also consider using random forests, which could improve the accuracy of deal prediction and reveal complex interactions among variables; for instance, I could attempt to uncover conditions such as increased probability of a good deal in big markets for weekday shows purchased closer to the event date.

Further research could also incorporate additional market and event context variables, such as competing events (other concerts, sports, or festivals in the same city and date), artist popularity metrics (recent chart performance, social media buzz, Google Trends), and tour leg or date (if it is opening night, the final show, weekend, or holiday shows, or unique high-interest events such as Beyoncé’s hometown shows and her birthday show[6] during this tour). Including these factors would provide a more nuanced understanding of the drivers behind ticket deal opportunities.

References

1. D. Commisso, "Live concerts make a comeback, but spending concerns take center stage," 2023, civicScience, accessed 2024-06-14. [Online]. Available: https://civicscience.com/live-concerts-make-a-comeback-but-spending-concerns-take-center-stage/
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4. C. Mello-Klein, "Why dynamic pricing is making concerts so expensive," 2024, northeastern Global News, accessed 2024-06-14. [Online]. Available: https://news.northeastern.edu/2024/10/02/dynamic-pricing-ticketmaster-oasis-taylor-swift/
5. I. Komonibo, "Team unbothered on the struggle to secure Beyoncé tickets," 2023, refinery29, accessed 2024-06-14. [Online]. Available: https://www.refinery29.com/en-us/2023/02/11287640/beyonce-renaissance-tour-tickets-fan-stories
6. C. Johnson, "The 8 best moments from Beyoncé's birthday concert at LA's SOFI stadium," 2023, billboard, accessed 2024-06-14. [Online]. Available: https://www.billboard.com/lists/beyonce-birthday-concert-best-moments-sofi-stadium/beyonce-is-the-celebrity-to-other-celebrities/

Appendix

About Seat Quality Criteria The score criteria I used combines factors like proximity to the stage, viewing angle, and overall concert experience based on user segmentation (feedback/reviews found online) of concerts in general. Most sites like SeatGeek and StubHub use proprietary formulas, often not published, and adjust them based on A/B testing and user research. For SeatGeek's Deal Score, they blend price and seat location using a weighted mean, but the weighting is not public. They have said they use past transaction data and expert input. More information on how their algorithm works can be found here.→(https://seatgeek.com/deal-score)

Code

```
section_scores <- df %>%
  group_by(Section_Group) %>%
  summarize(
    Median_ExpectedPrice = median(ExpectedPrice_reg, na.rm = TRUE)
  ) %>%
  ungroup() %>%
  mutate(
    Seat_Quality_Score = percent_rank(Median_ExpectedPrice)
  )
```

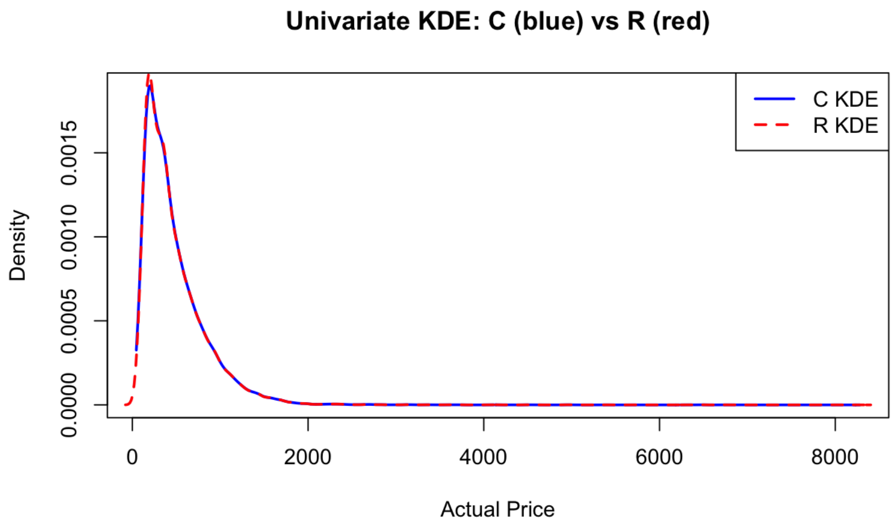


Fig. 1: Kernel density estimate (KDE) of overall ticket prices. Right skewed due to rare number of tickets sold at very high prices.

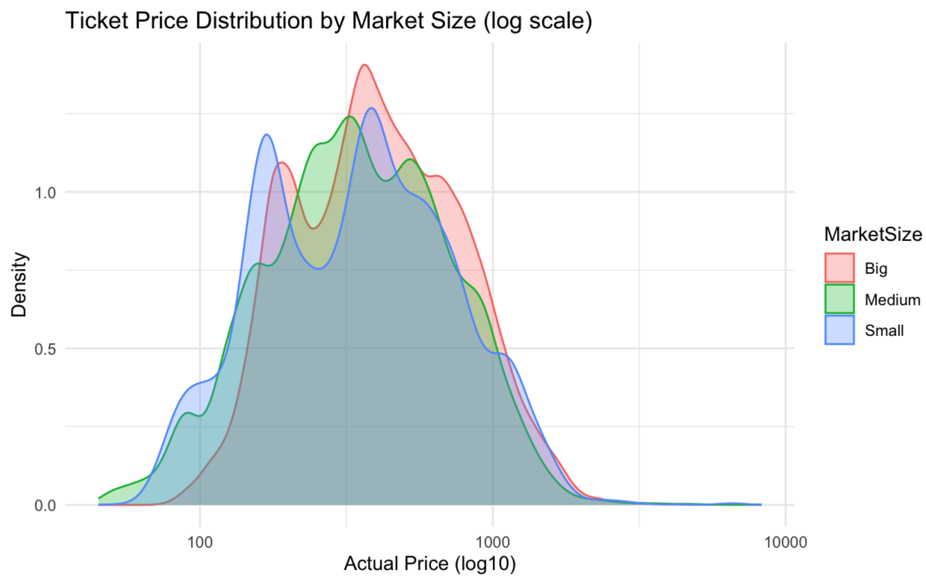


Fig. 2: Distribution of ticket prices by market size. Log-transformed for clarity purposes to visualize the overall spread and overlap across all market sizes. Most ticket prices were between \$50 and \$1000.

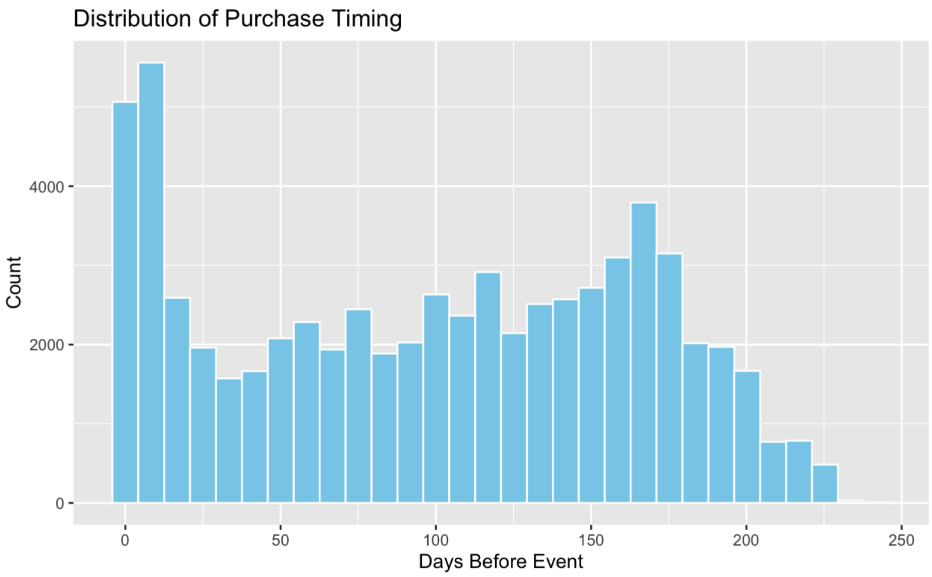


Fig. 3: Distribution of ticket purchases by days before each event. Presales occurred more than 225 days in advance. After presale, most buyers waited until about 180 days before the event to purchase, with another surge in last-minute purchases close to the show date.

Fig. 4: Proportion of good deals by market size.

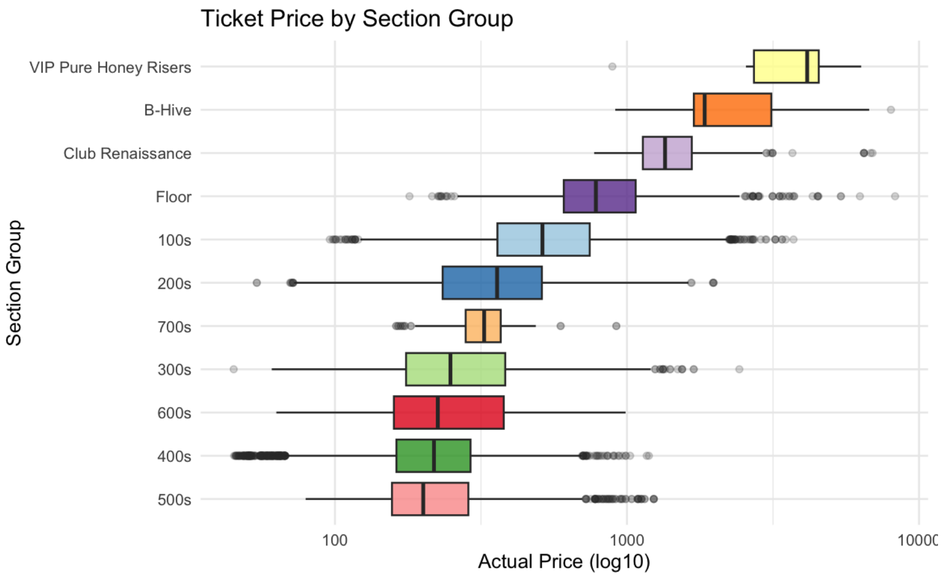


Fig. 5: Distribution of ticket prices by section group, shown on a log scale. Outliers indicate occasional high-priced sales in all sections.

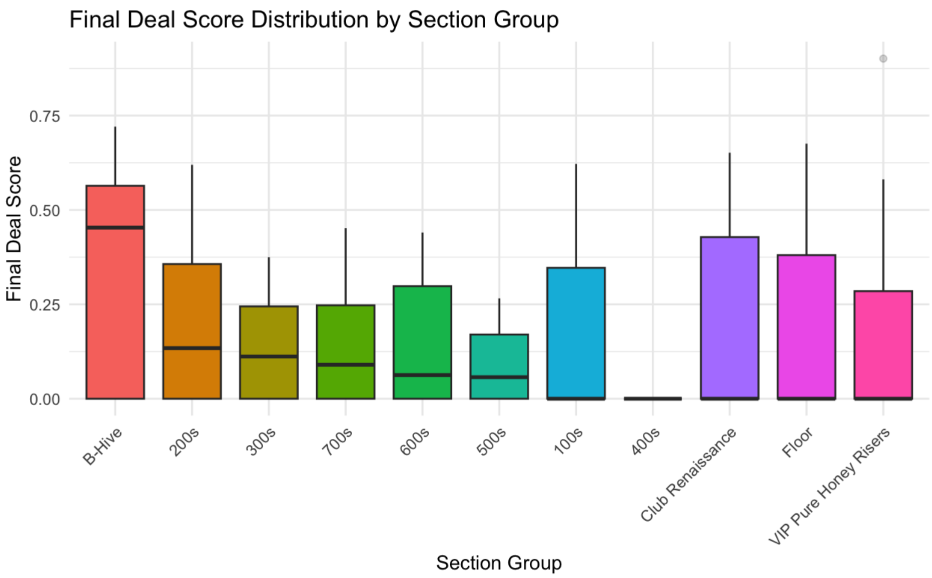


Fig. 6: Distribution of final deal scores by section group. Best all-in deals aren't always in the cheapest sections. The graph suggests that premium areas can sometimes be a smarter buy.

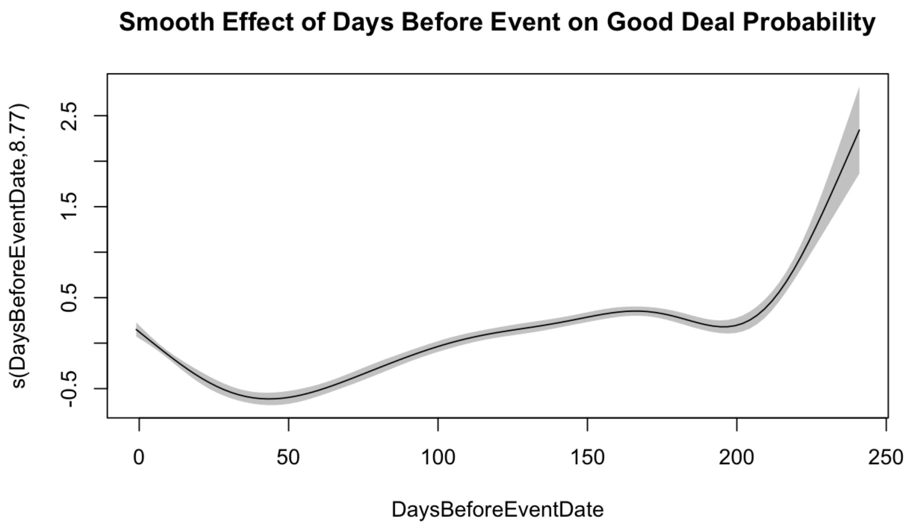


Fig. 7: Estimated smooth effect of days before the event on the probability of obtaining a good deal from the GAM model. The shaded region indicates the 95% CI, highlighting periods where buyers are more or less likely to find good deals.

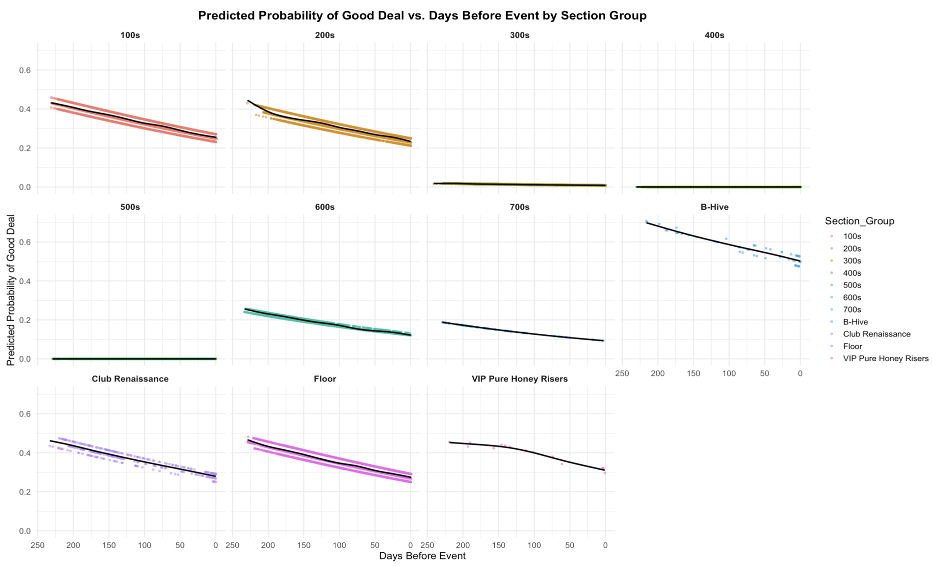


Fig. 8: Predicted probability of securing a good deal as a function of days before the event, by section group. Each panel shows results for a different section group, illustrating how timing effects vary across sections.

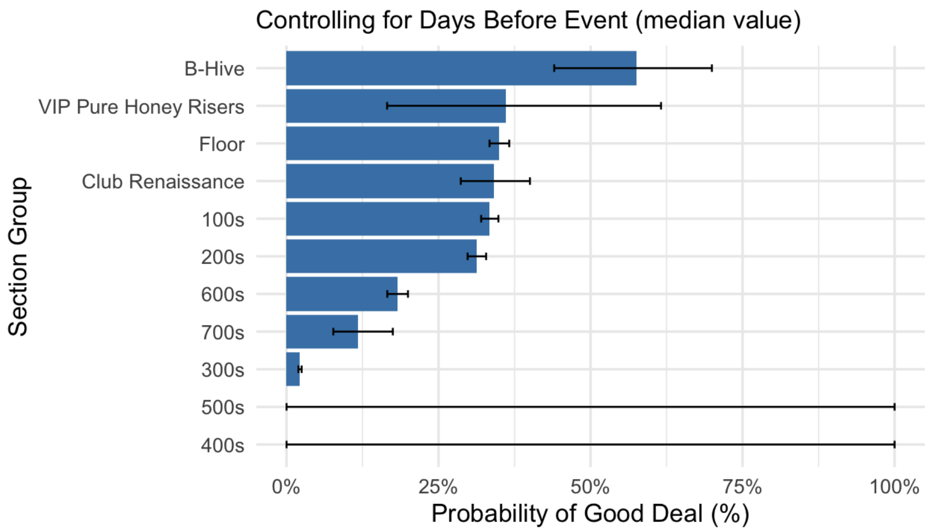
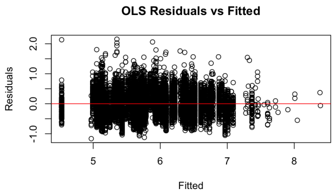


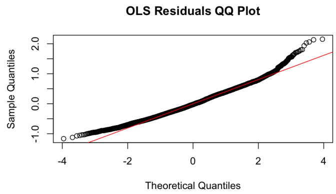
Fig. 9: Estimated probability of obtaining a good deal by section group, controlling for days before the event.

```
Family: binomial
Link function: logit

Formula:
GoodDeal ~ MarketSize + Section_Group + s(DaysBeforeEventDate)

Parametric coefficients:
                                   Estimate Std. Error z value Pr(>|z|)
(Intercept)                      -7.632e-01  1.864e-02 -40.935  < 2e-16 ***
MarketSizeMedium                  1.284e-01  2.355e-02   5.452 4.97e-08 ***
MarketSizeSmall                  -7.928e-02  3.259e-02  -2.433 0.014993 *
Section_Group200s                -1.161e-01  2.686e-02  -4.323 1.54e-05 ***
Section_Group300s                -3.743e+00  8.160e-02 -45.868  < 2e-16 ***
Section_Group400s                -3.496e+01  8.494e+05   0.000 0.999967
Section_Group500s                -3.479e+01  8.913e+05   0.000 0.999969
Section_Group600s                -8.056e-01  5.526e-02 -14.579  < 2e-16 ***
Section_Group700s                -1.240e+00  2.365e-01  -5.244 1.57e-07 ***
Section_GroupB-Hive               1.064e+00  2.759e-01   3.857 0.000115 ***
Section_GroupClub Renaissance     6.620e-02  1.272e-01   0.520 0.602767
Section_GroupFloor                1.211e-01  2.732e-02   4.433 9.29e-06 ***
Section_GroupVIP Pure Honey Risers  1.537e-01  5.320e-01   0.289 0.772647
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                         edf Ref.df Chi.sq p-value
s(DaysBeforeEventDate) 8.774  8.981  915.3  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.162   Deviance explained = 21.2%
UBRE = -0.21066  Scale est. = 1         n = 66704
```

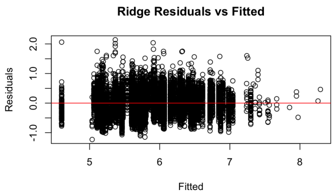
Fig. 10: Regression output for the smooth GAM model of good deal probability by market size, section group, and time before event. For MarketSize, "Big" is the reference. For Section_Group, "100s" is the reference.



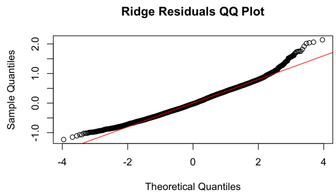
(a) OLS Residuals vs Fitted



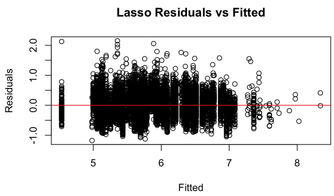
(b) OLS Residuals QQ Plot



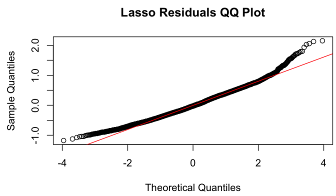
(c) Ridge Residuals vs Fitted



(d) Ridge Residuals QQ Plot



(e) Lasso Residuals vs Fitted



(f) Lasso Residuals QQ Plot

Fig. 11: Residual diagnostic plots for OLS, Ridge, and Lasso models. Left: Residuals vs Fitted. Right: QQ plots of residuals.