Theme Park Rides are Giffen Goods

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Abstract

Using a unique proprietary dataset on the behavior of guests visiting theme parks, I document evidence for Giffen behavior in the demand for theme park rides. On average, when the price of a ride increases, i.e. the wait time increases, then the probability of riding it increases. This relationship arises predominantly among demand for the least-desirable rides, it arises predominantly in the theme parks with the fewest number of substitute rides, and it is robust to controlling for expectations of future wait times and other sensitivity analyses. All of these patterns are consistent with Giffen behavior.

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I. Introduction

The law of demand states that when the price of a good increases, its quantity demanded decreases. Goods that violate the law of demand are called Giffen goods, or are said to exhibit Giffen behavior. Evidence for the existence of Giffen goods is scarce, though one possible example is the potato during the Irish potato famine.[1] Giffen behavior, i.e. upward-sloping demand, in the standard neoclassical model requires an inferior good (demand increases when income decreases) and an income effect dominating the price effect. Thus, it is only likely to be found among the very poor for subsistence goods like food staples.

However, a completely different decision-making environment is characterized by features that lend itself to Giffen behavior: the decisions of theme-park guests regarding which rides to wait for. Many theme parks feature *prix fixe* pricing – guests pay one entrance fee that gives them access to all rides and attractions.[2] Under *prix fixe* theme park pricing, the rides are not free; the price of a ride is not in dollars but in the time spent waiting in the queue. The law of demand dictates that when the wait time of a ride increases, the number of people willing to wait for the ride should decrease. The opposite will be true if demand for the ride exhibits Giffen behavior. The intuition for Giffen behavior for a theme park ride is the following. Given the budget constraint (i.e. the time constraint), when a ride's wait time is longer than expected, visitors are more willing to ride it. This is because the income effect from the higher wait time (the visitor is "poorer" in terms of the total number of rides they can experience in the park's fixed operating hours) makes the demand increase for rides that are inferior goods. Though a price effect also exists (the relative price of this ride has increased compared to other rides), if

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[1] See for example Dwyer and Lindsay (1984), Davies (1994), or Rosen (1999).

[2] See Oi (1971) for a discussion of monopoly behavior under *á la carte* pricing in theme parks, where each ride or attraction must be paid for with money.

the income effect dominates then we see Giffen behavior. Giffen behavior is perhaps more likely to be seen among theme park guests than in many other more traditional economic decision-making environments in part because the expenditure share on inferior goods can be a large percentage of total spending. That is, a relatively large fraction of a guest's time in the park may be spent on rides that are inferior goods.[3]

Giffen behavior among theme park rides can be explained by a utility function with a subsistence constraint, as I demonstrate in the model below. Obviously, there is not literally subsistence demand for rides (you don't need to ride rides to live, like you need to eat and drink), but theme park guests may act as if one existed. For example, guests may demand a minimum number of rides during a day at the park to feel that they "got their money's worth." This claim is consistent with anecdotal evidence and with the behavior of theme park operators, as described later. With such a constraint, I theoretically identify conditions when Giffen behavior arises, and I demonstrate that it is more likely to arise for rides with fewer substitutes and for low-demand rides (i.e. inferior goods).

The purpose of this paper is to test for this type of Giffen behavior in theme parks. I use a unique proprietary dataset, which contains observations from several hundred guests of several major theme parks in California and Florida. Each guest has at least one "touring plan," which is an itinerary of planned rides that the guest would like to do in the park. For each ride in the plan, I observe the ex-ante expected wait time, the actual wait time once the guest arrives at the ride, and the decision over whether the guest rode it. The key empirical test is the effect that the actual wait time, or the deviation between the actual and expected wait times, has on the

[3] A theme park ride being an inferior good means that if a guest's income (total time spent at the park) decreases, the guest's demand for the ride increases. For example, if you find that you have only 4 hours to spend at a park rather than 8 hours, you may choose to ride more of the low-wait-time rides like carousels.

probability of riding the ride. I argue that the variation in the actual wait times is plausibly exogenous to the individuals in my sample, and I control for weather and an extensive set of fixed effects. The law of demand says that a higher wait time should cause a decrease in the probability of riding; Giffen behavior suggests the opposite. I also test for whether this relationship differs based on the type of ride. Rides that are more likely to be inferior goods, for example those that are not the "headliner" attractions at the park, should be more likely to exhibit Giffen behavior. I test whether this relationship differs based on the number of rides available in a park. With more rides available, there are more substitutes available for the inferior rides, making Giffen behavior less likely. Finally, I also test whether the relationship between current wait time and the probability of riding is affected by expectations over future wait times. If that were true, then the observed relationship between wait time and riding could be explained without reliance on Giffen behavior.

Giffen goods are a well-known paradox arising from standard neoclassical economics. Real-world evidence is generally scarce. Jensen and Miller (2008) find evidence for Giffen behavior in demand for staple foods among poor households in China. Rosen (1999) argues that the example of potatoes during the Irish famine does not actually support Giffen behavior. Evidence of Giffen behavior among theme park guests would be one of the few examples of real-world Giffen behavior, albeit not in a traditional market setting.

There is a literature that studies the behavior of theme park guests. Birenboim et al. (2013) study the temporal patterns of visitors to a theme park in Spain by monitoring them with GPS technology. Several studies develop algorithms for optimizing tourism across a theme park. That is, they develop ways to plan a visit to minimize waiting time and maximize time spent on rides. Testa et al. (1999) frame the problem as a time-dependent traveling salesperson problem

(TDTSP) and solve it through designing a computational evolutionary algorithm.[4] Tsai and Chung (2012) collect individual guest behavior using RFID technology and tailor individualized recommendations based on observed patterns. Dvorachek (2018) proposes incorporating a decision support system into Walt Disney World's mobile application to assist guests, and Beloiu and Szekely (2018) develop and simulate an innovative virtual queuing system. I know of no other studies besides this one that examine theme park behavior in the context of a neoclassical economic optimization problem.

I find statistically significant evidence of Giffen behavior among theme park guests. On average, a ten-minute increase in the difference between the actual wait time of a ride and its ex ante expected wait time increases the probability of riding it by about three to five percentage points. This relationship holds under a variety of specifications and different controls, including controlling for weather, for overall park wait times, and for a set of user, ride, date, and time-of-day fixed effects. While true on average across all rides, I find that the effect predominantly arises from the rides that are the least desirable, i.e. not the headliner rides like roller coasters. These rides are more likely to be inferior goods and thus more likely to exhibit Giffen behavior. I show that the Giffen effect is larger in theme parks with a smaller number of substitute rides, consistent with the theory. The evidence is robust to controlling for various measures of future expectations of wait times. I demonstrate the intuition behind these results with a model of consumer optimization within a theme park.

Why is this important? There are two specific, practical reasons, and one more general reason. First, the results are of interest to those studying theme park touring behavior, including both decision scientists and theme park owners, as well as those who study queuing theory.

[4] This algorithm is the basis behind the website Touring Plans, where the dataset comes from.

Second, real-world evidence of Giffen behavior can be useful as a pedagogical tool for teaching economics students, as a way of demonstrating offsetting price and income effects. For many students, theme park rides might be a more relatable example than potatoes during a famine. Finally, there is a third, more general motivation. There is value in understanding the domains in which neoclassical economic decision-making applies. While usually used to explain behavior in traditional market settings, economics (e.g. utility maximization or game theory) has also been applied to decision-making in areas like sports, crime, or the family. However, that does not mean that it is appropriate or applicable to use economics everywhere; in some domains of life perhaps economics decision-making is not or should not be used (Anderson 1995). Identifying a domain in which neoclassical economic decision-making applies (here, at theme parks) helps the science to understand and clarify its impacts and its limitations.

The next section introduces a simple model to explain the Giffen behavior, and section III describes the data. In section IV, I discuss the empirical strategy and results.

II. Model

A motivating example, summarized in Table 1, provides intuition. Consider a theme park with just two rides: a high-demand ride with a long wait, like a roller coaster, and a low-demand ride with a short wait, like a carousel. A guest has made a touring plan based on the expected wait times for the rides – 15 minutes for the carousel and 120 minutes for the roller coaster – and on the total time spent in the park of seven hours. Given that budget constraint, the guest chooses three rides on the roller coaster (six hours) and four rides on the carousel (one hour). This is represented in the first row of Table 1. When the guest arrives in the park, she finds an unexpected increase in the wait time for the carousel, increased from 15 minutes to 30 minutes.

How does she change her behavior? One option (option 1, second row of Table 1) would be to maintain her three rides on the roller coaster, leaving her just enough time (one hour) for two rides on the carousel instead of four. This would reduce the total number of rides from seven to five. An alternate option (option 2, third row of Table 1) is to ride one fewer ride on the roller coaster (two instead of three), leaving her an extra two hours to ride the carousel, which would allow her six rides instead of the original four on the carousel. This would increase the total number of rides from seven to eight. This option amounts to Giffen behavior in her demand for the carousel; the price (wait time) increased, and her quantity demanded increased. The Giffen option is more likely to be chosen if the guest has some minimum total number of rides that she would like to achieve, similar to subsistence demand. While there is not literal subsistence demand when it comes to theme park rides, guest behavior may in fact mimic such behavior if guests behave as if they need to ride a minimum number of rides to "get their money's worth." Ahmadi (1997, p.1) cites a customer survey from a theme park suggesting that there is a "threshold level" of the number of rides ridden in a day, beyond which utility does not increase substantially. Barnes (2010) describes how Disney actively manages guests in its park in part to increase the total number of rides each guest can ride.[5]

To formalize this, I introduce a demand model with a subsistence constraint, based on van Marrewijk and van Bergeijk (1990) and Gilley and Karels (1991).[6] I begin with the two-ride (i.e. two-good) problem then generalize to more rides. The guest's utility function is $u(x_{lo}, x_{hi})$, where x_{lo} and x_{hi} are the quantities consumed of the low-demand ride (the carousel) and the

[5] Torres et al. (2018) studies the determinants of theme park guests' satisfaction based on a text-based analysis of online reviews, and finds that the keywords "ride," "time," and "line" are among the most relevant determinants. That paper also provides a literature review on the subject of theme park guest satisfaction. In Beloiu and Szekely's (2018) simulation of queuing systems, the primary performance metric is the number of attractions guests can ride in a day.

[6] The appendix of Jensen and Miller (2008) describes these models and compares them to other models that generate Giffen behavior.

high-demand ride (the roller coaster) respectively. For now, I ignore the real-world constraint that the number of rides (quantity consumed) must take an integer value. The budget constraint is $t_{lo}x_{lo} + t_{hi}x_{hi} \leq T$, where t_{lo} and t_{hi} are the wait times of each ride and T is the endowment of total time available to spend in the park. There is also a subsistence constraint, reflecting the fact that the guest may feel the need to ride a minimum number of rides to "get their money's worth." This constraint is $x_{lo} + x_{hi} \geq N$. The high-demand ride has a longer wait: $t_{hi} > t_{lo}$. This implies that the subsistence constraint is steeper than the budget constraint when the quantity of the high-demand ride is plotted on the vertical axis.

The main result from this two-ride model is that when both the budget constraint and the subsistence constraint bind, then demand for x_{lo} exhibits Giffen behavior. When both budget constraints hold with equality ($t_{lo}x_{lo} + t_{hi}x_{hi} = T$ and $x_{lo} + x_{hi} = N$), then they jointly determine the quantities demanded for both rides: $x_{lo} = \frac{Nt_{hi}-T}{t_{hi}-t_{lo}}$ and $x_{hi} = \frac{T-Nt_{lo}}{t_{hi}-t_{lo}}$. It follows that the derivative of the quantity demanded of the low-demand ride with respect to its wait time is positive: $\frac{\partial x_{lo}}{\partial t_{lo}} = \frac{Nt_{hi}-T}{(t_{hi}-t_{lo})^2} > 0$. When at the subsistence constraint, an increase in the price of the low-demand good means that the constraint can only continue to be met by reducing the quantity of high-demand rides and perfectly offsetting it with an increase in the quantity of low-demand rides. Giffen behavior does not arise for the high-demand ride: $\frac{\partial x_{hi}}{\partial t_{hi}} = -\frac{T-Nt_{lo}}{(t_{hi}-t_{lo})^2} < 0$. Only the cheaper (lower wait time) ride will be a Giffen good.

This result arises both from the assumption that the guest's two constraints are binding and from the assumption that there are only two rides. With more rides available, we might expect Giffen behavior to be less likely for low-demand rides; in response to a wait-time increase, the guest could switch to another low-demand ride rather than increasing her quantity of the ride whose time increased. To explore this, I extend the model to the next simplest case, where there are three rides. Two of the rides are low-demand rides like carousels (x_{lo1} and x_{lo2}), and the third ride is a high-demand ride (x_{hi}). The budget constraint is $t_{lo1}x_{lo1} + t_{lo2}x_{lo2} + t_{hi}x_{hi} \leq T$, and the subsistence constraint is $x_{lo1} + x_{lo2} + x_{hi} \geq N$. The high-demand ride has the longest wait time ($t_{hi} > t_{lo1}$ and $t_{hi} > t_{lo2}$). When both constraints bind, the number of each ride is no longer determined solely by the constraints (two binding constraints, but now three unknown variables). However, the constraints still create conditions that can be analyzed to consider Giffen behavior.

The constraints can be solved for the relationship between the quantity demanded of the two low-demand rides: $x_{lo1} = \frac{T - t_{hi}N + x_{lo2}(t_{hi} - t_{lo2})}{t_{lo1} - t_{hi}}$. It follows that the derivative of x_{lo1} with respect to its wait time is $\frac{\partial x_{lo1}}{\partial t_{lo1}} = \frac{(t_{hi} - t_{lo2})(t_{lo1} - t_{hi})\frac{\partial x_{lo2}}{\partial t_{lo1}} + \left(-t + t_{hi}N - x_{lo2}(t_{hi} - t_{lo2})\right)}{(t_{lo1} - t_{hi})^2}$. This is not a closed-form solution for the derivative, since it depends on another derivative ($\frac{\partial x_{lo2}}{\partial t_{lo1}}$) that is endogenous. The first term in the numerator is of the opposite sign as $\frac{\partial x_{lo2}}{\partial t_{lo1}}$, and the second term in the numerator is strictly positive. If $\frac{\partial x_{lo2}}{\partial t_{lo1}} < 0$, then the entire derivative is positive, and x_{lo1} exhibits Giffen behavior. The derivative $\frac{\partial x_{lo2}}{\partial t_{lo1}}$ is more likely to be negative when the two low-demand rides x_{lo1} and x_{lo2} are strongly complementary. Thus, when there is not a substitute for the low-demand ride, then it is more likely to be a Giffen good. When $\frac{\partial x_{lo2}}{\partial t_{lo1}} > 0$, which is more likely to be true when the two low-demand rides are substitutes for each other, then the derivative $\frac{\partial x_{lo1}}{\partial t_{lo1}}$ has two offsetting terms. As $\frac{\partial x_{lo2}}{\partial t_{lo1}}$ is more positive, indicating that the two low-demand rides are better substitutes for each other, then the likelihood of the derivative $\frac{\partial x_{lo1}}{\partial t_{lo1}}$ being negative increases. Thus, when there is a good substitute for the low-demand ride, Giffen behavior is less likely.

The model's examination of comparative statics between changes in wait times perfectly fits the empirical analysis, where I estimate effects of deviations in actual wait times from expected wait times. That is, the difference between the actual and expected wait time represents ∂t_{lo}, while the change in the probability of riding represents ∂x_{lo}; the estimated regression coefficient is the partial derivative presented in the model. An alternative decision-making process may go into making the plan itself, before arriving at the park. One might think that users will make more rational, thought-out decisions at this stage, when they have time to think about their choices, than when they are in the park responding in real time to variations in wait times. Unfortunately, I am unable to empirically apply such a model to the data, since I do not observe variation in the expected wait times that users face when they initially make their plans. The key advantage of the dataset I use is the ability to compare expected and actual wait times when at the park, so it is this margin that I focus on in the model and regressions.

The model's analysis of the three-ride model demonstrates the importance of the presence of substitutes in the possibility of Giffen behavior, but it relies on analyzing a non-closed-form expression for the derivative of interest. In Appendix A1, I present and analyze the full model solution and show that, though it is more complicated, this key finding remains.

The model assumes a continuous measure of demand x_{lo}, while in the empirical analysis I will estimate effects on the likelihood that a ride is completed. A more realistic modeling assumption would be to assume an integer constraint on the quantity demanded and see how that integer quantity demanded varies with changes in wait times. The model cannot incorporate an integer constraint and still yield closed-form solutions, but numerical simulations can explore the implications of the integer constraint. I present these simulation results in Appendix A2; the general finding of Giffen behavior with the subsistence constraint remains.

Finally, the appendix also considers a third extension to the model, one which includes two time periods to capture the dynamic decision-making involved. The previous models are static, but in fact theme park guests are responding both to current wait times and to expectations over future wait times. The model in Appendix A3 shows how Giffen behavior can still be present when these dynamic considerations are accounted for, and it motivates the empirical exercise of controlling for future wait times presented below.

III. Data

I use a unique proprietary data set based on theme park touring behavior provided by the firm Touring Plans. Touring Plans is a subscription-based service that provides theme park visitors with customized itineraries for their visit. Theme park rides and attractions[7] can have very long wait times of up to several hours, and Touring Plans offers its subscribers a method for minimizing the time spent waiting in line. Users can enter a set of attractions that they would like to experience during the day, and Touring Plans will "optimize" an order of visiting each attraction. The optimization technique is based on a methodology developed in Testa et al. (1999). An example of an optimized touring plan is shown in Appendix Figure A1. Plans are optimized taking into account expected wait times, predicted based on historical wait time data.

While in the theme park, guests with touring plans have the option of following their plan by using an app, which lists their plan steps along with the current expected waiting time for each ride. Guests can thus compare the wait time that was expected when they made their

[7] I use the words "attraction" and "ride" interchangeably, to refer to anything that could be included in a touring plan, which includes rides, shows, and character greetings.

touring plan (typically several days or weeks before their trip) to the actual wait time when currently in the park. Guests also have the option of checking off each step of the plan (each ride) that they have completed in the app.

Touring Plans gave me access to some of their proprietary data, based on actual touring plans and touring behavior made by subscribers for several days in 2018. The dataset includes 419 unique touring plans from 314 unique users. The plans are from the first week of February and the last week of June 2018. There are 6,058 total observations in the raw data, where each observation is one step in a plan. Each plan is composed of several steps, which can be either an attraction, a meal, or a break. The average plan has 14.5 steps, and of those steps 13.35 are an attraction while the rest are a meal or a break. I drop the 2.4% of observations (146 observations) where the date of the observation is different than the date of the start of a plan. Each observation is a planned step that the user made before beginning her visit to the park that day, or it is a ride that the user has added to the plan while at the park. Some users ride a single ride multiple times, and that can be reflected in the dataset; about 8 percent of all observations are "re-rides."

The data come from visits to one of eight theme parks in the United States: the four theme parks of Walt Disney World in Orlando, Florida (Magic Kingdom, Epcot, Hollywood Studios, and Animal Kingdom), the two theme parks of Disneyland Resort in Anaheim, California (Disneyland Park and California Adventure), and the two theme parks of Universal Orlando resort in Florida (Universal Studios and Islands of Adventure).

The key variable of interest that I exploit is an indicator for whether or not that step of the plan was completed during the day of the visit. A variable in the raw data gives the time at which the step was mark completed as submitted by the user. If this variable is non-missing, then the "completed" indicator variable equals one; if the variable is missing, then "completed" equals zero. The other important variables used in the analysis are measures of the expected and actual wait times for the attractions in the plan. The expected wait is how many minutes the Touring Plans software expected the wait to be when the user was expected to arrive at the attraction, predicted at the most recent time the user optimized the plan. This is typically predicted several days ahead of the visit to the park when the user is constructing the plan. The actual wait is the reported wait time when the user actually arrives at the attraction the day of the plan. The discrepancy is the prediction error. Wait times are only available for attractions, not for meals or breaks, and wait time data are frequently missing from the raw data file.

Tables 2 and 3 provide some summary statistics of the dataset. The first panel of Table 2 presents overall means, standard deviations, and number of non-missing observations for the percent of steps completed, and the expected and actual wait times of each step. 58.7% of the plan steps were marked as completed. The average expected wait time for an attraction is about 14 minutes, while the average actual wait time was about 29 minutes. The bottom panel of Table 2 presents the average wait times separately for those steps marked complete and those not marked complete. Attractions marked completed had a shorter expected wait (12 minutes vs. 16 minutes) but a longer actual wait (35 minutes vs. 20 minutes) compared to attractions not marked complete.

Table 3 presents these same summary statistics but breaks them up by several categories: by the eight theme parks included in the data (Panel A), by the time of day of the plan step (Panel B), and by whether rides are high-demand or low-demand (Panel C, defined below). The top rows of the Panel A are from the four Walt Disney World (Florida) theme parks, while the rows below that are from the two Disneyland (California) parks and the two Universal (Florida) parks. There is some variation across the theme parks in average expected and actual wait times, though all exhibit roughly the same pattern of longer actual than expected waits. It is unclear why this pattern persists, since the expected wait times are predicted based on years' worth of observed actual wait time data. It is possible that the handful of days that are represented in the dataset happened to be days that were unexpectedly busier than average. Alternatively, the discrepancy could be because from 2017 to 2018, Disney Parks changed the technology used to estimate their wait times. They phased out the use of physical red cards that were handed to guests in a queue to track their wait, and they instead began tracking guests' wait remotely with newly-patented RFIP technology.[8] This discrepancy should not affect the regression results below, which exploit the deviation between expected and actual waits and how they vary over different attractions. Panel B of Table 3 shows that earlier in the day, guests are more likely to complete their plan steps. Parks generally open around 8 or 9 am and close by midnight, though there are some observations from when parks are open outside those hours.

Because I rely on these user-submitted reports, misreporting may be an issue. If a user edits or modifies a plan, or rides a ride not originally on the plan, I can observe that if the user reports it. But it is possible that users are deviating from the plan in ways that go unreported. Most importantly, it might be the case that users stick to the plan more when wait times are high and deviate more without reporting it when wait times are high. In that case, the observed correlation that I find would not necessarily indicate Giffen demand. I will address the misreporting issue in several ways below in the robustness checks, though this caveat remains.

Each theme park contains a wide range of rides and attractions with different demand, including headliner attractions like large roller coasters (e.g. Space Mountain) and smaller and

[8] Mirarchi (2017) describes the phase-out of the use of the red cards; the patent application for the new technology is Rankin et al. (2019).

less-popular attractions (e.g. a teacup ride). The less-popular attractions are more likely to be inferior goods and thus more likely to exhibit Giffen behavior. I distinguish between more and less popular rides, what I call "high-demand" and "low-demand" rides, based on four different criteria. First, I delineate based on whether the touring plans include a recommendation for using a "Fastpass" on the ride. Fastpass is a system that was offered in the six Disney-owned theme parks in the dataset, where guests can reserve a time for a ride in advance of their visit to the park, and then use the Fastpass instead of waiting in the queue. Fastpasses are generally best used in the most-popular rides to avoid the longest wait times. For each ride in the dataset, I check whether a Fastpass is ever recommended in any touring plan. For those rides in which a Fastpass is ever recommended, I categorize them as "high-demand" rides, and for those in which a Fastpass is never recommended, I categorize them as "low-demand" rides. Fastpass is only available at the six Disney theme parks, but the two Universal theme parks have a similar system (Express Pass), and high-demand rides are defined the same way.

The second definition is based on whether the ride has a "Lightning Lane" entrance. Lightning Lane is the system that replaced Fastpass in 2021 and works essentially the same way. While Lightning Lane was not in existence during the time period that the data are from, almost all of the Lightning Lane rides were in existence, so I use the future existence of a Lightning Lane to classify a ride as high-demand. This definition is only available for rides at the six Disney theme parks, since Universal parks do not have Lightning Lane.

The third and fourth definitions of high-demand rides are based on survey data collected by Touring Plans from thousands of users. For each ride, I observe the number of ratings (number of users who have submitted ratings) and the average rating on a 5-point scale. Each of these is available by six age categories (e.g. preschoolers, teens). I take a simple average of the score across all age categories, and I take the sum total of ratings for each ride (a reasonable measure of demand). The third indicator of high-demand is if the average rating is 4 or higher, roughly the median value across all observations. The fourth indicator of high-demand is if the total number of ratings is 150,000 or higher, roughly the median value. The third and fourth definitions of high- and low-demand rides are available for most attractions at all eight theme parks, so long as ratings data exist.

Of the 370 rides included in the dataset, just 30% (108) are categorized as high-demand, according to the first definition of high-demand. But, of the observations in the dataset, 75% of those used in the regressions (those with non-missing expected and actual wait times) are observations from high-demand rides. High-demand rides are more popular and so more likely to appear in touring plans.

Panel C of Table 3 shows that the percent completed of high-demand rides (based on the first definition of high-demand) is slightly higher than that of low-demand rides (62% vs. 55%), but the wait times of high-demand rides are substantially higher than those of low-demand rides. The actual wait for a high-demand ride averaged 30 minutes, while the actual wait for a low-demand ride averaged just 10 minutes. This pattern is qualitatively similar for the other three definitions of high demand, though those are only available for a subset of the observations.

These wait time data are supplemented with two other data sources. First, I collect weather data from Weather Underground, which reports historical data collected at the Orlando International Airport (for the Orlando theme parks) and at the Los Alamitos Army Airfield (for the Anaheim theme parks). I use both daily average temperatures and precipitation totals, and hourly temperature and precipitation.

Second, I use a publicly-available dataset of historical wait times provided by Touring Plans.[9] These data include reported wait times at many attractions in the Walt Disney World parks, at five-minute intervals. The data are collected by continuously scraping from the park's official website, which posts real-time wait times. I use these data to create daily-level and time-of-day level measures of average wait times at the ride level. These data also report when a ride is listed as temporarily out of service (e.g., because of a maintenance issue). At the ride-day level, I create a measure of the fraction of the total time of the day that a ride is unavailable. Unfortunately, these data only cover the four Walt Disney World theme parks, and they do not cover the Universal Studios parks nor the Disneyland parks. They also do not include all attractions at each of these four parks. I choose two attractions at each of these four parks, and use these data to create these measures for these select attractions.

IV. Empirical Strategy and Results

The question of interest is whether an increase in actual wait times will increase or decrease the quantity demanded of the ride; that is, the probability of completing the step and riding the ride. If a higher wait time causes a higher probability of riding, then this is Giffen behavior in demand for the good. The basic regression strategy is to set the dependent variable to be an indicator for whether a step in the touring plan was marked as complete; that is, an indicator for whether the guest rode the attraction. The independent variables of interest will be measures of the wait time of the ride when the guest arrived and the expected wait time in the touring plan before arriving at the park.

[9] These data are available here: https://touringplans.com/walt-disney-world/crowd-calendar#DataSets.

The goal is to estimate individual demand curves (of the guests in the sample) using plausibly exogenous variation in prices (wait times) observed in the data. The fundamental identification challenge is whether the observed wait time variation is uncorrelated with the individual demand curves. If some confounder shifts up these individual demand curves and aggregate demand, the resulting increase in wait times may be correlated with an increase in quantity demanded, but this would be movement along an upward-sloping supply curve, not Giffen behavior.

Figure 1 presents some summary statistics on average wait times throughout the day for four illustrative rides (one at each of the four Orlando Disney parks). The top panel presents average wait times across all days within the sample period, and it shows that the general pattern is for wait times to begin the day low, increase throughout the morning, maxing out around lunchtime or shortly afterwards before slowly decreasing through the afternoon and evening. The bottom panel shows those same wait times for a given day, rather than averaging across all days. It shows that there can be substantial within-day variation in these wait times.

What is the source of variation in these observed wait times? This study is not a field experiment, exogenously manipulating these wait times, so it is impossible to precisely identify the source of variation. The wait time is an equilibrium outcome, so it depends on aggregate supply and on aggregate demand. Shifts in aggregate supply that could affect wait times include downtime, outages, or reduced capacity due to mechanical or staffing issues. Wait times affected by any of these supply shifters will not inhibit the identification strategy. The most obvious shifts in aggregate demand that could affect wait times are caused by the total number of guests in the park, or the total number wanting to ride a given ride at a given time.

In many empirical applications, when estimating an aggregate demand curve off of observed variation in equilibrium outcomes, an unobserved demand shifter is a threat to identification. However, in this study, the aggregate demand shifter caused by a change in the total number of guests in the park does not threaten my identification strategy. That is because I am estimating individual demand curves – the demand curves among the guests in my sample. An increase in the total number of guests will increase aggregate demand, and therefore increase wait times, but it will plausibly have no effect on an individual's demand curve. The individuals in my sample are already in the parks on the day in question with their touring plan. An individual will face a higher equilibrium wait time, exogenous to them, and will respond by moving along their demand curve, rather than shifting their individual demand curve.

A threat to my identification strategy will be a demand shifter that affects the aggregate demand through its effect on individual demands, including the individuals in my sample. The most obvious source of such a demand shifter is weather. When it is raining, fewer people want to ride rides, and many people want to leave the parks, or wait inside a restaurant or a gift shop. This will decrease equilibrium wait times, and the reduction in individual demand will decrease likelihood of riding a ride. A positive correlation between wait times and probability of riding would not be evidence of Giffen behavior in this case. Fortunately, weather can easily be controlled for, either through observed temperature or precipitation at the hourly level, or through park-by-date-by-time-of-day fixed effects.

What are other individual demand shifters that could potentially threaten my identification strategy? It cannot be simply the popularity of a given ride – I include a ride-fixed effect. It would have to be some kind of idiosyncratic taste-shifter that varies throughout the day, affecting one's desire to ride something independent of the wait time. It is hard to think of such a demand shifter, especially given that my sample is composed of guests who have already done enough research on the rides in the parks that they have developed touring plans before arriving. Therefore, I argue it is very plausible that the observed variation in wait times is caused either by supply shifters or demand shifters that are exogenous to individual demand curves, or by weather that can be easily controlled for, and so I am plausibly able to identify Giffen behavior, or upward-sloping individual demand curves, with this strategy.

One potential worry is highly inelastic supply or a lack of shifters of supply. The supply – the total number of ride-slots available – depends on the physical capacity of the ride and seems unlikely to vary in response to a change in wait times (prices) or anything else. Though it is true that supply is likely to be highly inelastic and invariant to wait times, there is some response, for example the park can run more ride vehicles during busier times.[10] Furthermore, exogenous supply shifters could include weather or unscheduled maintenance closures, both of which I will control for in robustness checks. However, even if supply is highly inelastic with few or no supply shifters, the preceding discussion describes how this is not necessarily a threat to the identification strategy here. Even if variation in ride wait times are caused primarily by aggregate demand shifters like the number of guests in the queue, that is plausibly exogenous to an *individual's* demand curve, which is what I am estimating. The response of the individuals in my sample to the higher equilibrium wait time, exogenous to each individual, traces out the demand curve.

IV.A. Main Results

[10] This blog article describes how Disney World varies the capacity of their "Lightning Lane" queues in response to the overall crowd levels: https://blogmickey.com/2021/11/disney-world-allocates-up-to-93-of-ride-capacity-to-lightning-lane/ .

Table 4 presents the main regression results. The dependent variable in each regression is the indicator for a step having been marked complete. The independent variable is the deviation between the step's actual wait time and the expected wait time for the step when the guest arrives at the ride. A positive value of the wait deviation means that the wait was longer than expected. The model in column 1 only controls for the wait deviation and a constant; the remaining columns report results with additional sets of controls.

In column 1, the coefficient on the wait deviation is significantly positive, indicating that a higher-than-expected wait time is correlated with a guest being more likely to report riding the ride. This is evidence of Giffen behavior. The magnitude is about 0.005, which indicates that a positive ten-minute deviation between the actual and expected wait times is correlated with a 5 percentage-point increase in the probability of completing the ride. This magnitude can be compared to the average of the expected and actual wait times of 13 minutes and 29 minutes, respectively, and the average percentage of rides completed of about 60%. Overall, this is a fairly small effect, though it is statistically significant (and will remain so throughout all of the specifications below). Given that Giffen behavior arises from two offsetting effects (an income effect and a price effect), it is perhaps not surprising that the magnitude of the net effect is small.

Column 2 adds two control variables. The first is the average wait times across all attractions in observed touring plans at the park that day; the average wait variable thus varies only at the park-date level. The second additional control variable is an indicator for whether that step on the touring plan recommended using a Fastpass. Controlling for these two variables slightly increases the magnitude of the coefficient on the wait time deviation, and it remains statistically significant. The coefficient on the average wait variable is negative and significant at just the 10% level; higher average wait times across all rides at the park that day decrease the probability of riding a given ride.[11] The control for average wait time across all rides in the park is equivalent to a control for the overall price level, or equivalently real income (given a fixed time budget), rather than the price of a specific ride. The coefficient on the recommendation for Fastpass is negative but not quite significant at the 10% level.

Column 3 adds a series of fixed effects to control for several issues that vary across observations. First, I add an indicator for each of the 370 rides in the dataset; some rides may be more likely to be completed than others. Second, I add an indicator for each of the 314 users in the dataset; some users may be more likely to complete rides or to mark complete than others. Third, I add an indicator for the hour of the day in which the step was scheduled, since Table 3 indicated that the percent of steps marked complete falls throughout the day.[12] Fourth, I add an indicator for the date of the touring plan; all of the data come from one of 12 days in February and June 2018. As Column 3 shows, including this wide array of fixed effect does not substantially change the magnitude on the coefficient on the wait time deviation.

Column 4 of Table 4 adds a set of fixed effects from the interaction of the park, the date, and the hour of the day, and thus in this regression the average wait variable (defined at the park-date level) is omitted. The time-of-day is measured in six four-hour-long segments. These fixed effects can flexibly control for weather, even allowing for different weather patterns between the different parks in the same city. (Later in the robustness checks I will also explicitly control for hourly temperature and precipitation.) Again, the coefficient of interest on the wait deviation is significantly positive, with a 10-minute increased wait deviation correlated with about a 5 percent increase in the probability of riding. Overall, the results in Table 4 provide evidence for

[11] These results are robust to creating the average wait time variable using a leave-out average; i.e., not including the observation in question when calculating the park-day average wait time.

[12] Daniels et al. (2017) provide evidence that theme park guests' subjective perceived wait times are higher during the mid- to late-afternoon.

Giffen behavior among the demand for theme park rides. When the price of a ride is higher than expected, i.e., when the wait time for a ride is longer than expected, then the guest is more likely, not less likely, to ride the ride.

IV.B. Tests for Giffen Behavior

This relationship holds overall under several specifications shown in Table 4. However, we would expect that the relationship would be different across different attractions. Perhaps some rides are Giffen goods while others are not. As the theory behind Giffen behavior shows, goods must be inferior goods to be Giffen goods. To test whether some types of rides are more likely to be Giffen goods, I exploit the delineation described earlier between low-demand and high-demand rides.

In Table 5, I present regressions where the dependent variable of interest, the deviation between actual and expected wait, is interacted with the indicator for whether a ride is a high-demand ride. Each column in Table 5 presents regressions using a different definition for high-demand and low-demand rides, described earlier. In column 1, the definition is based on whether a Fastpass is ever recommended for the ride; in column 2, the definition is based on whether a Lightning Lane is available for the ride; in column 3, the definition is based on the average user rating; and in column 4, the definition is based on the number of user ratings. The same specifications of controls and fixed effects are used as in column 4 of Table 4, except without a ride fixed effect since the definition of the high demand variable varies only at the ride level. Across specifications, the coefficient on the wait deviation is about 0.007 to 0.013 and significantly positive. The coefficient on the indicator for being a high-demand ride is also significantly positive; high-demand rides are more likely to be completed all else equal. The coefficient on the interaction term is significantly negative across all specifications. The effect of the wait deviation on the probability of riding is smaller for high-demand rides than it is for low-demand rides. This is consistent with the prediction that low-demand rides are more likely to be inferior goods and thus more likely to exhibit Giffen behavior.

In a two-good model like the one presented earlier, both goods cannot be Giffen goods. Extending that argument to this empirical exercise, if the low-demand rides exhibit Giffen demand, then the high-demand rides should not. The magnitude of the negative coefficient on the interaction term is about 60% to 80% of the magnitude of the positive coefficient on the wait deviation across all columns. Thus, there is no significant empirical evidence that the high-demand rides obey the law of demand. This does not mean, however, that all rides are Giffen goods, for several reasons. The positive net effect found for high-demand rides in Table 5 is not statistically significant. Furthermore, this positive net effect is found only under an aggregation of a set of rides. I do not have enough degrees of freedom to test for Giffen behavior among every single ride. Additionally, there are other uses of time that I am not able to observe and control for, including visiting restaurants, shops, or just resting in the park. The observed rides are not exhaustive of all possible consumption goods.

As suggested by the theoretical model, Giffen behavior is more likely when there are fewer substitutes available for the low-demand rides. To test this, I check the number of rides that are available (and which have at least one observation with an expected and actual wait time and so are in the regression sample) in each of the eight parks. I define the four parks with the highest number of attractions to be parks with high ride numbers, and the remaining four parks to be parks with low ride numbers.[13] I run the main regression specification but interact an

[13] The four high ride number parks are the Magic Kingdom, Disneyland Park, California Adventure, and Animal Kingdom.

indicator for whether the park is a high ride number park with the wait time deviation. Results are reported in Table 6. Because the high ride number indicator variable is defined at the park level, these regressions do not include park fixed effects or park-by-date-by-hour fixed effects (and so there are only three columns).

Across all columns, the coefficient on wait deviation is positive, indicating Giffen behavior. The coefficient on the indicator for being in one of the four parks with a high number of rides is significantly negative, indicating that users are less likely to complete rides on average in these four parks. The coefficient of interest is on the interaction variable, and it is significantly negative in the first two columns. Its sign indicates that in parks with a high number of attractions, the Giffen behavior is less pronounced (i.e. the coefficient on wait deviation is less positive). The magnitude of the negative coefficient on the interaction term is lower (about 0.001) than the magnitude of the positive coefficient on the wait deviation (about 0.006), so Giffen behavior is not absent in the parks with a high number of rides though it is of a smaller magnitude. In the third column where a full set of fixed effects is included, the magnitude of the coefficient on the interaction term is still negative but only about one-fifth as large and is not statistically significant. Overall, Table 6 provides some evidence, albeit weak, that parks with a higher number of substitute attractions are less likely to exhibit Giffen behavior than parks with fewer substitutes, as predicted by the theory.[14]

IV.C. Expectations of Future Wait Times

[14] I find this result when the parks with a high number of rides are defined as the four parks with the most rides. If instead I just choose the two parks with the highest number of rides (Magic Kingdom and Disneyland Park), there is never a negative coefficient on the interaction variable.

The preferred explanation for the observed positive correlation between wait times and the probability of riding is Giffen behavior. An alternative explanation is related to a guest's expectations of future wait times. When a guest sees a longer-than-expected wait, they may form a belief that the wait later in the day will be even longer still, compared to what they had expected it to be. So, they may choose to wait in the long line now in order to avoid the even longer (expected) wait in the future. Such a decision would not be Giffen behavior; it would be an outward shift in the demand for riding now based on an expectation of an increased price (wait time) of riding in the future.

Controlling for user-level expectations of ride wait times is impossible, but the Touring Plans data allows me to address this issue thoroughly. First, the park-by-date-by-hour-of-day fixed effects, included in the final column of most of the regression tables, can control for users' expectations of future wait times as they vary throughout the day (though there are not enough degrees of freedom to also include an interaction with user). In these specifications, the coefficient on the wait time deviation is almost identical to the specifications with the other set of fixed effects.

The second method of controlling for expectations is to use the Touring Plans data on actual wait times at rides later in the day. For each ride in the plan, I can observe the posted wait time of the ride at noon, 3pm, and at 6pm that day. In the regressions, I control for each of these three variables. If a guest's expectation of future wait times is accurate, then these observed wait times will control for those expectations. I only observe these actual wait time data for the observations from June 2018 and not from February 2018. These regression results are reported in Table 7. The coefficient on the wait deviation is still significantly positive and about the same magnitude as in the main results even after controlling for wait time expectations in this way, providing more evidence that this is Giffen behavior and not a shift in demand in response to changing expectations. The coefficients on future wait times are generally insignificant, though there is a slightly significant negative coefficient for the noon wait time.[15]

IV.D. Robustness Checks and Alternative Specifications

Appendix Table A1 presents an alternative specification where there are two key right-hand-side variables of interest – the actual wait time and the expected wait time – rather than just the difference between the two. We see a positive coefficient on the actual wait time, and a negative coefficient on the expected wait time. The negative coefficient on expected wait time indicates that users are less likely to ride a ride when the touring plan predicts that it will have a longer wait. However, the positive coefficient on the actual wait suggests Giffen behavior, since the actual price is represented by the actual wait.

As described earlier when describing the data, the self-reported nature of the data and in particular the "completed ride" indicator means that misreporting is an issue. There is no independent source to verify these data, but as a way of addressing potential misreporting, I run the main regression specifications but only use observations from earlier in the day, before 4:00pm. The concern addressed is that later in the day, users may be less careful and more prone to misreporting (e.g. failing to indicate they rode a ride when they actually did). The summary statistics in Table 3 indeed shows that the fraction of steps marked complete does drop off later in the day. Appendix Table A2 reports the results from the regressions dropping observations after 4:00pm; the main results are unchanged.

[15] Though I refer to this as controlling for future wait times, for many observations the step is after noon, and so the noon wait time control is for a wait time earlier in the day. This negative coefficient could be coming from observations after noon, under which a higher noon wait time meant users were more likely to ride the ride earlier rather than at their planned step.

In Appendix Table A3, the main regression results are repeated but replacing the key variable of interest – wait deviation – with an indicator equal to one if the actual wait is longer than the expected wait. (The actual wait is longer for 64% of the observations.) Users may simply respond differently depending on whether the wait is longer or shorter than their expectations, and not to the magnitude of the deviation in minutes. These results again provide evidence of Giffen behavior, since a longer-than-expected wait time is correlated with a higher probability of completion. In Appendix Table A4, the indicator for the wait being longer than expected is interacted with wait deviation in minutes. This specification picks up any asymmetry between how consumers respond to shorter vs longer than expected waits. Here, the coefficient on wait deviation is insignificant, but the interaction term's coefficient is positive. This means that users respond to the wait time deviation in minutes only for waits that exceed the expected wait. There still remains a large and significant effect from the longer wait indicator. The asymmetry is not explored in the theoretical model, and an extension to that model could provide some insight behind this response.

As described earlier, weather is a potential confounder of my claim that I am identifying movement along an upward-sloping demand curve. On a rainy day, or during a rainy period of the day, fewer guests are willing to ride attractions, including the guests in my sample, and so wait times are lower at the same time that the probability of a plan step being completed is lower. Fortunately, I can easily control for weather. Appendix Table A5 replicates the main regression results but includes hourly controls for the temperature and precipitation using the weather data described earlier. (The park-by-date-by-hour-of-day fixed effects cannot be included in this specification because of collinearity with the weather controls; I replace them with park-by-date fixed effects.) The evidence for Giffen demand is still strong and significant even with these weather controls. In the first two columns, there is a positive correlation between temperature and completing a ride, though this correlation disappears once date and time-of-day fixed effects are included in column 3.

An alternative regression specification collapses the data to the plan level, rather than keeping it at the plan step level. This specification keeps the partition between low-demand and high-demand rides that was used in Table 5. The left-hand-side variable is the number of low-demand rides that are completed. The variable of interest on the right-hand side is the average actual wait time of low-demand rides that day in the park, and I also control for the average actual wait time of high-demand rides that day in the park. This specification is more closely related to the theoretical model from section II, where the outcome is a continuous measure of quantity demanded for each type of ride. Alternatively, I can control for the average wait deviation between actual and expected wait times for the two types of rides. I can control for the average daily temperature and precipitation, and I can include park-by-date fixed effects, but because these regressions are aggregated to the plan level, I cannot include hourly weather, wait times, or ride or time-of-day fixed effects. The results are reported in Appendix Table A6. In all columns, the positive coefficient on low-demand wait times remains, indicating Giffen demand. The statistical significance is substantially lower here than in the other regressions, likely because the aggregation to the plan level reduces the number of observations by more than an order of magnitude.

One potential exogenous shifter of supply that I can take advantage of is an unannounced outage of a ride. These outages are not uncommon, and they can last from a few minutes to many hours. Data on outages are from the publicly-available dataset posted on the Touring Plans website, so these data only include select attractions from the four Walt Disney World parks. I create a ride-date level variable that is the fraction of minutes in a given day that the ride is unavailable (the median value is about 10%), and I include this as a control variable in Appendix Table A7 (since the control varies only at the ride-date level, I cannot include ride-by-date or park-by-date fixed effects). These results demonstrate that the Giffen behavior is still present after including this control.

While most of the regression tables include controls for the average wait of all rides in a given park-date, I am also able to control for wait times of specific rides within the park, again using the publicly-available wait time data from the four Walt Disney World parks. For each park, I choose two of the most popular attractions, and I create a variable for the average wait time of each ride in each one-hour window daily. Appendix Table A8 includes these two controls in each regression column. In the first two columns, there is evidence that a higher wait time on either of these two popular attractions slightly reduces the probability of the attraction in the plan step (which in most cases is not one of these two rides) being ridden. Once park and date fixed effects are included in column 3, the significance of these coefficients goes away. This suggests that that two hourly ride wait time controls are most likely picking up measures of overall park busyness, in the same way that the park-day average wait of all rides was doing (and in fact these two specific popular rides might be better measures of that busyness than the park-date overall average of all rides in the plan). In all specifications, the evidence for Giffen behavior remains.

I also test to see if other behavioral responses are correlated with longer-than-expected wait times, besides just the probability of riding. I observe whether a user updates their plan during the day of the visit. The update could include adding or removing rides from the plan, or it could just involve re-optimizing the order of the existing rides based on current wait times. I regress an indicator for whether a plan was updated on all of the controls and fixed effects in the main regression specifications. As shown in Appendix Table A9, I find no significant relationship between the wait time deviation and the indicator for updating a plan.[16] These results also speak to the issue of misreporting. Re-optimization is more likely on days when average waits park-wide are shorter, as indicated by the negative coefficients in columns 2 and 3. At first glance, this appears to be evidence for the source of bias discussed earlier, that users stick to the plan more on days with longer waits. But in fact this result is more consistent with the opposite response: on days with shorter waits, users are more likely to re-optimize, which means they are more likely to be engaged with the app on their device where they report their rides, so less likely to fail to report when they have completed a step.

V. Conclusion

Using a unique proprietary dataset based on the behavior of guests at theme parks, I document evidence for Giffen behavior in the demand for theme park rides. When the wait time (i.e. the price of the ride) is longer than expected, then guests are more likely to ride the ride. This Giffen behavior can be explained by a model that features a "subsistence" constraint: guests may feel the need to ride a minimum number of rides to get their money's worth. The theory predicts that rides that are inferior goods – i.e. low demand rides like carousels – are more likely to be Giffen goods than other rides – i.e. high demand rides like roller coasters. The theory also predicts that parks with a higher number of rides provide a higher number of substitute rides and therefore are less likely to exhibit Giffen behavior than are parks with low numbers of rides.

[16] The reported regressions are at the step level, where the indicator does not vary within a plan. I have also run regressions on the data collapsed to the plan level, controlling for the average wait time deviation across all steps in the plan, with similar results.

Both predictions are supported in the data. I also control for expectations of future wait times to rule out a shift in demand in response to those expectations as an explanation for the observed correlations, and I perform an extensive set of robustness tests. I thus provide evidence for the existence of the neoclassical prediction of Giffen goods, outside of a traditional market setting.

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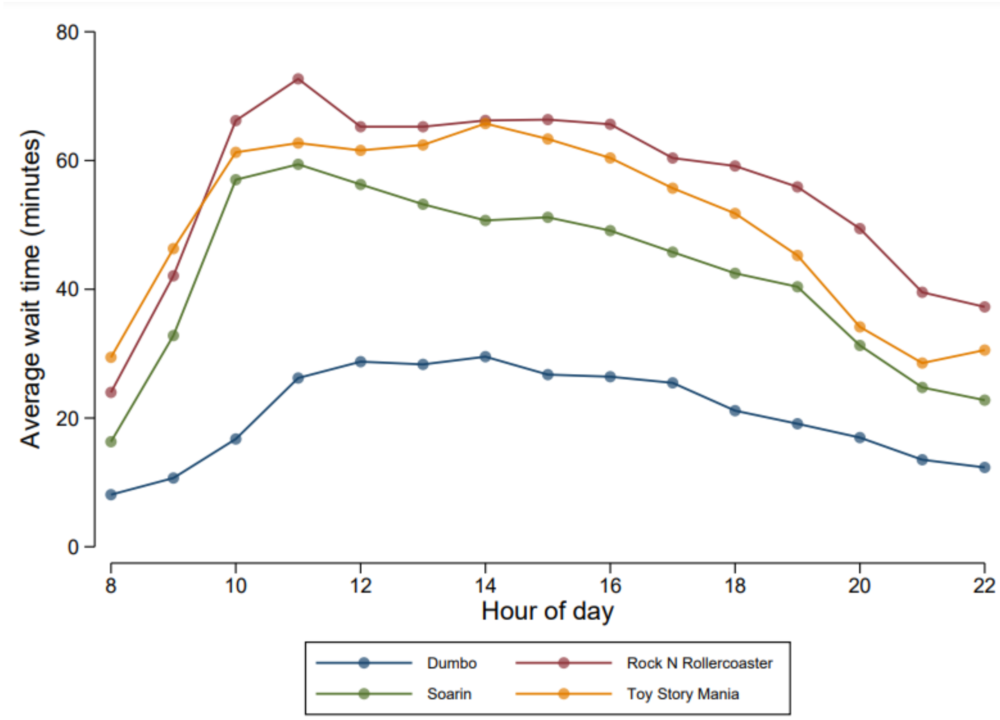
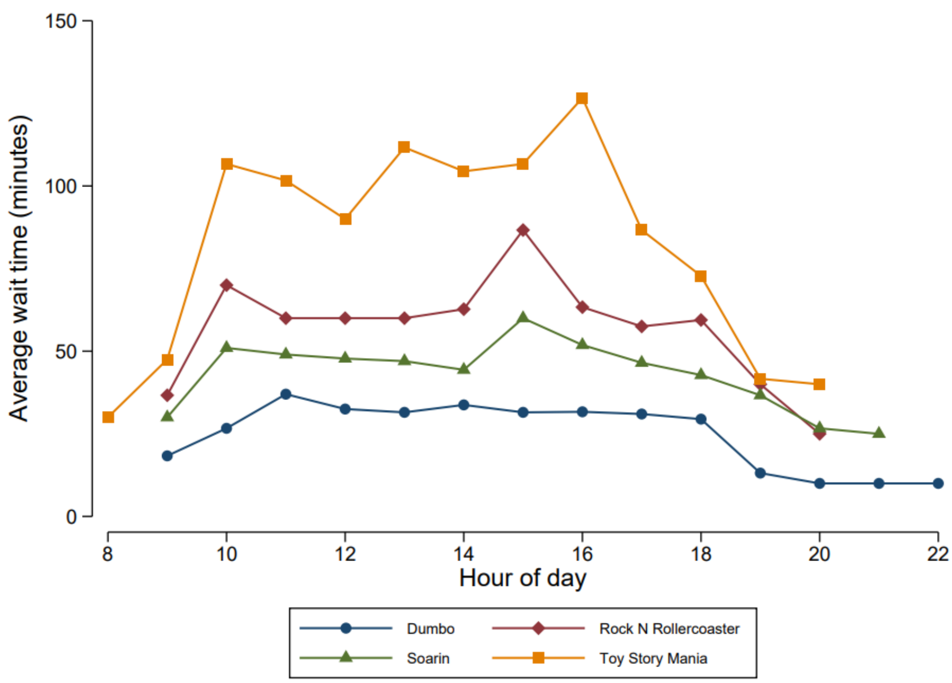
Figure 1: Wait Times throughout the Day





Notes: The top panel presents average wait times for four specific rides, averaged over all of the days in the sample, by hour of day. The bottom panel presents these four rides' wait times by hour of the day for one specific day within the sample (February 2, 2018).

Table 1: Motivating Example of Giffen Behavior

	Carousel		Roller Coaster		
	Wait time per ride (minutes)	Number of rides	Wait time per ride (minutes)	Number of rides	Total time (hours)
Expected (plan)	15	4	120	3	7
Actual (option 1)	30	2	120	3	7
Actual (option 2)	30	6	120	2	7

Notes: This table demonstrates the possibility of Giffen behavior in a theme park. The first row represents the guest's plan based on the ex-ante expected wait times, but the actual wait times turn out different than expected. The second and third rows represent two different alternatives that the guest could take in response to the actual wait times; the third row represents Giffen behavior in the demand for the carousel.

Table 2: Summary Statistics

Overall		
Percent Completed		58.73 (49.24) [5912]
Expected Wait (minutes)		13.47 (20.03) [5352]
Actual Wait (minutes)		28.63 (29.19) [3581]
Completed vs. Non-completed		
	Completed Steps	Non-completed Steps
Expected Wait (minutes)	11.79 (15.47) [3112]	15.80 (24.85) [2240]
Actual Wait (minutes)	34.69 (31.01) [2074]	20.29 (24.12) [1507]

Notes: Mean values are reported, followed by standard deviations (in parentheses) and number of non-missing observations [in brackets].

Table 3: Summary Statistics by Park, Time of Day, and Demand

Panel A

	Magic Kingdom	Epcot	Hollywood Studios	Animal Kingdom
Percent Completed	.58	.55	.59	.60
	(.49)	(.50)	(.49)	(.49)
	[1980]	[911]	[575]	[879]
Expected Wait (minutes)	14.62	10.4	15.33	15.84
	(18.02)	(17.86)	(19.24)	(25.28)
	[1805]	[815]	[518]	[794]
Actual Wait (minutes)	28.93	27.79	31.22	41.96
	(26.59)	(25.23)	(29.42)	(47.72)
	[1434]	[450]	[244]	[466]
	Disneyland	California Adventure	Universal Studios	Islands of Adventure
Percent Completed	.64	.54	.61	.59
	(.48)	(.50)	(.49)	(.49)
	[703]	[312]	[310]	[242]
Expected Wait (minutes)	10.64	12.79	8.80	17.58
	(14.69)	(15.93)	(10.31)	(39.41)
	[662]	[277]	[266]	[215]
Actual Wait (minutes)	20.71	25.14	20.89	20.71
	(16.48)	(23.58)	(17.34)	(19.53)
	[454]	[200]	[178]	[155]

Panel B

	12:00am-4:00am	4:00am-8:00am	8:00am-12:00pm
Percent Completed	0	.96	.81
	(0)	(.20)	(.39)
	[27]	[307]	[2080]
Expected Wait (minutes)	85.17	15.86	11.15
	(105.40)	(25.30)	(15.51)
	[24]	[291]	[1911]
Actual Wait (minutes)	14.2	15.54	30.85
	(10.45)	(18.85)	(29.34)
	[15]	[195]	[1418]

	12:00pm-4:00pm	4:00pm-8:00pm	8:00pm-12:00am
Percent Completed	.58	.34	.11
	(.49)	(.47)	(.31)
	[1637]	[1308]	[397]

Expected Wait (minutes)	12.92 (16.11) [1500]	14.79 (18.48) [1192]	17.14 (27.79) [387]
Actual Wait (minutes)	34.46 (31.42) [895]	26.45 (29.62) [765]	15.21 (16.27) [293]

Panel C

	High-Demand	Low-Demand
Percent Completed	.62 (.49) [3149]	.55 (.50) [2763]
Expected Wait (minutes)	17.83 (21.90) [3095]	7.49 (15.24) [2258]
Actual Wait (minutes)	34.49 (30.93) [2710]	10.41 (9.39) [871]

Notes: Mean values are reported, followed by standard deviations (in parentheses) and number of non-missing observations [in brackets].

Table 4 – Main Regression Results

	(1)	(2)	(3)	(4)
Wait deviation	0.00497***	0.00539***	0.00441***	0.00490***
	(18.93)	(16.90)	(14.43)	(13.82)
Average wait		-0.00208*	-0.00163	
		(-2.01)	(-0.54)	
Fastpass recommended		-0.0398	-0.0330	-0.0393
		(-1.89)	(-1.68)	(-1.87)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date*Hour F.E.	No	No	No	Yes
Observations	3581	3581	3581	3581

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 5 – High vs Low Demand Rides

	(1)	(2)	(3)	(4)
Wait deviation	0.00824***	0.0125***	0.00808***	0.00744***
	(5.90)	(9.24)	(11.65)	(11.88)
High demand	0.0917***	0.150***	0.0502***	0.102***
	(5.28)	(8.58)	(3.35)	(5.69)
Wait deviation * High demand	-0.00460**	-0.00913***	-0.00473***	-0.00441***
	(-3.23)	(-6.78)	(-6.86)	(-6.88)
Observations	3581	3248	3418	3418

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. A different measure for high-demand rides is used in each of the four columns as described in the text. All regressions include park, user, hour-of-day, date, and park-by-date-by-hour fixed effects. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 6 – High vs Low Number of Rides

	(1)	(2)	(3)
Wait deviation	0.00594***	0.00629***	0.00371***
	(11.90)	(12.07)	(8.58)
High number of rides	-0.0524**	-0.0553**	-0.124***
	(-2.79)	(-2.88)	(-3.99)
Wait deviation * High number of rides	-0.00130*	-0.00120*	-0.000244
	(-2.22)	(-2.03)	(-0.51)
Average wait		-0.00125	-0.00262
		(-1.19)	(-1.26)
Fastpass recommended		-0.0472*	0.00140
		(-2.22)	(0.08)
Park F.E.	No	No	No
User F.E.	No	No	Yes
Hour-of-day F.E.	No	No	Yes
Date F.E.	No	No	Yes
Park*Date F.E.	No	No	No
Observations	3581	3581	3581

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. T-statistics are presented in parentheses; asterisks indicate statistical significance (* p < 0.05, ** p < 0.01, *** p < 0.001).

Table 7 – Future Wait Times

	(1)	(2)	(3)	(4)
Wait deviation	0.00512***	0.00589***	0.00458***	0.00443***
	(11.99)	(11.93)	(10.14)	(8.69)
Noon wait time	-0.00133*	-0.00134*	-0.00166*	-0.00173
	(-2.17)	(-2.15)	(-2.06)	(-1.94)
3pm wait time	0.0000428	0.000106	0.000547	0.000666
	(0.06)	(0.15)	(0.67)	(0.75)
6pm wait time	-0.000591	-0.000643	0.000159	0.000262
	(-0.80)	(-0.88)	(0.20)	(0.30)
Average wait		0.00281	0.0104	
		(1.15)	(1.68)	
Fastpass recommended		-0.103**	-0.0792**	-0.0583
		(-3.25)	(-2.64)	(-1.81)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date*Hour F.E.	No	No	No	Yes
Observations	1633	1633	1633	1633

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. The wait time of each ride associated with the observation is controlled for, at noon, 3pm, and 6pm (regardless of when the step was planned or completed). T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix

A.1. Three-Ride Model Full Solution

The three-ride problem is

$$\max_{x_{lo1},x_{lo2},x_{hi}} U(x_{lo1}, x_{lo2}, x_{hi})$$

$$\text{such that } t_{lo1}x_{lo1} + t_{lo2}x_{lo2} + t_{hi}x_{hi} \leq T \text{ and } x_{lo1} + x_{lo2} + x_{hi} \geq N$$

The first-order conditions are

$$U_1 + \lambda t_{lo1} + \mu = 0$$

$$U_2 + \lambda t_{lo2} + \mu = 0$$

$$U_3 + \lambda t_{hi} + \mu = 0$$

Here λ is the Lagrange multiplier for the budget constraint, and μ is the Lagrange multiplier for the subsistence constraint, assuming both constraints bind. These first-order conditions yield the equations

$$\frac{U_1}{t_{lo1}} = \frac{U_2}{t_{lo2}} = \frac{U_3}{t_{hi}}$$

That is, the marginal utility per minute wait time is equalized across all three rides. This condition holds also in the model without a subsistence constraint, though without that constraint the marginal utility per minute wait time will not be the same as it is with the constraint.

Using the third first-order condition to solve for μ and the second to solve for λ, then substituting into the first yields

$$U_1(t_{hi} - t_{lo2}) + U_2(t_{lo1} - t_{hi}) + U_3(t_{lo2} - t_{lo1}) = 0$$

Using the two constraints to solve for x_{lo2} and x_{hi} in terms of x_{lo1} yields

$$x_{lo2} = \frac{T - t_{hi}N + x_{lo1}(t_{hi} - t_{lo1})}{t_{lo2} - t_{hi}}$$

$$x_{hi} = \frac{-T + t_{lo2}N + x_{lo1}(t_{lo1} - t_{lo2})}{t_{lo2} - t_{hi}}$$

Apply the implicit function theorem on the re-arranged first-order condition above, using the above solutions for x_{lo2} and x_{hi} and their appropriate derivatives, to find an expression for $\frac{\partial x_{lo1}}{\partial t_{lo1}}$. This expression is very long and complicated. But, it can be simplified and interpreted by applying an assumption that the wait times of the two low-demand rides are equal to each other: $t_{lo1} = t_{lo2}$. Under this assumption the derivative can be shown to equal

$$\frac{\partial x_{lo1}}{\partial t_{lo1}} = \frac{x_{lo1}(U_{12} - U_{22}) + U_2 - U_3}{(t_{lo} - t_{hi})(U_{11} - 2U_{12} + U_{22})}$$

The denominator is strictly positive (due to the assumption that $t_{hi} > t_{lo}$). Because of the first-order condition equating the marginal utility per minute of wait time and the assumption that $t_{hi} > t_{lo}$, $U_3 > U_2$, so the second half of the numerator is strictly negative. Giffen behavior is possible only when $x_{lo1}(U_{12} - U_{22})$ is positive and greater than $U_2 - U_3$ in absolute value. This is more likely to be true when U_{12} is large and positive, which is true when the two low-demand rides are strong complements. When the two rides are substitutes, U_{12} is small or negative, and Giffen behavior is unlikely.

Thus, from this more thorough analysis of the three-ride problem, we reach the same conclusion reached in the simpler analysis in the main paper: Giffen behavior is less likely when there is a good substitute available for the low-demand ride.

A2: Model with Integer Constraint

The model in the text includes a continuous measure of demand for each ride, x_{lo} and x_{hi}. In reality, the quantity of each ride must be an integer. To investigate the importance of this integer constraint, I perform numerical simulations of the two-good model, assuming a simple structure to utility and arbitrary parameter values, to verify the presence of Giffen behavior even under this constraint.

In the numerical model, utility is Cobb-Douglas: $u(x_{lo}, x_{hi}) = x_{lo}^{\alpha} x_{hi}^{1-\alpha}$, where $\alpha = 0.3$. The total time endowment T is 8 hours (480 minutes), the wait time of the high-demand ride t_{hi} is 60 minutes, and the subsistence constraint minimum number of rides N is 10. I vary the wait time of the low-demand ride t_{lo} between 5 minutes and 45 minutes. For each wait time value, I numerically solve for the utility-maximizing bundle of quantities x_{lo} and x_{hi}, subject to the time budget constraint, the subsistence constraint, and the constraint that x_{lo} and x_{hi} both be non-negative integers. I do this by simply looping through all integer combinations of values and selecting the combination that yields the highest utility while satisfying the constraints.

The demand curve for the low-demand ride (labeled just x) is presented in the top panel of Appendix Figure A2. For ease of interpretation, the exogenously-varied price (the wait time) is presented on the horizontal axis, while the utility-maximizing quantity demanded is presented on the vertical axis. On the right-hand side of the curve, once the wait time is above about 27 minutes, the Giffen behavior is clearly demonstrated, along with the integer constraint. That is, an increase in the wait time is increasing the quantity demanded, although the increase is step-wise rather than smooth. However, on the left-hand side of the curve we see something closer to downward-sloping demand; this is because the subsistence constraint is not binding in this region, when the wait time for the low-demand ride is so low. We generally see downward-sloping demand, but it is not monotonically decreasing, due to the integer constraint. For example, when the wait time increases from 15 minutes to 16 minutes, the quantity demanded increases from 4 rides to 7 rides. This is because this increase leads to one fewer ride on the high-demand ride, freeing up 60 additional minutes and allowing for the three additional rides of the low-demand ride.

Finally, to emphasize the importance of the subsistence constraint, the bottom panel of Appendix Figure A2 presents the demand curve where all parameters of the model are identical to the top panel except that the subsistence constraint is not included. Here, there is no Giffen behavior on the right-hand side of the figure. For lower wait times, we still do occasionally see non-monotonic decreases due to the integer constraints as described above.

Appendix A3: Two-Period Model

The model in the text is static. In the real world, theme park guests can respond both to the current wait time of a ride and to their expectations over future wait times. To incorporate this dynamic response, I extend the two-good model to also include two periods, 1 and 2.

The agent in the model now chooses the quantity of each of four variables: $x_{lo,1}$, the quantity of low-demand rides in period 1, $x_{lo,2}, x_{hi,1}$, and $x_{hi,2}$, defined analogously. The wait times for each type of ride in each period are given by $t_{lo,1}, t_{lo,2}, t_{hi,1}$, and $t_{hi,2}$. I ignore uncertainty or imperfect beliefs and assume that these wait times are known with certainty across all periods. The agent has two time budget constraints: $t_{lo,1}x_{lo,1} + t_{hi,1}x_{hi,1} \leq T_1$ and $t_{lo,2}x_{lo,2} + t_{hi,2}x_{hi,2} \leq T_2$. The subsistence constraint is: $x_{lo,1} + x_{lo,2} + x_{hi,1} + x_{hi,2} \geq N$.

If all three constraints bind with equality, they can be used to solve for $x_{lo,1}$ as a function of just $x_{lo,2}$ and the exogenous parameters:

$$x_{lo,1} = \frac{Nt_{hi,1} - T_1 - T_2 \frac{t_{hi,1}}{t_{hi,2}} - x_{lo,2}\left(t_{hi,1} - t_{lo,2}\frac{t_{hi,1}}{t_{hi,2}}\right)}{t_{hi,1} - t_{lo,1}}$$

Then, the derivative $\frac{\partial x_{lo,1}}{\partial t_{lo,1}}$ can be evaluated using the quotient rule, accounting for the fact that $x_{lo,2}$ is endogenous and also a function of $t_{lo,1}$:

$$\frac{\partial x_{lo,1}}{\partial t_{lo,1}} = \frac{\left(t_{hi,1} - t_{lo,1}\right)\left(-\frac{\partial x_{lo,2}}{\partial t_{lo,1}}\left(t_{hi,1} - t_{lo,2}\frac{t_{hi,1}}{t_{hi,2}}\right)\right) + Num}{\left(t_{hi,1} - t_{lo,1}\right)^2}$$

Here the expression Num is the numerator in the expression for $x_{lo,1}$ above and is strictly positive. The denominator is also strictly positive. The first term in the numerator is of the opposite sign of $\frac{\partial x_{lo,2}}{\partial t_{lo,1}}$.

If $\frac{\partial x_{lo,2}}{\partial t_{lo,1}} < 0$, then the entire expression for $\frac{\partial x_{lo,1}}{\partial t_{lo,1}}$ is strictly positive and so demand for x_{lo} exhibits Giffen behavior in the first period. If $\frac{\partial x_{lo,2}}{\partial t_{lo,1}} > 0$, then the expression for $\frac{\partial x_{lo,1}}{\partial t_{lo,1}}$ has two offsetting effects, and whether demand slopes upwards or downwards depends on their relative magnitudes. The effect captured in the Num term is the Giffen behavior that arises from the time budget and subsistence constraints and is present in the one-period model. The potentially offsetting effect arises from how the first period's wait time for the low-demand ride affects its demand in the second period. If $\frac{\partial x_{lo,2}}{\partial t_{lo,1}} > 0$, then a higher first-period wait time causes an increase in demand for the ride in the second period. This is reasonable to assume, since the agent will be able to substitute their rides from the first period in response to a longer wait time. If this substitutability is large enough, then the Giffen behavior will be mediated or reversed.

As with analysis of the three-good model in the text, this expression above is not a closed-form solution and relies on the value of an unknown derivative. A closed-form solution for this 4-good problem is possible in theory to present, though it would be long and difficult to interpret. A yet more complicated model could consider uncertainty and expectations about future ride wait times and could include a fully dynamic recursive problem. Nevertheless, the analysis presented here demonstrates that extending the model to multiple time periods can affect the possibility of observing Giffen behavior, though that possibility still remains. Empirically, the regressions in Table 7 implement this consideration by controlling for wait times at other periods in the day besides the plan step.

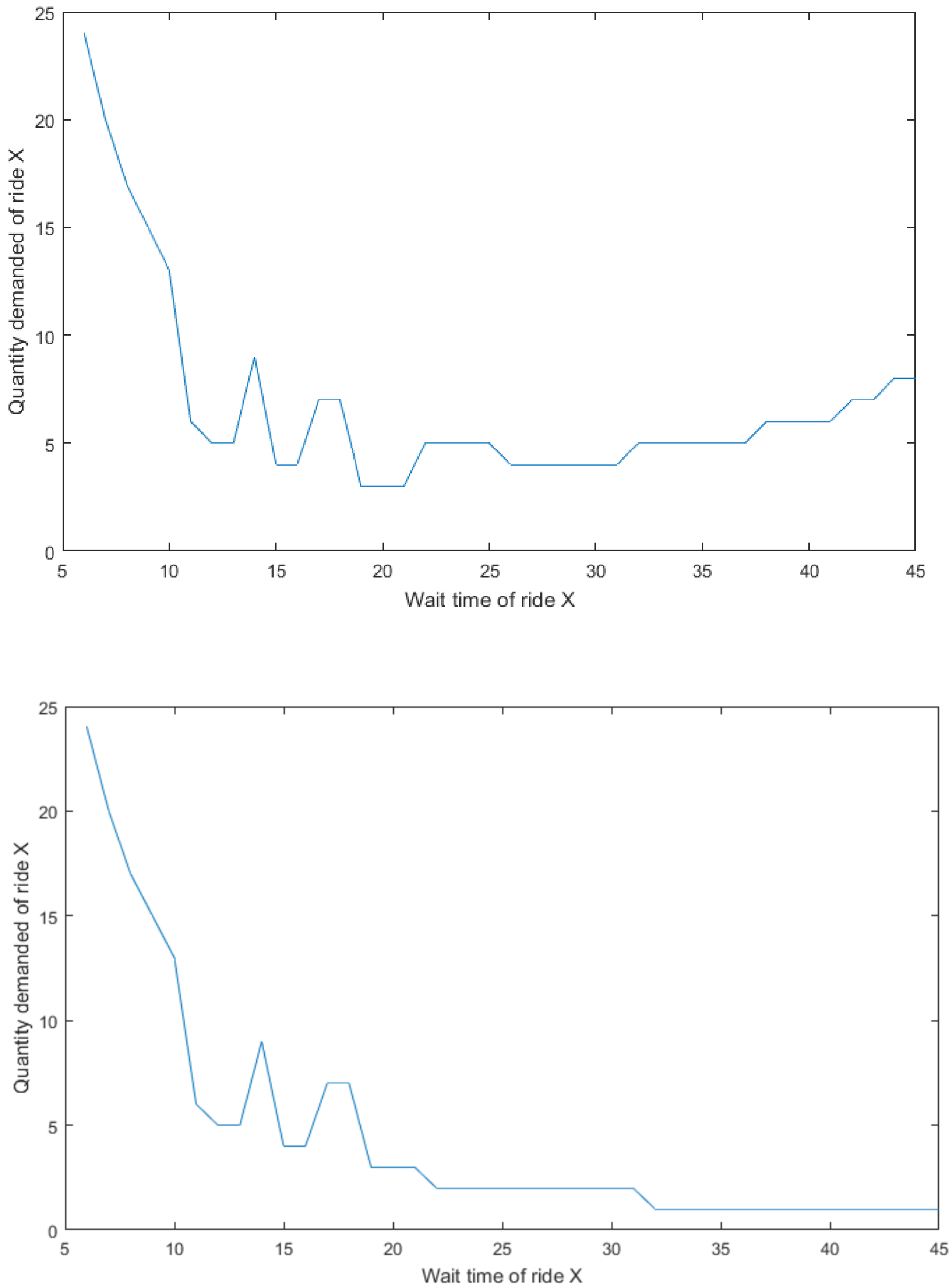
Appendix Figure A1: Sample Optimized Touring Plan

Your Plan Steps (drag to reorder)

STEP		ARRIVAL	WAIT	DURATION	FREE TIME	WALK TIME
1) **Peter Pan's Flight** Move Down	Edit X	9:11am	23	3	0	2
2) **Mickey's PhilharMagic** Move Up | Move Down	Edit X	9:39am	6	12	0	2
3) **Seven Dwarfs Mine Train** *Minimum Height: 38 in* Move Up | Move Down	Edit X	9:59am	28	3	0	4
4) **Dumbo the Flying Elephant** Move Up | Move Down	Edit X	10:34am	6	2	0	6
5) **Space Mountain** *Minimum Height: 44 in* Move Up | Move Down	Edit X	10:48am	19	10	0	2
6) **Walt Disney's Carousel of Progress** Move Up | Move Down	Edit X	11:19am	5	21	0	1
7) **Tomorrowland Transit Authority PeopleMover** Move Up	Edit X	11:46am	0	10	0	9
PLAN TOTALS:		174 TOTAL	87 IN LINE	61 BUSY	0 FREE	26 WALKING

ADD ATTRACTION | ADD FASTPASS+ | ADD MEAL | ADD BREAK

Appendix Figure A2: Simulated Demand with Integer Constraint Model



Note: The top panel presents the demand curve for the low-demand ride x_{lo} under a subsistence constraint $N = 10$. The bottom panel is the same demand curve where all parameters are identical except that there is no subsistence constraint.

Appendix Table A1: Actual and Expected Wait Time

	(1)	(2)	(3)	(4)
Actual wait	0.00510***	0.00556***	0.00645***	0.00646***
	(18.00)	(16.44)	(16.43)	(14.84)
Expected wait	-0.00460***	-0.00490***	-0.00219***	-0.00269***
	(-11.24)	(-10.92)	(-5.40)	(-5.33)
Average wait		-0.00241*	-0.00314	
		(-2.28)	(-1.06)	
Fastpass recommended		-0.0389	-0.00431	-0.00269
		(-1.85)	(-0.22)	(-0.12)
Ride F.E.	No	Yes	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date*Hour F.E.	No	No	No	Yes
Observations	3581	3581	3581	3437

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A2 – Dropping Observations from Late in the Day

	(1)	(2)	(3)	(4)
Wait deviation	0.00373***	0.00467***	0.00512***	0.00525***
	(12.37)	(12.79)	(12.95)	(11.71)
Average wait		-0.00135	0.000836	
		(-1.20)	(0.25)	
Fastpass recommended		-0.105***	-0.0744**	-0.0853***
		(-4.58)	(-3.17)	(-3.33)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date*Hour F.E.	No	No	No	Yes
Observations	2330	2330	2330	2330

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. Only observations that occur before 4:00pm are included. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A3 – Regress on Indicator for Longer Wait than Expected

	(1)	(2)	(3)	(4)
Longer wait	0.431***	0.454***	0.220***	0.182***
	(27.59)	(26.23)	(14.16)	(10.81)
Average wait		0.00175	0.000823	
		(1.82)	(0.27)	
Fastpass recommended		-0.0564**	0.0259	0.0468*
		(-3.03)	(1.44)	(2.44)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date*Hour F.E.	No	No	No	Yes
Observations	3581	3581	3581	3581

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Longer Wait is an indicator equal to one if the actual wait time was greater than the expected wait time. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A4 – Regress on Indicator for Longer Wait than Expected and Interaction

	(1)	(2)	(3)	(4)
Wait deviation	0.000191	0.000199	-0.000718	-0.000508
	(0.34)	(0.35)	(-1.32)	(-0.64)
Longer wait	0.368^{***}	0.396^{***}	0.166^{***}	0.130^{***}
	(20.24)	(21.33)	(10.28)	(7.34)
Longer wait*Deviation	0.00230^{***}	0.00375^{***}	0.00617^{***}	0.00598^{***}
	(3.48)	(5.43)	(9.07)	(6.51)
Average wait		0.00175	0.000823	
		(1.82)	(0.27)	
Fastpass recommended		-0.158^{***}	-0.102^{***}	-0.0799^{***}
		(-7.50)	(-5.13)	(-3.76)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date F.E.	No	No	No	Yes
Observations	3581	3581	3581	3581

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Longer Wait is an indicator equal to one if the actual wait time was greater than the expected wait time. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A5 – Hourly Weather Controls

	(1)	(2)	(3)	(4)
Wait deviation	0.00479***	0.00510***	0.00439***	0.00427***
	(18.58)	(16.26)	(14.34)	(14.02)
Hourly temperature, °F	0.00986***	0.00979***	0.00299	0.00350
	(12.07)	(11.97)	(1.15)	(1.31)
Hourly precipitation, In	-0.167	-0.164	0.107	0.100
	(-1.85)	(-1.82)	(1.31)	(1.23)
Average wait		-0.00180	-0.00173	
		(-1.77)	(-0.58)	
Fastpass recommended		-0.0274	-0.0329	-0.0270
		(-1.32)	(-1.68)	(-1.38)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-Day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	No
Park*Date F.E.	No	No	No	Yes
Observations	3581	3581	3563	3563

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A6 – Plan-level Regressions, Low-Demand vs. High-Demand Rides

	(1)	(2)	(3)	(4)	(5)	(6)
Average wait, low-demand rides	0.0844* (2.59)	0.0665* (1.99)	0.0326 (0.86)			
Average wait, high-demand rides	-0.0107 (-0.67)	-0.00813 (-0.51)	0.000139 (0.01)			
Wait deviation, low-demand rides				0.0861 (1.79)	0.0578 (1.18)	0.0672 (1.19)
Wait deviation, high-demand rides				0.0356 (1.80)	0.0369 (1.88)	0.0345 (1.44)
Weather controls	No	Yes	No	No	Yes	No
Park*Date F.E.	No	No	Yes	No	No	Yes
Observations	241	241	227	206	206	196

Note: Data in these regressions are aggregated to the plan level. The dependent variable in all regressions is the number of low-demand rides marked complete. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A7 – Control for Ride Outages

	(1)	(2)	(3)
Wait deviation	0.00415***	0.00447***	0.00386***
	(13.24)	(11.24)	(9.27)
Outage fraction	-0.541***	-0.550***	-0.176
	(-9.03)	(-9.07)	(-1.54)
Average wait		-0.000701	-0.00633
		(-0.45)	(-0.96)
Fastpass recommended		-0.0374	-0.0137
		(-1.24)	(-0.49)
Ride F.E.	No	No	Yes
User F.E.	No	No	Yes
Hour-of-day F.E.	No	No	Yes
Observations	1768	1768	1748

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. Outage Fraction is the fraction of the time in the given day that the attraction from that observation is indicated as being out or unavailable. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A8 – Control for Wait Times of Other Rides

	(1)	(2)	(3)	(4)
Wait deviation	0.00544***	0.00561***	0.00495***	0.00488***
	(16.65)	(13.39)	(11.94)	(11.84)
Ride #1 wait	-0.000841*	-0.000963*	-0.00150	-0.000993
	(-2.55)	(-2.53)	(-1.28)	(-0.84)
Ride #2 wait	-0.000893***	-0.000766*	0.000473	0.000523
	(-3.54)	(-2.36)	(0.78)	(0.87)
Average wait		-0.00127	-0.00104	
		(-0.67)	(-0.22)	
Fastpass recommended		-0.0154	-0.0133	-0.0133
		(-0.57)	(-0.55)	(-0.55)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date F.E.	No	No	No	Yes
Observations	2234	2234	2225	2225

Note: The dependent variable in all regressions is an indicator for whether the step was marked complete. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. Ride #1 Wait and Ride #2 Wait are the hourly wait times of two specific popular rides in the park in question, taken at the hour of the plan step. T-statistics are presented in parentheses; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix Table A9 – Determinants of Re-Optimizing Plan

	(1)	(2)	(3)	(4)
Wait deviation	-0.000290	-0.000128	0.000158	0.00000314
	(-1.39)	(-0.51)	(1.23)	(0.02)
Average wait		-0.00615***	-0.0392***	
		(-5.46)	(-22.49)	
Fastpass recommended		0.000550	-0.00180	-0.00314
		(0.03)	(-0.21)	(-0.37)
Ride F.E.	No	No	Yes	Yes
User F.E.	No	No	Yes	Yes
Hour-of-day F.E.	No	No	Yes	Yes
Date F.E.	No	No	Yes	Yes
Park*Date*Hour F.E.	No	No	No	Yes
Observations	1911	1911	1886	1826

Note: The dependent variable in all regressions is an indicator for whether the plan was re-optimized during the day of the visit. Wait deviation is the difference (in minutes) between the actual ride wait time and the expected ride wait time in the touring plan. T-statistics are presented in parentheses; asterisks indicate statistical significance (* p < 0.05, ** p < 0.01, *** p < 0.001).