

Before They Turn Pro: Superstar Attendance Effects in the Ontario Hockey League (2011-2019)

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Abstract

This paper researches superstar player effects on the announced attendance and the probability of a sellout in the Ontario Hockey League for the 2011-2012 to the 2019-2020 regular seasons. Using a rich panel data set of game-level information, I find superstar players have a significant positive effect on the attendance of regular season games. Superstar players are also found to have an economically significant impact on the probability of a sellout, but this latter result is in most cases statistically insignificant. Finally, the superstar effect for sellouts and attendance are seen to change depending on the definition of a superstar, and also if the superstar plays on the home or away team.

1. INTRODUCTION

An intriguing topic in the field of sports economics is the study of attendance demand. Investigating which factors influence fans to attend live sporting events has major implications for sports franchises and leagues, local economies, and also further contributes to our understanding of consumer choice.

Papers which study attendance demand for sport primarily focus on professional leagues such as the National Hockey League (e.g. Jones and Ferguson, 1988; Leadley and Zygmunt, 2006), Major League Baseball (e.g. Coates and Harrison, 2005; Clapp and Hakes, 2005), and the National Basketball Association (e.g. Berri and Schmidt, 2006; Jane, 2016). There is a consensus that both on ice/field performance metrics and external factors have effects on attendance.¹ More precisely, a team's winning percentage (mainly for the home team) and whether a game is played on a weekend or later in the season are consistently shown to significantly impact attendance (e.g. Forrest and Simmons, 2002; Villar and Guerrero, 2009).² However, one factor with mixed results is the presence of a highly-skilled superstar player, as effects tend to change depending on the chosen definition of a superstar. For example, in Major League Soccer, Lawson et al. (2008) find that the impact of the arrival of David Beckham to the LA Galaxy increased ticket sales (as a percentage of capacity) by over 50 percentage points. However, in the same league, Jewell (2015) defines seven players as superstars and finds only three out of seven players to be significant in terms of attracting attendance.

¹ External factors are factors that are not directly related to on ice/field performance. These include when the game was played, regional economic conditions, and whether it is a new stadium/arena, among others.

² Other common findings are positive attendance effects for higher ranked teams, and rivalry games. See section 2 for more details.

Amateur and junior sports leagues have seen far less attention in the attendance demand literature, accounting for only a small fraction of studies on the topic (e.g. Paul and Weinbach, 2011; Paul et al., 2019). However, to the best of my knowledge, none of these papers account for superstar players. This paper presents findings on superstar attendance effects using a rich panel dataset with game-level information across nine (2011-2012 to 2019-2020) Ontario Hockey League (OHL) regular seasons. Therefore, this paper fills a gap in the literature by being the first attendance demand study to identify superstar player effects at the amateur/junior level.

There are several reasons why the OHL provides a natural setting to study the effects of superstar players on attendance. The OHL features players who are one step away from playing professional hockey, and the league consistently produces several of the highest-ranked National Hockey League (NHL) Entry Draft picks. More specifically, for the top junior prospects, there is also a strong correlation between their performance at the junior level and subsequent performance in the NHL. Given that most OHL teams play in smaller urban setting that have relatively small arenas, fans have the unique opportunity to see these future NHL superstars play up close in their communities, at a fraction of the cost of attending an NHL game.³ The fact that there are 20 teams in the OHL, and they only play 34 home games per season, also means that having such opportunities could be scarce, particularly if the superstar plays for an opposing team.⁴ Finally, the OHL typically has a low percentage of sold-out games. This allows for a more precise

³ OHL team websites were consulted for their 2019-2020 single-game ticket prices. The prices for regular-season adult admission typically fell in the range of 10-30 Canadian dollars. All OHL teams used variable pricing of some form, mostly changing prices for different sections within the arena, age of the ticket buyer, or when the ticket was purchased. For example, the Peterborough Petes had seven different adult ticket prices ranging from \$13.00 for Family Zone tickets to \$29.50 for Premium Club seats.

⁴ Teams that play in different conferences typically only play one away game against each other. For example, the Sault Ste. Marie Greyhounds only travel to play Eastern Conference teams such as the Niagara IceDogs, Hamilton Bulldogs and the Mississauga Steelheads once a season, often playing all three of these away games in the span of four consecutive days.

measurement of actual demand and mitigates some data truncation issues found in professional leagues where sellouts are more common.⁵

The way to define a superstar in the context of the OHL is not controversial. I define a superstar player as the highest-ranked OHL player in the top five of the TSN pre-season draft prospect rankings in a given season.⁶ Although I rely on the widely respected TSN ranking, there is usually very little disagreement when it comes to the top prospects. One tends to see more variation across rankings for players outside the top five, and particularly beyond the top ten. Finally, top prospects in the OHL are solid commodities; an OHL player that is viewed as a top prospect prior to the start of the season is typically still well-viewed by the end of the season. To put this into perspective, of the 11 OHL players identified as a top five prospect by TSN, all were chosen in the first round of the NHL draft, and all but three were a top six pick.

I employ a linear probability fixed effects model to measure the effect of superstar players being in the lineup on games being sold-out. Sellouts in the OHL are rare, and I investigate if superstar players can influence this probability. I also employ a censored Tobit fixed effects model to estimate the effects superstars have on announced attendance. If fans prefer to see top-quality talent, I would expect to see positive effects for games with a superstar player in the lineup, compared to if no superstar was present. Guided by the literature, I include a rich set of controls, and add them sequentially as to better understand the superstar effect. Specifically, I control for

⁵ This benefit can also be argued to be more present in terms of the sport of hockey. For example, in amateur college football, NCAA games typically see a larger percentage of games sold out in comparison to my sample, maintaining the same issue of data truncation (Groza, 2010).

⁶ The NHL draft occurs after the end of each OHL season, and all superstar players defined by this study do not play OHL games after they are drafted. OHL players are draft eligible if they are 18 years old on or before September 15th and younger than 20 years old before December 31th in a given year.

team performance to capture the potential effect of individual players, separate from overall team quality.

The main findings of my paper indicate that most OHL superstars have an economically large effect on attendance. Using my richest (and preferred) specification, a superstar being in the lineup is estimated to positively affect attendance by 179.3 people (4.3 percent of league-average attendance). The effect increases as my definition of a superstar becomes stricter, as 379.4 more fans are estimated to attend when a top global prospect is in the lineup. The number of opportunities fans have to see a player has a significant effect as well, as estimates are generally higher for away superstar players compared to home superstars. The linear probability model results also show positive superstar player effects for the probability of a sellout; however findings are broadly not statistically significant.⁷

Many of my findings with respect to team performance metrics and external factors show significant positive effects. Home team win percentage shows an economically large positive estimate, indicating that fans prefer to attend games when the home team wins often. Away team win percentage also seems to have a positive effect, but to a lesser extent. This suggests that some fans also choose to buy tickets to games featuring quality away teams. Attendance is shown to increase as the season progresses, especially for games close to the end of the season. This would seem to indicate that an overall league product likely exists in the OHL, as games near the end of the season (March) often see teams vying to qualify for the OHL Playoffs. Contrary to the literature, I find the deterioration of economic conditions, as measured by an increase in the regional unemployment rate, to have a positive effect on attendance. This could be due to the

⁷ Given the relatively large standard errors, the superstar estimates would have to be very large for the superstar effect to be statistically significant.

inexpensive nature of the league, as it may be a cheaper alternative to more expensive entertainment substitutes.

The rest of the paper proceeds as follows. Section 2 provides a review of the literature on attendance demand across various sports and leagues. Section 3 describes my data, as well as provides notable features of arenas within the OHL. I outline the methodology employed by this study in section 4, followed by the results of my study in section 5. I provide some robustness checks of my results in section 6. Finally, section 7 concludes.

2. LITERATURE REVIEW

Many studies have presented a wide variety of factors that influence attendance figures across sports. Attendance demand effects are generally separated into two main categories. First, factors have been identified which directly relate to the game and the field of play itself, such as the presence of talented superstars, overall team quality, or outcome uncertainty. Second, some factors influence attendance beyond the field of play, such as arena novelty effects, economic conditions, or nearby entertainment substitutes.

This section seeks to review the literature on attendance demand, providing both theoretical and empirical studies on the topic. First, I review studies presenting theoretical factors that influence attendance. Second, I discuss empirical papers that are primarily focused on factors relating to the field of play, highlighting superstar attendance effects. Lastly, I cover literature dedicated to attendance effects that go beyond the field of play, namely arena, and stadium novelty effects.

2.1. Background

To begin, it is important to discuss theoretical literature which sets the foundation for studying attendance demand. The definition of the product being purchased when the consumer buys a ticket to a game has seen considerable debate. Sutton and Parrett (1992, 8) argue “the core product is defined as the game itself, that is whatever takes place on the field of play including the manner in which the contest is conducted.” If the product is based solely on the field of play, anything off the ice in my study should not have any significant impact on demand. Others define the product differently as Morrow (1999) discusses that the product stretches beyond the field of play, and includes fans who contribute to the atmosphere of the game. This paper views the product being demanded by the consumer as access to view of the field of play from a designated area, as well as access to off-ice value-added features, such as food and drink options, off-ice entertainment, giveaways, or game-day promotions.

Factors which theoretically should influence attendance at hockey games have been presented through theoretical papers. Jones (1969) provides a theoretical framework on the economics of the NHL which motivates the study of attendance at hockey games. From this, Jones (1969) identifies three notable theoretical positive effects on attendance demand: i) there exists an influence of striving to reach the playoffs as the regular season progresses,⁸ ii) whether the game is played during the weekend instead of mid-week, iii) the drawing power of a particular "superstar" or team irrespective of the projected outcome of the game.

⁸ This is explained by many papers who discuss that the league product is greater than the sum of all individual games, as it includes other elements such as team standing effects, and playoff implications (Jones, 1969; Borland and Macdonald, 2003; Paul and Weinbach, 2011).

Additional factors are provided by Szymanski (2003). The paper summarizes the demand for attendance into three main categories which include uncertainty of outcome, the likelihood of home team success, and the aggregate of the player talent on display (Szymanski, 2003). These three main theoretical points are tested throughout the literature on sports demand, as different leagues and sports are used to provide evidence on which factors influence fans to attend games.

The seminal work of Rottenberg (1956) discusses sports attendance in the context of Major League Baseball (MLB). The paper argues that attendance demand is a positive function of the population and level of income in the surrounding territory, the convenience of traveling to the ballpark, and the size of the stadium (Rottenberg, 1956). The paper also theorizes factors which are negative functions of attendance, such as the quality of leisure substitutes for baseball in the surrounding area, and the dispersion of games won (as a percentage) by the teams in the league (Rottenberg, 1956). Overall, the paper mostly identifies factors that are beyond the field of play that effect attendance, giving empirical studies a foundation of theory to build on.

Substitutes being available to the consumer have also been discussed to influence attendance (Borland and Macdonald, 2003; Feehan, 2006; Gitter and Rhoads, 2010). This is relevant to my study as some OHL franchise cities have available NHL substitutes nearby. Examples of this are found in markets such as Mississauga being close to Toronto or Windsor being close to Detroit. However, consumers in smaller rural markets like Owen Sound, may not have other substitutes readily available, leaving OHL hockey as the highest caliber sport in the region. This can lead to plausible monopoly pricing situations, causing many studies to abstract from pricing issues (Szymanski, 2003). Since OHL cities have a large variety in terms of location and available substitutes, different options are available for consumers depending on where they live.

Borland and Macdonald (2003) provide further guidance on factors that influence the demand for spectating a sport. Factors include consumer preference for risk, market factors, seating availability, characteristics of the contest, and the supply capacity (Borland and Macdonald, 2003). All these factors help guide empirical research to determine various independent variables that are both on and off the field of play. Field of play factors which are characteristics of the game itself are variables such as winning probability of the home team, the presence of a superstar player, and uncertainty of outcome. Off the field of play, the paper discusses possible variables such as the time and date of the game, ticket prices, travel costs, and arena specific elements such as food and arena age (Borland and Macdonald, 2003).

The issue of endogeneity as it pertains to the study of attendance demand has been discussed by Noll (2013). The paper identifies issues with papers which use price in their demand equation, often leading to positive or economically insignificant estimates (Noll, 2013). The coefficient on price is said to only be accurately identified where nearly all games are sold-out and in leagues that play in stadiums of widely varying capacities (Noll, 2013). This is relevant in terms of the OHL, where regular season games are rarely sold-out. Noll (2013) also comments on the supply of (or lack thereof) homogenous seats, and the possibility of arena capacities being an endogenous variable. While acknowledging that the capacities could be an issue, the paper also explains that sports facilities have a long lifespan which, as interest fluctuates over time, implies it to be exogenous for almost all years for all arenas (Noll, 2013).

2.2 Field of Play Factors Influencing Attendance

Purchasing a ticket to an OHL game allows each ticket holder access to view the field of play. The characteristics of the game itself may cause fans to want to purchase tickets to a specific game, or even increase the frequency of their attendance over a given season. If a superstar player

or a team with a high win percentage is coming to town, fans may choose to attend these games in higher numbers. Other fans may want to see more or less scoring, and if the home team has been known to score more during their games, this may have a significant effect on attendance. These are just a few examples of factors that have been discussed in the literature as having an impact on the number of fans who purchase tickets.

Uncertainty of outcome has been debated across the literature, with some papers theorizing or finding positive effects (Rottenberg, 1956; Neale, 1964; Forrest and Simmons, 2002) while others find the effect to be negative or not economically significant (Buraimo and Simmons, 2008; Coats and Humphreys, 2012; Pawlowski and Anders, 2012;). Among studies that find the uncertainty of outcome to be unimportant is Pawlowski and Anders (2012), who use a generalized Tobit estimator to study attendance in the German Bundesliga. They find that fans prefer a less balanced match in comparison to one where matches are to be predicted to be uncertain. The paper finds that a strong brand image of the away team is much more significant in terms of attracting attendance, as teams with major televised football contracts draw more interest around Germany, regardless of their team quality in a given season (Pawlowski and Anders, 2012).

Similar to outcome uncertainty, there is a section of literature which studies if home fans are risk-averse in terms of game outcomes. If fans are risk-averse on the outcome of a game, one would expect to see attendance increase when the home win percentage is high because of the lower probability of seeing the home team lose. Conversely, if fans prefer seeing uncertain outcomes, one would see attendance increase when two teams have similar win percentages. Coates and Humphreys (2012) study how outcome uncertainty and team performance relate to attendance demand in the NHL. Their findings indicate that attendance is larger when the home team is expected to win, however, they also find positive attendance effects when the away team

is favored to win by a large margin. This result of both the home and away team win percentages carrying positive coefficients shows that while fans may prefer to see the home team win, they also may attend games featuring highly skilled visiting teams as well.

If the majority of attendance is a function of players themselves and outcomes on the field of play, superstar effects should have a significant impact on demand. A paper primarily focused on superstar effects in the sport of hockey is Deutscher and Schneemann (2017). The paper explores attendance demand effects in the context of the German and Czech hockey leagues while the NHL was on lockout during the 2012-2013 season. During the lockout, NHL players who signed temporary contracts to play in the two leagues were defined as superstars. The study uses a dependent variable which is the ratio of attendance to the capacity of arenas, which is argued to adjust for various stadium capacities (Welki and Zlatoper, 1999; Deutscher and Schneemann, 2017). Their results are mixed, showing positive attendance effects in the Czech league, while superstar effects in the German league are not significant. Interestingly, the paper also presents home and away superstar effects separately to see if the estimates are different. Superstars in the Czech league show large positive and significant coefficients for NHL players on the away team, but the authors only find home team superstars impacting attendance in the German league (Deutscher and Schneemann, 2017).

Another recent study covering superstar effects on sports outside North America is Li et al. (2019). The paper considered superstar effects in the context of the Chinese Soccer League. The paper differentiated stars based on if they were on the home or away team, and also if they were domestic or foreign players. Foreign star players had to exceed an annual salary level, and play more than 100 games in a European soccer league, while domestic stars had to be members of the Chinese national team (Li et al., 2019). In regards to superstars, the paper

finds that attendance was negatively impacted by the number of national team players on the home team, however finds large statistically significant effects for foreign star players (Li et al., 2019).

Jane (2016) uses a censored normal Tobit regression to study the effect of star players on attendance demand in the context of the National Basketball Association (NBA). Due to many teams in the NBA reaching capacity consistently, the censored model recognizes capacity constraints and identifies demand which is not captured due to the arena capacity. The dependent variable used by Jane (2016) is the ratio of attendance to stadium capacity to account for arenas that have different capacities. This method allows for all the different right-censored points to be the same and equal 100 percent. The study finds clear evidence of a positive effect of superstar presence on game attendance, which was robust to different specifications. The effects of superstars ranged from 3.3 percent to 8.1 percent increases for attendance, which differed based on how strict a definition was put on superstars (Jane, 2016).⁹

Berri and Schmidt (2006) discuss basketball superstar effects but specifically identify effects when superstars play on the visiting team over four NBA seasons. They suggest that road attendance is a function of team performance and star appeal. The authors define superstars as the top 25 players in the NBA All-Star Game fan voting. This allows them to have a measure of superstars based solely on fan preference. They find that team wins and lagged playoff wins are statistically significant and find that the revenue generated by star players is more valuable for a star player's opponent than their own team.

The definitions authors use to identify superstar players vary significantly across the literature. The definition typically depends on the league and sport of study; however, some

⁹ Jane (2016) uses various definitions of superstars. Examples of definitions used are the top 30 performance players, top 30 salary players, as well as the top 12 and top 25 players in NBA All-Star Game fan voting.

common trends emerge. In the case of basketball, Scott et al. (1985) identified superstars if they were on the All-Pro team five times, while also including players new to the league if they dominated their position. Within the same sport, Brown et al. (1991), limited the definition to a player who qualified for the NBA All-Star Game in at least half of their professional seasons. Depending on the league, other studies have used the MLB All-Star game and NHL All-Star game participants to identify superstars as well (Clapp and Hakes, 2005; Berri and Schmidt, 2006; Hong et al., 2011). These examples show that quantifying a superstar is often league and sport-specific, with many possible definitions being able to identify superstar talent.

Specifically studying major junior hockey, Paul and Weinbach (2011) contribute to the literature by focusing on the determinants of attendance in the Quebec Major Junior Hockey League (QMJHL). This two-season study focuses itself almost purely on on-ice effects such as fighting, win percentages, and scoring. The authors find a positive effect of win percentage on demand, however, the paper does not find any significant impacts of higher goals per game, or fights per game. Their findings contradict studies that focus solely on professional hockey such as (Jones, 1984; Jones et al., 1996; Paul, 2003). This signals that there may be external effects that are not seen solely on the ice which are having effects on attendance numbers in junior hockey. Lastly, the paper finds statistically significant effects on games that are close to the end of the season, as well as games scheduled on weekends.

Another paper that studies hockey attendance at the major junior level is Paul et al. (2019) which specifies an attendance model for the Canadian Hockey League (CHL). The paper uses OLS regressions with the natural log of attendance for their dependent variable. On-ice independent variables used include both points-per-game and fights-per-game measured as season running averages. Paul et al. (2019) use betting odds data to calculate home team win probability and

include the home team win probability squared in their quadratic specification. The paper finds no significant effect of home win probability when it is specified linearly, and even find it to have a negative effect when the variable is squared. One unique feature of Paul et al. (2019) is the inclusion of both temperature and precipitation variables which, in the case of precipitation, shows a statistically significant negative effect for attendance. This shows that on-ice factors may not be the only determinant of attendance in the CHL, as other variables off the ice could potentially be significant.

2.3. External Factors Influencing Attendance

Another section of the literature highlights external factors that influence attendance beyond the field of play. It is reasonable that some fans may take more holistic views of sporting events and may care about more than the game itself. Examples of this could be going to an arena that is new or renovated for the novelty of seeing a new facility or attending a game with a certain promotion. Attendance could also be influenced by economic conditions in the region, such as the unemployment rate, which may affect consumer choice. This section will detail studies that primarily focus on factors that are not directly attributed to the field of play. These studies include a variety of interesting regressors and results which inform decisions made in this paper's specification.

Other factors that are not related directly to the field of play have been investigated to see which elements could influence attendance figures. Coates and Harrison (2005) study the impact of labor strikes between players and management on attendance in the MLB from 1969 to 1996. The authors use dummy variables to identify the eight years of MLB strikes within their data, and control for several variables such as population, real per capita income, and the age of the stadium and team (Coates and Harrison, 2005). The paper finds that in years in which a strike occurred,

attendance per game was lowered by 12 to 13 percent compared to average attendance (Coates and Harrison, 2005). Overall, the paper provides evidence suggesting that events that happen beyond the game itself, can influence fan decisions to attend games.

New stadium effects are discussed by Clapp and Hakes (2005) who present findings on the effects of new ballparks in the MLB. The paper is focused primarily on stadiums, but also uses numerous on-field control variables in their study, including a variable indicating how many players on each team played in the MLB All-Star game. The impact of new ballparks showed to be economically significant, as on average, new stadiums increased attendance by 32 to 37 percent during the opening year after construction (Clapp and Hakes, 2005). However, the ‘honeymoon effect’ is short-lived and only lasts between two and ten seasons, depending on the style of the ballpark. The authors explain that fans may have initial excitement of amenities and the novelty of seeing the new facility, but then adjust expectations as time goes on (Clapp and Hakes, 2005).

Jones and Ferguson (1988) focus on the location of arenas in the NHL, and their viability using several interesting variables. The location of an arena is shown to have a statistically significant impact on attendance. Jones and Ferguson (1988) note the importance of Canadian locations by generating dummy variables for games that are played in Canada. The paper also considers variables capturing socioeconomic features about NHL cities such as population, and income per capita. The study finds positive coefficients for Canadian-based teams, this result is of particular interest as my study includes teams from both Canada and the United States.

The longevity of novelty effects for ice hockey arenas is studied at the professional league level by Leadley and Zygmunt (2006). The paper uses a Tobit fixed-effects model to investigate the amount of time that new NHL arenas have a positive effect on attendance after they are built. The paper also takes into account new teams in the league by adding a dummy variable for the

first 10 years of a new city team. The paper finds that the ‘honeymoon’ effect is found to increase attendance by around fifteen to twenty percent up until around eight years after construction (Leadley and Zygmunt, 2006).

Mason et al. (2007) give a qualitative perspective on arenas in the broader CHL,¹⁰ and how the arenas themselves contribute to their economic development on a much wider scale than just junior hockey. Their limiting of analysis to cities where no higher caliber hockey exists uniquely applies to small and mid-sized communities. They note that building new arenas do not always have the sole purpose of simply expanding capacity, as naming rights, luxury, and club seats all add to profit generation (Mason et al., 2007).

An empirical study that focuses on amateur hockey arenas is Soebbing et al. (2016). The paper identifies arena novelty effects in the context of the broader CHL from the 1996-1997 to the 2006-2007 regular season. The paper finds that novelty effects only seem to exist for the first five years of a new arena in the CHL (Soebbing et al., 2016). The dependent variable the authors use is yearly average attendance and uses team performance variables such as team points per game as regressors. Their controls also include if a team qualified for the playoffs in a particular season, and age of the home franchise. However, the main focus of the study is the arenas themselves, as they narrow their focus to the effect a new arena has on attendance, separate from the on-ice product. An interesting variable they use is if a team was located in a remote location which results in a positive coefficient estimate. The authors explain this effect is positive because there are fewer nearby substitutes available in rural markets (Soebbing et al., 2016).

¹⁰ The CHL is composed of three separate amateur major junior hockey leagues: The Western Hockey League, the OHL, and the Quebec Major Junior Hockey League.

Research has been done specifically on minor league hockey, as different variables have been identified which affect spectator enjoyment at games. Zhang et al. (2004) dive into sociodemographic variables with a survey of minor league hockey fans in the U.S. A questionnaire was developed by the team of researchers which sought to identify fans based on sociodemographic factors such as age, race, gender, and income (Zhang et al., 2004). Using a Likert 10-point scale ("very much" to "not at all") questions, they targeted game enjoyment variables including player appeal, people watching, and speed of the game. The results of the survey showed that a major proportion of attendees were young Caucasian males who had an income which was medium to high. Overall, the paper suggests that minor league hockey fans focus more on the amusement nature of the game, compared to major league spectators who may focus more on the field of play itself (Zhang et al., 1997; 2004).

The professional American Hockey League (AHL) is similar to the OHL, as it features players who have the potential to eventually play in the NHL. Paul and Chatt (2011) present linear regression findings on how regional demographic and socioeconomic features of AHL markets affect attendance. The paper uses per-game attendance as their dependent variable and includes off-ice explanatory variables such as promotional game data, regional population, and income per capita. They find that attendance is predictably higher on weekends and grows as the season progresses (Paul and Chatt, 2011). In regards to promotions, the paper finds mixed results, as the direction of the effect changes depending on the type of promotion advertised.

3. DATA

3.1 Data Sources

This paper relies on detailed game-level information of nine (2011-12 through 2019-20) OHL regular seasons.¹¹ Each OHL regular season includes 20 different teams who each play a total of 68 games, evenly split between home and away games. This results in 680 games to be played in each regular season, totaling 6,120 scheduled games.

Each observation (i.e. game) includes various information such as when the game was played (date and time) and the arena the game was played at. It also includes the teams involved, the lineups of each team, the final score, and the announced attendance. Other information such as the arena capacity and the regional unemployment rate at the time and location of each game is also recorded for each observation.

The primary dataset used is retrieved from <https://hockey.sigmagfx.com>, a compiler of attendance data for a wide variety of leagues around the world. The main advantage of this data is it includes the essential game information for a relatively longer timeframe than seen in comparable studies. The rich dataset provides linkages to the official score sheets which allow for identifying the lineups for each game, critical for studying superstar player effects.

In complementing this primary dataset, times of the games needed to be added. The times were able to be linked from both scoreboard.com and ontariohockeyleague.com.¹² This data allowed for the necessary identification of weekday matinee games which often host large numbers

¹¹ While OHL playoff data are available, this study focuses on regular-season games which have a comparable context and schedule. OHL Playoff games typically feature back-to-back games against the same opponent and have far higher sellout rates than games played during OHL regular seasons.

¹² Times for the 2011-2012 regular season are taken from ontariohockeyleague.com, while times for games for the 2012-2013 through the 2019-2020 seasons are taken from scoreboard.com.

of students from local schools. Another piece of information needed are the capacities of OHL arenas. This data is taken from ohlarenaguide.com, a common data source for arena capacities when dealing with OHL arenas. The capacity of each arena was necessary to identify which games were sold-out, which would cause an underestimation of superstar effects if an arena was at capacity. This also enables calculation of announced attendance as a percentage of the arena capacity for each game.

Choosing which players merit being identified superstars requires different criteria depending on the league and sport of study. To do this in the OHL context, I rely on the yearly TSN pre-season draft prospect rankings to determine which players are considered to be superstars. These lists are unveiled before each OHL season and include NHL draft-eligible players from various leagues around the world. Since fans attending games would not know the actual results of the following year's draft, the lists provide my study with reliable expert opinions and analysis for who the superstars would have been before a given OHL season. While acknowledging differences in pre-season projections compared to the actual results of the NHL draft, all superstar players identified in this paper went on to be drafted in the first round, with three being the first overall pick. This gives confidence that the TSN pre-season draft prospect rankings are an accurate indication of who the top players in the world were in each season.

I define a superstar player as the highest-ranked OHL player in the top five of the TSN pre-season draft prospect rankings in a given season. This definition only allows for only one superstar player to be identified in a given season. Notably, two seasons in my sample (2016-2017 and 2018-2019) do not include a superstar as no OHL player was in the top five draft prospects.¹³ The

¹³ This results in a list of seven players over nine seasons to narrow my focus: Nail Yakupov (Sarnia Sting), Sean Monahan (Ottawa 67's), Aaron Ekblad (Barrie Colts), Connor McDavid (Erie Otters), Jakob Chychrun (Sarnia Sting), Andrei Svechnikov (Barrie Colts), and Quinton Byfield (Sudbury Wolves).

motivation for this definition was to identify the most sought-after player in the league for each season, while also maintaining that they were ranked in the top five worldwide. To fans, these NHL draft-eligible superstar players will likely play professional hockey in the following season, and often never play OHL games after they are drafted.¹⁴ The full list of TSN pre-season draft rankings are available in Table A.1, with superstar players identified and also where they eventually were selected in the NHL Entry Draft.

As superstar presence is the key variable of this study, accuracy in ensuring if they were in the lineup of a game was important. Since players have the possibility of being injured, suspended, or scratched, official lineups of each game needed to be consulted. For each superstar player, official scorers' sheets were manually checked for every regular-season game their team played to validate whether a superstar player was in the lineup. This step of verification is especially important for the OHL context due to the World Junior Hockey Championship (WJHC), which sees many top players missing significant numbers of regular games in December and January while they are loaned out to their country teams.

To account for labor market conditions at the time and location of each game, regional unemployment rates surrounding the arenas were needed. Monthly CMA and MSA level unemployment rates were retrieved from Statistics Canada and the Bureau of Labour Statistics. Where OHL franchises were not located in a CMA or MSA, Census Agglomeration or Micropolitan Statistical Area unemployment rates were used. This data was used to account for labor market changes throughout the sample in OHL markets.

¹⁴ The top five players chosen by TSN's pre-season draft prospect rankings typically are drafted in at least the top 10 of the NHL Entry Draft. The prospect rankings are less accurate in terms of lower-ranked players (#6-#10), where large differences can be seen between predictions and realized draft results.

The data for this study does have limitations that must be addressed. First, there is no differentiation between season ticket holder attendance demand and single-game demand. The data does not include the ratio between buyers who purchase a ticket to all home games in a season, partial season ticket packages, or single-game tickets. This limits my analysis to focusing on total (per-game) announced attendance, as I cannot measure the effect a superstar player may have on a specific type of ticket (i.e. the number of season ticket holders). Second, I do not have any information on the demographics of the ticket purchasers, and cannot differentiate effects based on gender, age, or other factors. For example, in most markets, Friday and Saturday night games are marketed far differently than Sunday afternoon games and may include far different demographics.

I impose the following restrictions on my sample. First, I drop every team's first five home and away games of the season.¹⁵ This is done because I use lagged season-performance variables in my regression analysis. For example, I include the home teams' winning percentage to date as an explanatory variable. Imposing such a restriction ensures that season-performance variables are based on the outcome of at least five games. Second, I remove all 2019-2020 regular season games played after December 31st, 2019 to avoid any negative effects of the COVID-19 pandemic.¹⁶ Although the 2019-2020 season was canceled as of March 18th, 2020 (due to COVID-19), I introduce an earlier cut-off because it is possible that fan attendance (a key variable of interest in this paper) was being affected by the news of the outbreak. Finally, games featuring a team outside

¹⁵ This restriction can result in more than five home games being dropped for a particular team in a particular season. For example, a team's sixth home game of the season would be dropped from the sample if it was the away team's fourth away game. A similar point can be made for away games. 1,022 games were dropped due to this restriction.

¹⁶ This restriction results in 276 games being dropped from the sample.

the OHL, or at arenas which are not the regular home arena of the home team are dropped.¹⁷ After having imposed these restrictions I am left with a sample of 4,750 OHL regular season games.

3.2 Attendance and On-Ice Performance

Table 1 displays summary statistics for my sample. In regards to attendance specific variables, OHL games are shown to have an average of 4,104 announced attendees.¹⁸ The range of announced attendances is substantial, with the lowest recorded attendance being 1,034 for a Wednesday evening game at the Compuware Arena (Plymouth, Michigan) and the highest being 16,406 fans on a Monday matinee at the Canadian Tire Centre (Ottawa, Ontario). The average arena capacity across the league is only 6,069, causing the average game to only be at 71.8 percent of capacity.¹⁹ This results in sold-out games being relatively rare when looking at the entire league, with only 12 percent of games being at capacity.²⁰

Superstar players are only in the lineup of 6 percent of games, showing that players often do not play all of their scheduled regular-season games. If each superstar player played all games, this would represent a total of 8.4 percent of games in my sample. This is especially true in terms

¹⁷ For example, when the Ottawa 67's played the Gatineau Olympiques of the QMJHL and also examples such as when the Erie Otters played the Niagara IceDogs at the First Niagara Center (NHL arena of the Buffalo Sabres) on October 22nd, 2014. The imposition of this restriction led to 17 games being dropped from the sample.

¹⁸ Announced attendance is controversial in nature. However, it is the only figure publicly available to measure demand. I recognize that there are other ways to influence this number quite significantly outside of the number of tickets scanned, which causes many authors to debate the definition of attendance and use substitutes where available (Villar and Guerrero, 2009). Teams may offer complimentary tickets, visiting team tickets, or unused season tickets which all can boost these figures without actually representing the true number of people who attended the game.

¹⁹ For arena capacity, I use the total amount of tickets that can be sold for each building. This accounts for the many buildings that have standing room area tickets which add to the supply of tickets available, which could falsely indicate a sellout if seated capacity was used.

²⁰ Games are identified as sold-out if announced attendance is greater than 97 percent of arena capacity. I choose 97 percent for two reasons: 1) Many arenas have standing room areas which do not provide a ticket holder an actual seat, possibly causing fans to not attend games if only standing room tickets were available; 2) The availability of multiple seats beside each other can be significantly reduced as the number of tickets sold approaches capacity. If fans purchase tickets in pairs or groups, using 100 percent as a sellout may be problematic. As a robustness check, I define a sellout if announced attendance equals (or exceeds) 100 percent of arena capacity, and results were not substantially different.

of the OHL, where top players typically play in the WJHC tournament and miss a substantial number of games in late December and early January. A feature that is notable about superstars is the OHL schedule, which only allows for teams to travel to arenas in the other conference once a season.²¹ This limits the number of opportunities some fans have to see a superstar player play in their city. Summary statistics in Table 1 reveal that superstar players on home and away teams did not miss significantly more home games than away games.

The sample shows evidence that home teams win more often on average than away teams, as home teams have an average winning percentage of 57 percent. This motivates the need to consider home and away win percentages differently, due to a clear ‘home-ice advantage’ being present.²² In regards to goals, the data shows how high scoring OHL games can be, as the most goals scored by the home and away team in a single game are 12 and 13, respectively. The summary statistics reveal that home teams average more goals (3.7 goals) than away teams (3.3 goals) over the sample. For comparison, NHL games only averaged 5.49 goals-per-game,²³ over the 2011-2012 to the 2018-2019 NHL seasons, which is less frequent than scoring in the OHL.

²¹ For example, the Sault Ste. Marie Greyhounds only travel to play Eastern Conference teams such as the Niagara IceDogs, Hamilton Bulldogs, and the Mississauga Steelheads once a season, often playing all of these away games in the span of four consecutive days.

²² If spectators take home and away win percentages into account, it is important to be specific in the definition of team win percentage. The definition allows for measuring teams who may perform better at home than on the road, which may increase fans expectations of seeing the team win when they play at their home arena.

²³ Based on data from ESPN.com.

Within the data, there are several characteristics which add context to the league, and the communities that host OHL teams. Due to the cost of travel and school-age players, 72 percent of games take place on Friday, Saturday, and Sunday in my sample. On a given weekend, teams will typically play back-to-back home or away games so that the number of total bus trips is minimized.²⁴ Games are evenly distributed throughout the season with approximately 20 percent of games played each month. I also see that an overwhelming majority of games are played in Canada, with under 16 percent of games played in the U.S. The regional unemployment rates see a substantial range throughout the data as the minimum was 1.8 percent, with the highest being 11.8 percent.

One anomaly of OHL regular seasons are high average attendances for weekday matinee games. These special games represent 4.5 percent of the entire sample and are identified differently than other games on the schedule. I choose to identify these games differently as their high announced attendances are explained by local schools that bring all of their students to a game during the day. This phenomenon is quite different compared to a typical OHL game with regular ticket purchasers and was important enough to merit controlling for these games in the subsequent regression analysis.²⁵

3.3 Arenas

This section will discuss characteristics of OHL arenas, and their differences across the league. Most OHL teams operate in arenas which they are the primary tenant. However, major junior hockey teams differ from NHL teams in that arenas are typically owned and operated by the

²⁴ This is a common feature of all leagues within the broader CHL. On a given weekend, most teams will either play a three-game homestand or have a road trip where they play three games at three different away arenas.

²⁵ An observation where this is seen is on Tuesday, March 5th, 2013 at 10:45 AM. The Saginaw Spirit hosted a weekday matinee against the Plymouth Whalers, which saw a sold-out announced attendance of 5,527, ranking in the top 10 highest announced attendances in Saginaw in the years covered by my sample.

cities in which they play, and they usually do not have upfront financial stakes in the arena itself. (Mason et al., 2007). The arenas across the league have a wide variety of capacities and average attendances which differ depending on market size.

Table 2 displays arena summary statistics for each team in my sample. The different venues exhibit a fairly large attendance variance overall with a few exceptions. OHL arenas with sellout percentages that are below five percent are commonplace, as many arenas never record a sellout in the sample. OHL sellout percentages are quite different in comparison to leagues such as the NHL, where a large percentage of regular season games are sold-out (Leadley and Zygmunt, 2006; Keller and McGuire, 2011). This is one of the primary motivations for choosing the OHL as most attendance data points are uncensored, with the vast majority of games having hundreds of unsold tickets.

The average announced attendance in my sample is 4,103.66 people. However, there exhibits a large amount of variation of announced attendance averages among OHL arenas. For example, the London Knights consistently have had higher attendance figures than any other franchise in recent history. In 2002, the team moved from being the primary tenant of the London Ice House which had a capacity of 5,075 to a new, 9,090 seat Budweiser Gardens which has a total capacity of 9,140 people. Since moving to the new arena, the Knights have seen success on the ice, winning four OHL championships and two Memorial Cups. Ticket sales have also been successful, as Budweiser Gardens has been 98 percent full on average, with an average announced attendance of 8,997. By contrast, there are arenas such as the FirstOntario Centre that has an above-average attendance 4,204, but only averages to be 24 percent full due to its NHL size capacity.

The data suggests that there may have been teams that were not able to keep attendance figures high enough to be sustainable for survival in the OHL. Within my sample period, three

notable changes occur in the composition of the OHL, with attendance similarities among them.²⁶ The Powerade Centre, Yardmen Arena, and the Compuware Arena were the only three arenas to record average attendances which were below 2,700 fans. Each team (Brampton, Belleville, and Plymouth) that played at these arenas all relocated to different cities within my sample. After moving, each franchise showed higher average attendance in their new cities (North Bay, Hamilton, and Flint). Whether or not an average of 2,700 attendees is the ‘tipping point’ for a franchise to relocate, it does show that attendance is important for the viability of an OHL team.

A more subtle change shown in Table 2 are renovations at the Erie Insurance Arena. The renovation added 1,333 to the arena’s capacity and was completed before the 2013-2014 season. The timing of the renovation comes one year after the arrival of superstar player Connor McDavid, as all of his draft year home games were played at the newly renovated building. Table 2 shows that after construction, the average attendance in Erie increased by 1,172, an increase of 38.6 percent. This increase in average attendance is notable for Erie as I would expect it to be attributed to both a superstar player attendance effect and an arena novelty effect.

In 2014, the Niagara IceDogs moved from the 3,100-seat Gatorade Garden City Complex to the newly built 5,300-seat Meridian Centre. While increasing the number of tickets the IceDogs could sell per-game by 2,200, the move provided additional value-added amenities such as suites, new food options, and a new in-game atmosphere for their fans.²⁷ Since moving to the Meridian Centre, all Niagara IceDogs regular season home attendances have exceeded the capacity of the

²⁶ This is why my study includes 26 different arenas instead of the typical 20 OHL arenas which are active in a given OHL season.

²⁷ The Niagara IceDogs attendance data shows that while there were many capacity crowds at the Gatorade Garden City Complex, an average of 144 available tickets still available for these games.

former arena, boosting team revenues significantly.²⁸ Niagara IceDogs regular season attendance within my sample can be seen visually in Figure A.1, which includes games played at the Gatorade Garden City Complex and Meridian Centre. The most important aspect of the IceDogs upgrade to the Meridian Centre was that it came without any added travel conveniences. The new arena is less than a kilometer away from the prior venue and is still located in the downtown core of the city. This interesting feature allows for a better measure of the novelty effect compared to if a city built an arena in a far different location.

4. METHODOLOGY

This section provides my methodology for studying the effects of superstars on two key dependent variables. First, I provide methodology on measuring superstar effects in regards to sold-out games using a linear probability model. Following this, the methodology is presented for estimating the impacts of superstars on announced attendance using a censored Tobit regression.

4.1 Sold Out Games

The first focus of this paper is identifying superstar effects on games being sold-out. I use an econometric model which takes the following form:

$$sellout_{a,t} = \beta_0 + \beta_1 star_{a,t} + \beta_2 hwpct_{a,t-1} + \beta_3 awpct_{a,t-1} + \beta_4 hgoals_{a,t-1} + \beta_5 agoals_{a,t-1} + \beta_6 urate_{a,t} + \beta_7 matinee_{a,t} + X_{a,t}\phi + W_{a,t}\Upsilon + \mu_a + \varepsilon_{a,t} \quad (1)$$

²⁸ In 2017, via a court order, the Niagara IceDogs were forced to present their financial documents. The financials reveal that while the IceDogs were playing at the Garden City Complex, the franchise generated 2.8 million dollars in revenue for the fiscal year ending May 31st, 2014, representing a loss of \$103,093. The move to the Meridian Centre saw the IceDogs revenue total \$4.2 million in the fiscal year 2015, for a profit of \$438,679. The profitability continued in the fiscal year 2016 with 4.6 million dollars of revenue, and a profit of \$643,544.

where $sellout_{a,t}$ is the dependent variable which equals one if announced attendance was equal or above 97 percent of capacity at arena a at time t , and zero otherwise. $star_{a,t}$ is a dummy variable that equals one if a superstar player was included in the lineup of the game, and zero otherwise. Recall, superstar players are defined as the top OHL player within the top five of the TSN pre-season draft rankings in a given season.

Other independent variables are defined as follows: $hwpct_{a,t-1}$ is the season average home win percentage of the home team playing prior to each game.²⁹ $awpct_{a,t-1}$ is the season average away win percentage of the away team playing prior to each observation. $hgoals_{a,t-1}$ and $agoals_{a,t-1}$ are running season averages of the number of home and away goals scored by the home and away team prior to each game at time t .³⁰ $urate_{a,t}$ is the monthly regional unemployment rate where each game was played. $matinee_{a,t}$ is a dummy variable which equals one if a game was played on a weekday before 3:00 PM local time, and zero otherwise. $X_{a,t}$ and $W_{a,t}$ are both vectors of binary variables which represent the month and day of the week which the game was played.³¹ Finally, μ_a denotes arena fixed effects.

4.2 Announced Attendance

To study the effects superstar players have on announced attendance, I use an econometric model which takes the following form:

²⁹ As an example, the Oshawa Generals hosted the Hamilton Bulldogs on October 27th, 2019 which was their sixth home game of the season. $hwpct_{a,t-1}$ was calculated using Oshawa's home win percentage over the previous five home games, which was 0.6 (as they won three out of their first five home games). The same logic is used for $awpct_{a,t-1}$ using the away team. As each season progresses, these averages take into account each additional game played.

³⁰ Using the game played by the Oshawa Generals and Hamilton Bulldogs on October 27th, 2019, $hgoals_{a,t-1}$ was calculated using Oshawa's average home goals scored using their previous five home games of the season. The same logic is used for $agoals_{a,t-1}$ using the away team. As each season progresses, these averages take into account each additional game played.

³¹ OHL games are only played during the months September to May, with the exception of the 2019-2020 regular season which ended early in March due to the COVID-19 pandemic.

$$attendance_{a,t} = \beta_0 + \beta_1 star_{a,t} + \beta_2 hwpct_{a,t-1} + \beta_3 awpct_{a,t-1} + \beta_4 hgoals_{a,t-1} + \beta_5 agoals_{a,t-1} + \beta_6 urate_{a,t} + \beta_7 matinee_{a,t} + X_{a,t}\phi + W_{a,t}\Upsilon + \mu_a + \varepsilon_{a,t} \quad (2)$$

where $attendance_{a,t}$ is the announced attendance of a game at arena a at time t . All independent variables maintain the same definitions as in equation (1). I estimate my model using a censored Tobit regression to account for arena capacity constraints.³² For example, if a superstar player came to an arena with a relatively high sellout rate, such as the Meridian Centre, fans who might have wanted to go the game may have not been able to attend due to the lack of available tickets.³³ While sellouts only occur in 12 percent of games in my sample, it still poses a significant problem in estimating demand and would underestimate superstar attendance effects if it was ignored.

5. RESULTS

5.1 Linear Probability Model - Sellout Probability

Table 3 presents the OLS results of equation (1) where control variables are added sequentially.³⁴ The results are to be interpreted as marginal effects, as I am using a linear probability model. (i.e. how a change in an explanatory variable affects the probability of a sellout).

Having a superstar in the line-up increases the probability of a sellout, however, it is not statistically significant at conventional significance levels. In the more parsimonious specification, where I only control for arena fixed effect (i.e. column (1)), the sell out probability increases by 1.6 percentage points. The effects are somewhat dampened as controls are added. In column (2), the effect decreases to 1.1 percentage points and then falls to 0.9 percentage points in column (3).

³² Said differently, the Tobit regression allows me to account for the fact that desired attendance is constrained by the capacities of OHL arenas.

³³ Attendance figures that represent 97% or more of arena capacity are treated as top-coded. As such, top-coding will vary from one arena to the next. For example, in the case of Sudbury Community Arena (home of the Sudbury Wolves), arena capacity is 5,100. As such, attendance for the Sudbury Community Arena is top-coded at 4,947 (97% of capacity).

³⁴ Standard errors in Table 3, and all subsequent tables of regression results, are robust standard errors that are clustered at the arena level.

By the time one reaches column (4), my richest and preferred specification, having a superstar on the ice increases the probability of a sell out by 0.9 percentage points. For context, only 12 percent of games in my sample are sold-out, making such an increase economically significant. However, due to the relatively large standard errors, these results are not statistically significant, not even at the 10 percent level.³⁵

Most of my estimates related to control variables show the expected sign, it is clear that sellouts are sensitive to home team performance. A 10 percentage-point increase in the home win percentage of the home team increases the probability of a sellout by 1.2 percentage points. This statistically significant result contributes to the idea that fans enjoy watching winning home teams, and a team with a low win percentage is less likely to have a sold-out arena. When controlling for win percentages, how many goals the home and away teams score on average does not seem to have any economically or statistically significant effect on sellouts. Therefore, effects seem to lead toward arenas selling out with fans wanting to see teams that win more often, irrespective of how many goals they score.

While team performance shows to be significant in terms of the probability of a sellout, contextual variables also matter. The regional unemployment rate has coefficient estimates which are large in magnitude. The unemployment rate shows a positive statistically significant coefficient has two possible explanations. OHL games are relatively inexpensive to attend, and could be seen as an inferior good compared to other substitutes such as professional hockey games. Games identified as weekday matinees show positive economically significant effects that are statistically significant at the one percent level. The magnitude of the weekday matinee is also economically

³⁵ If one were to look at the results of column (1), a superstar effect of 3.13 percentage points would be needed to be significant at the five percent level. Given that results using announced attendance are more statistically significant, the low power of this model might be due to the relatively low variation of sold-out games.

large, showing a statistically significant effect of 6 percentage points. This shows the impact of long weekends and schools bringing their students to games on selling out arenas. Overall, the three estimates show how other factors off the ice contribute to sellouts in the OHL.

The date a game is played shows to be a large and significant factor for the probability of a sellout. Month dummy variables show that the probability of sellouts increase as the season progresses, especially in the case of games in March. A game played in March increases the probability of a sellout by 10 percentage points compared to the reference group November. This shows that arena sellouts are far more probable in the last month season for the ‘push to the playoffs’ rather than games played in the middle of the season. Statistically significant effects differ depending on the day of the week a game is played too, as games on Saturdays increase the probability of sellout by 6 percentage points.

Table 4 presents OLS regression results of equation (1) using a full set of controls, but for different definitions of how to quantify a superstar. I do this because superstars who are the number one or two ranked prospects globally may have a different effect than the best OHL player in the top five of the TSN pre-season draft rankings. Additionally, relaxing the definition of a superstar to the top OHL prospect who was in the top 10, allows for there to be one superstar player for every year of my sample. For Panel A, a superstar is defined as the top prospect in the OHL out of the top 10 players in the TSN pre-season draft rankings. Panel B reiterates the results for my preferred definition (i.e. column (4) of Table 3). Finally, Panels C and D restrict superstars to the top player in the OHL, but only if they are in the top two, or the number one prospect respectively.

For ease of presentation, I only report the superstar findings, and only present the results for my richest and preferred specification.³⁶

The results of Table 4 show that as the superstar definition becomes stricter in terms of how high the top player in the OHL needs to be ranked to be considered a superstar, the higher the effect of a sellout. When using the top 10 definition, the effect is essentially zero with no statistical significance. However, when superstars are restricted to the best player in the league while only using the top two prospects, the effect becomes economically significant at 1.1 percentage points, but still not statistically significant. The effect becomes both economically and statistically significant (at the five percent level) when the definition narrows to the top prospect worldwide.³⁷ A prospect of this caliber in the lineup increases the probability of a sellout by 5.3 percentage points. This result is intuitive and shows that the number one prospect worldwide can attract capacity crowds around the league when they are in the lineup.

5.2 Censored Tobit Regression - Announced Attendance

Table 5 presents censored Tobit regression results for effects on announced attendance using equation (2). Using the censored Tobit regression allows for more variation in my dependent variable than using a method such as OLS. Similarly, using announced attendance compared to sold out games, also adds variation to my model. Explanatory variables are added sequentially as in Table 3. Table 5 shows a positive statistically significant effect (at the five percent level) for superstar players which stay relatively stable when adding control variables. The superstar effect decreases slightly from 229.6 to 179.3 as more controls are added. The estimates are economically

³⁶ The control variables show similar results regardless of which superstar definition is used.

³⁷ The three players identified as superstars using the strict definition of the number one prospect worldwide (Nail Yakupov, Aaron Ekblad, and Connor McDavid) all eventually went on to be picked number one overall in the NHL Entry Draft. This indicates that, at the very minimum, these three players were known to be of higher quality than all other players in their draft class far before the actual draft.

significant when viewed in the context of the OHL. Recall, average OHL announced attendance is only 4,104, making the superstar effect an increase between 4.3 and 5.5 percent. This result shows a visible increase in both attendance and revenue for the home team for games where a superstar is in the lineup.

Censored Tobit results in column (4), my preferred specification, are in line with findings of the linear probability model. The effects of both home and away win percentages show to be positive and significant at the one percent level, with a far higher coefficient for the home team. This result is expected and aligns with the story of fans preferring to watch teams that win often, especially in regards to the home team. The away team coefficient estimate being positive is not surprising either, as it is reasonable to assume fans will attend games featuring a competitive or quality visiting team. Goals seem to be less important in terms of their impact on attendance, as coefficient estimates are small in terms of magnitude and not statistically significant in my preferred specification.

There are interesting findings concerning which day (of the week) the game is played. Not surprisingly, there is increased attendance on the weekend, and the effect is both economically and statistically significant.³⁸ The Saturday effect is particularly large; attendance increases by 567.6 when a game is played on a Saturday, as compared to a mid-week (i.e. Wednesday) game. Monday games have the highest positive effect, an increase of 696.7 on attendance. At first glance, it would appear to be counterintuitive. It should be noted, however, that only 2.2 percent of games in my sample are played on Mondays, and a large number of these are afternoon games played on holiday long weekends where higher attendance would be expected.³⁹

³⁸ One can consider Friday to be the start of the weekend.

³⁹ For example, the Ontario Family Day holiday is always celebrated on the 3rd Monday of February.

Table 6 presents censored Tobit regression results using equation (2) for different definitions of how to quantify a superstar.⁴⁰ As with Table 4, I only report superstar findings and only show results for the richest specification.⁴¹ Control variable estimates did not change significantly when altering the definition of a superstar. Results from Table 6 show that using stricter definitions of a superstar increases superstar attendance effects substantially. When defining superstars as the top player in the OHL in the top 10 of TSN's rankings, the effect is 137.5 which is significant at the 10 percent level. With the strictest definition, OHL superstars being the top prospect globally, the effect is 379.4 and significant at the one percent level. This translates into 25,799 more fans throughout the regular season if a superstar player played all 68 games. This result shows the demand these players create as scouts, media, and fans want to watch these players before they are drafted and play in the NHL.

5.3 Superstar Effects - Home vs Away

Since superstars play approximately half of their games in the same home arena, the superstar attendance effect may differ depending on which team (home or away) they were on in a given game. I decided to separate the variable $star_{a,t}$ into two dummy variables, ($hstar_{a,t}$ and $astar_{a,t}$) which are dummy variables which equal one if a superstar player was in the lineup of the home team and away team respectively, and zero otherwise. This allows for the differentiation of fan reaction to superstar presence if they only have a couple of opportunities to see the player on an away team compared to the player playing several home games in their area.

⁴⁰ The definitions are the same as Table 4. Panel A defines a superstar as the top prospect in the OHL out of the top 10 players in the TSN pre-season draft rankings. Panel B is my preferred definition, while Panel C and Panel D restrict superstars to the top player in the OHL, only if they were in the top 2, or the number one prospect respectively.

⁴¹ Control variable estimates do not change significantly when altering the definition of a superstar.

Table 7 contains marginal effect results for my richest and preferred specification of equation (1) using the linear probability model. For each column of this table, I use a different definition of a superstar as well as identify superstar effects separately if they were on the home or away team. Table 8 is designed similarly, and presents results from equation (2) using my preferred specification and differentiates the effect of home and away superstars on attendance. All results within Table 8 are from censored Tobit regressions, with only superstar effects reported.

The results from Table 7 estimate superstar effects but differentiate whether they were on the home or away team. In Panel A, B and C, I do not find statistically significant superstar effects, while in Panel D, statistically significant effects are found for superstar players on the home team. The interesting takeaway from Table 7 is that estimates are consistently higher for superstars on the away team, and magnitudes increase as the definition of a superstar becomes stricter. In Panel D, estimates are economically large, with home superstars increasing the probability of sellout by 3.6 percentage points. Away superstars show an increase of 6.9 percentage points, however this is not statistically significant.

Table 8 concludes my main results by providing estimates which show convincing evidence of away superstar effects in the OHL. The estimates for away superstars are all statistically significant and large in magnitude. Depending on which definition is chosen, the estimates range from 200.6 to 332.2 which increases as the definition becomes stricter. Marketing of highly ranked superstars coming to play against the home team may be a contributing factor to this difference, as home teams may promote games based on who is on the visiting team. Interestingly, the largest estimate (425.3) is for the top global prospect when they are in the lineup at home. This could be due to season ticket sales rising when the top prospect in the world plays

in a community. It also may be that fans may travel further distances to see the top prospect play, as home arenas which the top prospects played in are fairly close to other OHL markets.

6. ROBUSTNESS CHECKS

In this section, I carry out two robustness checks. First, instead of defining a sellout as greater than 97 percent of capacity, I now use a stricter sellout definition (i.e. 100 percent of capacity). Second, I check to see how much of an influence the WJHC tournament may have on superstar effects by restricting my sample to post-WJHC games.

Table A.3 presents results for both the linear probability model (columns (1) and (2)) and censored Tobit regressions (columns (3) and (4)). Columns (2) and (4) show results when a sellout is equal or above 100 percent of capacity, whereas columns (1) and (3) use my original definition of a sellout (i.e. 97 percent or more of capacity).

In regards to the censored Tobit regressions, results are essentially the same for both superstar effects and other explanatory factors. It should be mentioned that, one does see a difference in regards to the linear probability model. The superstar effect is now essentially zero and is still not statistically significant. There are also some differences in other explanatory factors, such as home team win percentage which now becomes economically and statistically insignificant. However, having an arena reach 100 percent capacity is extremely rare for OHL regular season games, accounting for only 4.1 percent of my sample. As such, there is not much variation in my explanatory variable.

Table A.4 presents results for both the linear probability model and censored Tobit regressions, using different sample sizes to compare my results with a sample including only games played after the WJHC tournament. The tournament gives OHL superstar players

substantial global exposure and sees the top prospects under the age of 20 play in international competition.

Quite expectedly, the results using a restricted sample including games played after the WJHC show large increases to the superstar effect. The superstar effect on announced attendance almost doubles in the second half of the season, and both home and away win percentages show increased effects as well. An entire paper could be dedicated to studying the impact of the WJHC on superstar player effects, as the results seem to show that superstar drawing power is far greater after the tournament.

7. CONCLUSION

This study examines how OHL superstar players affect attendance demand and the probability of a sellout in the OHL. I aim to expand on the literature by providing regression analysis of superstar attendance effects in the context of amateur major junior hockey. Due to this, my analysis includes more sub-sellout attendance variation than seen in professional leagues. Furthermore, I also contribute to the literature by using a dependent variable of sold-out games, which is uncommon in attendance demand studies.

Through the use of two different econometric models, this study presents results for the OHL. I find evidence of OHL superstars having an economically and statistically significant positive effect on announced attendance. When separating the effect into home and away superstars, away superstar players showed higher estimates for announced attendance, except for when the superstar player is the number one global prospect. There seems to be an economically significant change in the probability of a sellout using most definitions of superstar players,

however, it is largely statistically insignificant. OHL superstars show a positive effect on announced attendance which is robust to a variety of superstar definitions.

The possibilities for further studies on amateur hockey superstars are intriguing. The Western Hockey League and QMJHL also have seen superstar players develop and it would be interesting to see if results are similar throughout the CHL. Also, studying if superstars can influence a sellout may be different in the context of professional leagues with a focus on teams who struggle to attract sold out crowds. These studies could help sports teams and leagues further understand potential superstar effects, and gain insight on the true value of superstar players.

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Table 1. Summary Statistics

Variables	Mean	Min	Max
Sold-out Game (<i>sellout</i>)	0.120 (0.325)		
Announced Attendance (<i>attendance</i>)	4,104 (1,758)	1,034	16,406
Arena Capacity	6,069 (2,989)	3,145	20,500
% of Arena Capacity	0.718 (0.217)		
Superstar Player in Lineup (<i>star</i>)	0.0602 (0.238)		
Superstar Player on Home Team (<i>hstar</i>)	0.0299 (0.170)		
Superstar Player on Away Team (<i>astar</i>)	0.0303 (0.171)		
Home Team: Home Win Percentage	0.570 (0.173)		
Home Final Score	3.727 (2.036)	0	12
Away Final Score	3.321 (2.013)	0	13
Unemployment Rate % (<i>urate</i>)	0.063 (0.016)	0.018	0.167
Game Played in Canada	0.848 (0.359)		
Weekday Matinee (<i>matinee</i>)	0.0453 (0.208)		
Game Played on Monday	0.0223 (0.148)		
Game Played on Tuesday	0.0312 (0.174)		
Game Played on Wednesday	0.0823 (0.275)		
Game Played on Thursday	0.134 (0.341)		
Game Played on Friday	0.279 (0.449)		
Game Played on Saturday	0.243 (0.429)		
Game Played on Sunday	0.208 (0.406)		
Game Played in October	0.060 (0.238)		
Game Played in November	0.219 (0.414)		
Game Played in December	0.182 (0.386)		
Game Played in January	0.203 (0.403)		
Game Played in February	0.197 (0.398)		
Game Played in March	0.138 (0.345)		
Obs.	4,750		

Notes. Standard deviations are in parentheses.

Table 2. Arena-Level Summary Statistics

Arena	Home Team	Obs.	Mean Attendance	Capacity	% of Arena Capacity	Percentage of Games Sold-out
Colts Centre	Barrie Colts	238	3,745.97	4,195	0.893	0.287
Yardmen Arena	Belleville Bulls	115	2,510.18	3,757	0.668	0.017
Powerade Centre	Brampton Battalion	57	2,106.09	4,959	0.425	0.000
Erie Insurance Arena	Erie Otters	57	3,036.81	5,500	0.552	0.000
Erie Insurance Arena (Renovated)	Erie Otters	184	4,209.28	6,833	0.616	0.046
Dort Federal Event Center	Flint Firebirds	125	2,858.58	4,400	0.650	0.021
Sleeman Centre	Guelph Storm	236	4,261.54	4,666	0.913	0.341
FirstOntario Centre	Hamilton Bulldogs	129	4,204.95	17,500	0.240	0.000
Leon's Centre	Kingston Frontenacs	239	3,564.84	5,380	0.663	0.123
Kitchener Memorial Auditorium	Kitchener Rangers	242	6,939.53	7,700	0.901	0.004
Budweiser Gardens	London Knights	235	8,997.55	9,100	0.989	0.932
Paramount Fine Foods Centre	Mississauga Steelheads	237	2,744.43	6,000	0.457	0.000
Gatorade Garden City Complex	Niagara IceDogs	87	3,020.89	3,145	0.960	0.448
Meridian Centre	Niagara IceDogs	152	4,798.74	5,300	0.905	0.375
North Bay Memorial Gardens	North Bay Battalion	177	2,855.09	4,246	0.672	0.016
Tribute Communities Centre	Oshawa Generals	237	5,157.21	6,125	0.842	0.120
Canadian Tire Centre	Ottawa 67s	60	5,586.08	20,500	0.275	0.016
TD Place	Ottawa 67s	174	4,119.68	9,862	0.418	0.005
Harry Lumley Bayshore Centre	Owen Sound Attack	236	2,986.43	3,500	0.853	0.012
Peterborough Memorial Centre	Peterborough Petes	234	2,744.17	4,069	0.674	0.000
Compuware Arena	Plymouth Whalers	116	2,669.37	4,000	0.667	0.060
Dow Event Center	Saginaw Spirit	240	3,590.10	5,497	0.653	0.076
Progressive Auto Sales Arena	Sarnia Sting	233	3,228.70	5,200	0.621	0.004
GFL Memorial Gardens	Soo Greyhounds	237	4,120.68	5,000	0.824	0.125
Sudbury Community Arena	Sudbury Wolves	241	3,507.52	5,100	0.688	0.015
WFCU Centre	Windsor Spitfires	232	5,080.18	6,500	0.782	0.044
Total		4,750	4103.66	6,069	0.718	0.120

Notes. Within my sample, three teams relocated to new cities: The Brampton Battalion changed to the North Bay Battalion, the Plymouth Whalers changed to the Flint Firebirds, and the Belleville Bulls changed to the Hamilton Bulldogs.

Table 3. Linear Probability Model Results

Variables	(1)	(2)	(3)	(4)
Superstar Player in Lineup (<i>star</i>)	0.0159 (0.0120)	0.0111 (0.0117)	0.00946 (0.0113)	0.00889 (0.0107)
Home Team: Home Win Percentage (<i>hwpct</i>)		0.119** (0.0482)	0.119** (0.0468)	0.125** (0.0475)
Away Team: Away Win Percentage (<i>awpct</i>)		0.0525* (0.0269)	0.0433 (0.0263)	0.0464 (0.0285)
Home Team: Average Home Goals (<i>hgoals</i>)		-0.00100 (0.00878)	0.00183 (0.00916)	0.000349 (0.00836)
Away Team: Average Away Goals (<i>agoals</i>)		0.00542 (0.00631)	0.00777 (0.00633)	0.00852 (0.00642)
Unemployment Rate (<i>urate</i>)			1.107*** (0.315)	0.642** (0.298)
Weekday Matinee (<i>matinee</i>)				0.0607* (0.0338)
Game Played in October				-0.0395* (0.0225)
Game Played in December				0.0265** (0.0123)
Game Played in January				0.0378*** (0.0135)
Game Played in February				0.0279* (0.0138)
Game Played in March				0.101*** (0.0312)
Game Played on Monday				0.124** (0.0495)
Game Played on Tuesday				0.0275 (0.0337)
Game Played on Thursday				-0.0898* (0.0497)
Game Played on Friday				0.0415** (0.0189)
Game Played on Saturday				0.0617*** (0.0196)
Game Played on Sunday				0.0249 (0.0180)
Constant	-0.000279 (0.000210)	-0.107** (0.0410)	-0.208*** (0.0518)	-0.214*** (0.0636)
Arena FE	YES	YES	YES	YES
Obs.	4,750	4,750	4,750	4,750
R-squared	0.454	0.458	0.460	0.490

Notes. The dependent variable is a binary variable which equals one if the game was a sellout, and equals zero otherwise. Cluster robust standard errors are in parentheses. (***) p<0.01, ** p<0.05, * p<0.1).

Table 4. Linear Probability Results, Different Superstar Definitions

Variables	(1)
<i>Panel A</i>	
Highest Ranked Superstar Player in Lineup (Top 10)	-0.00702 (0.0156)
Obs.	4,750
R-squared	0.4902
<i>Panel B</i>	
Highest Ranked Superstar Player in Lineup (Top 5)	0.00889 (0.0107)
Obs.	4,750
R-squared	0.4902
<i>Panel C</i>	
Highest Ranked Superstar Player in Lineup (Top 2)	0.0110 (0.0143)
Obs.	4,750
R-squared	0.4902
<i>Panel D</i>	
Highest Ranked Superstar Player in Lineup (#1)	0.0534** (0.0234)
Obs.	4,750
R-squared	0.4902

Notes. The dependent variable is a binary variable which equals one if the game was a sellout, and equals zero otherwise. Preferred specification of equation (1) is used for each regression. Controls include: home and away team win percentages, home and away average goals scored, the regional unemployment rate, weekday matinee dummy variable, month dummy variables, day of the week dummy variables, and Arena FE. Cluster robust standard errors are in parentheses. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 5. Censored Tobit Regression Results

Variables	(1)	(2)	(3)	(4)
Superstar Player in Lineup (<i>star</i>)	229.6*** (84.86)	194.9** (84.41)	180.7** (84.26)	179.3** (77.99)
Home Team: Home Win Percentage (<i>hwpct</i>)		818.0*** (145.5)	827.5*** (145.2)	848.9*** (132.9)
Away Team: Away Win Percentage (<i>awpct</i>)		346.9*** (113.7)	283.5** (113.4)	303.5*** (103.7)
Home Team: Average Home Goals (<i>hgoals</i>)		36.46 (32.01)	54.51* (32.10)	48.20* (29.13)
Away Team: Average Away Goals (<i>agoals</i>)		-1.057 (28.44)	15.33 (28.43)	19.82 (26.07)
Unemployment Rate (<i>urate</i>)			8,191*** (973.2)	5,194*** (908.2)
Weekday Matinee (<i>matinee</i>)				873.6*** (162.5)
Game Played in October				-356.3*** (53.15)
Game Played in November				71.26* (40.01)
Game Played in December				169.9*** (38.54)
Game Played in January				216.6*** (44.89)
Game Played in February				553.6*** (44.82)
Game Played on Monday				696.7*** (230.5)
Game Played on Tuesday				-190.9 (128.4)
Game Played on Thursday				-67.16 (74.62)
Game Played on Friday				385.1*** (65.16)
Game Played on Saturday				567.6*** (60.28)
Game Played on Sunday				245.6*** (64.25)
Constant	5,091*** (53.69)	4,333*** (128.7)	3,625*** (160.9)	3,531*** (162.1)
Arena FE	YES	YES	YES	YES
Obs.	4,750	4,750	4,750	4,750

Notes. Dependent variable in each regression is announced attendance. Cluster robust standard errors are in parentheses. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 6. Censored Tobit Regression, Different Superstar Definitions

Variables	(1)
<i>Panel A</i>	
Highest Ranked Superstar Player in Lineup (Top 10)	137.5** (63.09)
Obs.	4,750
<i>Panel B</i>	
Highest Ranked Superstar Player in Lineup (Top 5)	179.3** (77.99)
Obs.	4,750
<i>Panel C</i>	
Highest Ranked Superstar Player in Lineup (Top 2)	203.6*** (64.84)
Obs.	4,750
<i>Panel D</i>	
Highest Ranked Superstar Player in Lineup (Top 1)	379.4*** (80.00)
Obs.	4,750

Notes. Dependent variable in each regression is announced attendance. Preferred specification of equation (2) is used for each regression. Controls include: home and away team win percentages, home and away average goals scored, the regional unemployment rate, weekday matinee dummy variable, month dummy variables, day of the week dummy variables, and Arena FE. Robust standard errors are in parentheses. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7. Linear Probability Model Results, Superstar Effects at Home and Away

Variables	(1)
<i>Panel A</i>	
Highest Ranked Superstar Player on Home Team (Top 10)	-0.0414 (0.0256)
Highest Ranked Superstar Player on Away Team (Top 10)	0.0203 (0.0167)
Obs.	4,750
R-squared	0.4909
<i>Panel B</i>	
Highest Ranked Superstar Player on Home Team (Top 5)	-0.00849 (0.0140)
Highest Ranked Superstar Player on Away Team (Top 5)	0.0230 (0.0188)
Obs.	4,750
R-squared	0.4904
<i>Panel C</i>	
Highest Ranked Superstar Player on Home Team (Top 2)	-0.0142 (0.0153)
Highest Ranked Superstar Player on Away Team (Top 2)	0.0327 (0.0207)
Obs.	4,750
R-squared	0.4905
<i>Panel D</i>	
Highest Ranked Superstar Player on Home Team (Top 1)	0.0368*** (0.00589)
Highest Ranked Superstar Player on Away Team (Top 1)	0.0696 (0.0457)
Obs.	4,750
R-Squared	0.4910

Notes. The dependent variable is a binary variable which equals one if the game was a sellout, and equals zero otherwise. Preferred specification of equation (1) is used for each regression. Controls include: home and away team win percentages, home and away average goals scored, the regional unemployment rate, weekday matinee dummy variable, month dummy variables, day of the week dummy variables, and Arena FE. Cluster robust standard errors are in parentheses. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 8. Censored Tobit Regression Results, Superstar Effects at Home and Away

Variables	(1)
<i>Panel A</i>	
Highest Ranked Superstar Player on Home Team (Top 10)	61.33 (104.1)
Highest Ranked Superstar Player on Away Team (Top 10)	200.6*** (71.33)
Obs.	4,750
<hr/>	
<i>Panel B</i>	
Highest Ranked Superstar Player on Home Team (Top 5)	142.2 (133.3)
Highest Ranked Superstar Player on Away Team (Top 5)	210.8** (84.18)
Obs.	4,750
<hr/>	
<i>Panel C</i>	
Highest Ranked Superstar Player on Home Team (Top 2)	113.5 (79.29)
Highest Ranked Superstar Player on Away Team (Top 2)	284.9*** (100.9)
Obs.	4,750
<hr/>	
<i>Panel D</i>	
Highest Ranked Superstar Player on Home Team (Top 1)	425.3*** (105.0)
Highest Ranked Superstar Player on Away Team (Top 1)	332.2*** (119.2)
Obs.	4,750

Notes. Dependent variable in each regression is announced attendance. Preferred specification of equation (2) is used for each regression. Controls include: home and away team win percentages, home and away average goals scored, the regional unemployment rate, weekday matinee dummy variable, month dummy variables, day of the week dummy variables, and Arena FE. Cluster robust standard errors are in parentheses. (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1. Niagara IceDogs Home Attendance, 2011-2019

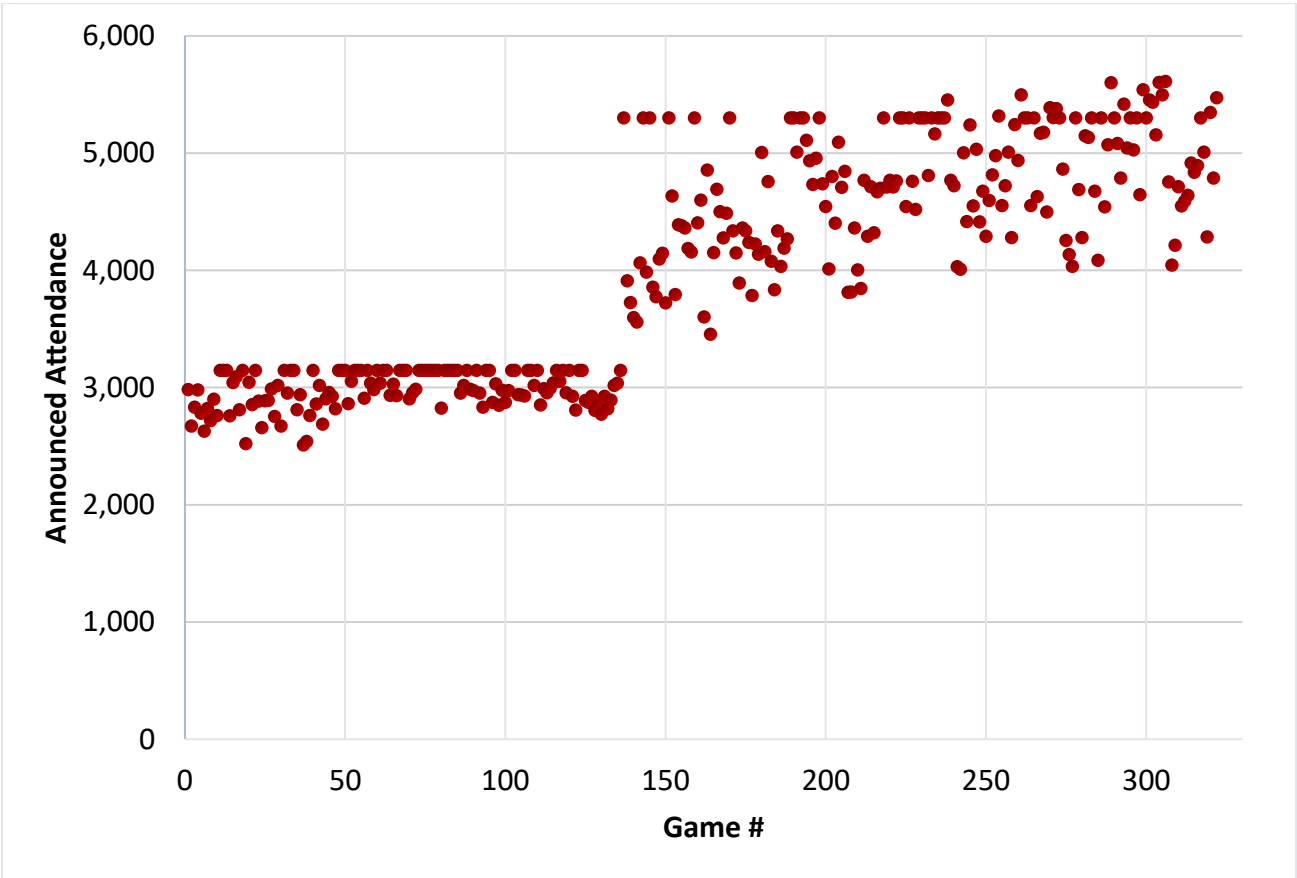


Table A.1. TSN Pre-Season Draft Prospect Lists

2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020
Nail Yakupov OHL-SAR (R1 #1)	Nathan MacKinnon (QMJHL) (R1 #1)	Aaron Ekblad OHL-BAR (R1 #1)	Connor McDavid OHL-ERE (R1 #1)	Auston Matthews (SUI) (R1 #1)	Nolan Patrick (WHL) (R1 #2)	Rasmus Dahlin (SWE) (R1 #2)	Jack Hughes (USHL) (R1 #1)	Alexis Lafreniere (QMJHL) (TBD)
Matt Dumba (WHL) (R1 #7)	Seth Jones (USHL) (R1 #4)	Sam Reinhart (WHL) (R1 #2)	Jack Eichel (USHL) (R1 #2)	Jakob Chychrun OHL-SAR (R1 #16)	Timothy Liljegren (SWE) (R1 #17)	Andrei Svechnikov OHL-BAR (R1 #2)	Dylan Cozens (WHL) (R1 #7)	Quinton Byfield (OHL) (TBD)
Filip Forsberg (SWE) (R1 #11)	Sean Monahan OHL-OTT (R1 #6)	Sam Bennett OHL-KGN (R1 #4)	Noah Hanifin (NCAA) (R1 #5)	Jesse Puljujarvi (FIN) (R1 #4)	Klim Kostin (RUS) (R1 #31)	Brady Tkachuk (NCAA) (R1 #4)	Kaapo Kakko (FIN) (R1 #2)	Lucas Raymond (SWE) (TBD)
Ryan Murray (WHL) (R1 #2)	Elias Lindholm (SWE) (R1 #5)	Leon Draisaitl (WHL) (R1 #3)	Pavel Zacha OHL-SAR (R1 #6)	Patrik Laine (FIN) (R1 #2)	Maxime Comtois (QMJHL) (R2 #50)	Adam Boqvist (SWE) (R1 #8)	Vasili Podkolzin (RUS) (R1 #10)	Cole Perfetti (OHL) (TBD)
Alex Galchenyuk OHL-SAR (R1 #3)	Rasmus Ristolainen (Finland) (R1 #8)	Michael Dal Colle OHL-OSH (R1 #5)	Lawson Crouse OHL-KGN (R1 #11)	Matthew Tkachuk OHL-LDN (R1 #6)	Eeli Tolvanen (FIN) (R1 #30)	Joe Veleno (QMJHL) (R1 #30)	Kirby Dach (WHL) (R1 #3)	Alexander Holtz (SWE) (TBD)
Mikhail Grigorenko (QMJHL) (R1 #12)	Aleksander Barkov (Finland) (R1 #2)	Nick Ritchie OHL-PBO (R1 #10)	Dylan Strome OHL-ERE (R1 #3)	Alex Nylander OHL-MISS (R1 #8)	Gabe Vilardi OHL-WSR (R1 #11)	Quinn Hughes (NCAA) (R1 #7)	Bowen Byram (WHL) (R1 #4)	Yaroslav Askarov (RUS) (TBD)
Morgan Rielly (WHL) (R1 #5)	Andre Burakowsky (SWE) (R1 #23)	Jake Virtanen (WHL) (R1 #6)	Mathew Barzal (WHL) (R1 #16)	Mike McLeod OHL-MISS (R1 #12)	Kristian Vesalainen (FIN) (R1 #24)	Filip Zadina (QMJHL) (R1 #6)	Philip Broberg (SWE) (R1 #8)	Hendrix Lapierre (QMJHL) (TBD)
Nick Ebert OHL-WSR (R7 #211)	Jacob de la Rose (SWE) (R2 #34)	Haydn Fleury (WHL) (R1 #7)	Oliver Kylington (SWE) (R2 #60)	Pierre-Luc Dubois (QMJHL) (R1 #3)	Owen Tippett OHL-MISS (R1 #10)	Ty Smith (WHL) (R1 #17)	Raphael Lavoie (QMJHL) (R2 #38)	Jamie Drysdale (OHL) (TBD)
Derrick Pouliot (WHL) (R1 #8)	Curtis Lazar (WHL) (R1 #17)	William Nylander (SWE) (R1 #8)	Mitch Marner OHL-LDN (R1 #4)	Kale Clague (WHL) (R2 #51)	Cal Foote (WHL) (R1 #14)	Ryan Merkley OHL-GUE (R1 #21)	Peyton Krebs (WHL) (R1 #17)	Anton Lundell (FIN) (TBD)
Matia Marcantuoni OHL-KIT (R4 #92)	Kerby Rychel OHL-WSR (R1 #19)	Nikolaj Ehlers (QMJHL) (R1 #9)	Travis Konecny OHL-OTT (R1 #24)	Max Jones OHL-LDN (R1 #24)	Lias Andersson (SWE) (R1 #7)	Bode Wilde (USHL) (R1 #41)	Ryan Suzuki OHL-BAR (R1 #28)	Justin Barron (QMJHL) (TBD)

Notes. Bolded players are identified as superstars based on this paper's criteria. Actual NHL Entry Draft pick in parenthesis.

Table A.2. NHL Entry Draft Results

2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020
Nail Yakupov (OHL)	Nathan MacKinnon (QMJHL)	Aaron Ekblad (OHL)	Connor McDavid (OHL)	Auston Matthews (SUI)	Nico Hischier (QMJHL)	Rasmus Dahlin (SWE)	Jack Hughes (USHL)	TBD
Ryan Murray (WHL)	Aleksander Barkov (FIN)	Sam Reinhart (WHL)	Jack Eichel (USHL)	Patrik Laine (FIN)	Nolan Patrick (WHL)	Andrei Svechnikov (OHL)	Kaapo Kakko (FIN)	
Alex Galchenyuk (OHL)	Jonathan Drouin (QMJHL)	Leon Draisaitl (WHL)	Dylan Strome (OHL)	Pierre-Luc Dubois (QMJHL)	Miro Heiskanen (FIN)	Jesper Kotkaniemi (FIN)	Kirby Dach (WHL)	
Griffin Reinhart (WHL)	Seth Jones (WHL)	Sam Bennett (OHL)	Mitch Marner (OHL)	Jesse Puljujarvi (FIN)	Cale Makar (AJHL)	Brady Tkachuk (NCAA)	Bowen Byram (WHL)	
Morgan Rielly (WHL)	Elias Lindholm (SWE)	Michael Dal Colle (OHL)	Noah Hanifin (NCAA)	Olli Juolevi (OHL)	Elias Pettersson (SWE)	Barrett Hayton (OHL)	Alex Turcotte (USHL)	
Hampus Lindholm (SWE)	Sean Monahan (OHL)	Jake Virtanen (WHL)	Pavel Zacha (OHL)	Matthew Tkachuk (OHL)	Cody Glass (WHL)	Filip Zadina (QMJHL)	Moritz Seider (DEL)	
Matt Dumba (WHL)	Darnell Nurse (OHL)	Haydn Fleury (WHL)	Ivan Provorov (WHL)	Clayton Keller (USHL)	Lias Andersson (SWE)	Quinn Hughes (NCAA)	Dylan Cozens (WHL)	
Derrick Pouliot (WHL)	Rasmus Ristolainen (FIN)	William Nylander (SWE)	Zack Werenski (NCAA)	Alex Nylander (OHL)	Casey Mittelstadt (USHL)	Adam Boqvist (SWE)	Philip Broberg (SWE)	
Jacob Trouba (USHL)	Bo Horvat (OHL)	Nikolaj Ehlers (QMJHL)	Timo Meier (QMJHL)	Mikhail Sergachev (OHL)	Michael Rasmussen (WHL)	Vitali Kravtsov (KHL)	Trevor Zegras (USHL)	
Slater Koekoek (OHL)	Valeri Nichushkin (KHL)	Nick Ritchie (OHL)	Mikko Rantanen (FIN)	Tyson Jost (BCHL)	Owen Tippett (OHL)	Evan Bouchard (OHL)	Vasili Podkolzin (RUS)	

Notes. Bolded players are identified as superstars based on this paper's criteria.

Table A.3. Linear Probability Model and Censored Tobit Results, (97% vs 100% Capacity as a Sellout)

Variables	LPM 97% Capacity (1)	LPM 100% Capacity (2)	Tobit 97% Capacity (3)	Tobit 100% Capacity (4)
Superstar Player in Lineup (<i>star</i>)	0.00889 (0.0107)	-0.00388 (0.0101)	179.3** (77.99)	160.3** (73.11)
Home Team: Home Win Percentage (<i>hwpct</i>)	0.125** (0.0475)	0.0498 (0.0415)	848.9*** (132.9)	774.2*** (129.6)
Away Team: Away Win Percentage (<i>awpct</i>)	0.0464 (0.0285)	0.0353** (0.0159)	303.5*** (103.7)	276.2*** (98.23)
Home Team: Average Home Goals (<i>hgoals</i>)	0.000349 (0.00836)	0.00941 (0.00836)	48.20* (29.13)	51.65* (28.09)
Away Team: Average Away Goals (<i>agoals</i>)	0.00852 (0.00642)	0.00530 (0.00498)	19.82 (26.07)	15.88 (24.83)
Unemployment Rate (<i>urate</i>)	0.642** (0.298)	0.486** (0.187)	5,194*** (908.2)	4,952*** (840.1)
Weekday Matinee (<i>matinee</i>)	0.0607* (0.0338)	0.0370 (0.0293)	873.6*** (162.5)	817.0*** (152.6)
Game Played in October	-0.0395* (0.0225)	-0.0161 (0.0129)	-356.3*** (53.15)	-340.5*** (51.57)
Game Played in December	0.0265** (0.0123)	0.0145 (0.0105)	71.26* (40.01)	55.55 (38.30)
Game Played in January	0.0378*** (0.0135)	0.0178** (0.00771)	169.9*** (38.54)	154.0*** (36.68)
Game Played in February	0.0279* (0.0138)	0.0168 (0.0132)	216.6*** (44.89)	206.7*** (42.69)
Game Played in March	0.101*** (0.0312)	0.0485* (0.0249)	553.6*** (44.82)	516.9*** (42.26)
Game Played on Monday	0.124** (0.0495)	0.0326 (0.0376)	696.7*** (230.5)	646.0*** (213.8)
Game Played on Tuesday	0.0275 (0.0337)	0.00538 (0.0164)	-190.9 (128.4)	-170.4 (123.8)
Game Played on Thursday	-0.0898* (0.0497)	-0.0483 (0.0285)	-67.16 (74.62)	-24.37 (72.30)
Game Played on Friday	0.0415** (0.0189)	0.0102 (0.00639)	385.1*** (65.16)	347.8*** (64.41)
Game Played on Saturday	0.0617*** (0.0196)	0.0260** (0.0112)	567.6*** (60.28)	539.9*** (59.68)
Game Played on Sunday	0.0249 (0.0180)	0.00661 (0.00999)	245.6*** (64.25)	230.2*** (63.66)
Constant	-0.200*** (0.0563)	-0.1645** (0.0662)	3,531*** (162.1)	3,591*** (156.5)
Arena FE	YES	YES	YES	YES
Obs.	4,750	4,750	4,750	4,750
R-squared	0.490	0.267		

Notes. Dependent variable for linear probability model is a binary variable which equals one if the game was a sellout, and equals zero otherwise. Dependent variable for censored Tobit regression is announced attendance. Preferred specification is used for each model and regression. Cluster robust standard errors are in parentheses. (***) p<0.01, ** p<0.05, * p<0.1).

Table A.4. Linear Probability Model and Censored Tobit Results, (Post WJHC)

Variables	LPM	LPM	Tobit	Tobit
	Full Sample (1)	Post WJHC (2)	Full Sample (3)	Post WJHC (4)
Superstar Player in Lineup (<i>star</i>)	0.00889 (0.0107)	-8.86e-05 (0.0178)	179.3** (77.99)	298.4*** (89.37)
Home Team: Home Win Percentage (<i>hwpct</i>)	0.125** (0.0475)	0.0452 (0.0565)	848.9*** (132.9)	1,071*** (171.4)
Away Team: Away Win Percentage (<i>awpct</i>)	0.0464 (0.0285)	0.0803* (0.0458)	303.5*** (103.7)	779.2*** (157.9)
Home Team: Average Home Goals (<i>hgoals</i>)	0.000349 (0.00836)	0.0121 (0.0120)	48.20* (29.13)	37.27 (44.37)
Away Team: Average Away Goals (<i>agoals</i>)	0.00852 (0.00642)	0.00949 (0.0103)	19.82 (26.07)	-72.11* (43.20)
Unemployment Rate (<i>urate</i>)	0.642** (0.298)	0.427 (0.334)	5,194*** (908.2)	5,465*** (1,242)
Weekday Matinee (<i>matinee</i>)	0.0607* (0.0338)	0.0626 (0.0452)	873.6*** (162.5)	609.7*** (173.5)
Game Played in October	-0.0395* (0.0225)	-	-356.3*** (53.15)	-
Game Played in December	0.0265** (0.0123)	-	71.26* (40.01)	-
Game Played in January	0.0378*** (0.0135)	o.	169.9*** (38.54)	o.
Game Played in February	0.0279* (0.0138)	-0.000551 (0.00890)	216.6*** (44.89)	70.21* (37.29)
Game Played in March	0.101*** (0.0312)	0.0292 (0.0201)	553.6*** (44.82)	379.0*** (41.86)
Game Played on Monday	0.124** (0.0495)	0.0160 (0.0386)	696.7*** (230.5)	861.9*** (205.6)
Game Played on Tuesday	0.0275 (0.0337)	-0.00944 (0.0299)	-190.9 (128.4)	-33.09 (130.8)
Game Played on Thursday	-0.0898* (0.0497)	-0.0598* (0.0333)	-67.16 (74.62)	164.5* (89.28)
Game Played on Friday	0.0415** (0.0189)	0.0150 (0.0113)	385.1*** (65.16)	623.4*** (74.45)
Game Played on Saturday	0.0617*** (0.0196)	0.0400** (0.0172)	567.6*** (60.28)	909.4*** (71.98)
Game Played on Sunday	0.0249 (0.0180)	0.00510 (0.0138)	245.6*** (64.25)	562.2*** (76.50)
Constant	-0.200*** (0.0563)	-0.165** (0.0662)	3,531*** (162.1)	3,509*** (214.1)
Arena FE	YES	YES	YES	YES
Obs.	4,750	2,558	4,750	2,558
R-squared	0.490	0.267		

Notes. Dependent variable for linear probability model is a binary variable which equals one if the game was a sellout, and equals zero otherwise. Dependent variable for censored Tobit regression is announced attendance. Preferred specification is used for each model and regression. Cluster robust standard errors are in parentheses. (***) p<0.01, ** p<0.05, * p<0.1).