If one considers the list of the most highly paid players in the NHL, many of the top players are also great goal scorers – to the surprise of no one (Sports Reference LLC, 2020). The intent, after all, is to win the Stanley Cup, and a given team must score more than their opponents to do so. Based on this principle, the interest of this paper is to predict playoff success based on a team’s offensive prowess. In particular, the main inquiry is if the presence of a high-scoring player on a team contributes to more playoff wins, even when many other variables are considered. The benchmark this paper will use for determining if a player is “high-scoring” is 50 adjusted goals in a regular season. This metric considers context, like scoring trends and lockouts, to standardize goal scoring over different NHL eras (Sports Reference LLC, n.d.-a). Such a measure reflects the fact that scoring 50 goals in 1982, when league-wide scoring was at its highest in the modern era, was quite a different feat than scoring 50 goals at any other time in NHL history (Sports Reference LLC, n.d.-b). Quantifying the effects of a superstar scorer on playoff success could better assess the value of having such a player on a roster.

One researcher, Demers (2015), was also interested in predicting NHL playoff performance. However, his approach was more holistic, in the sense that he was not particularly interested in offensive effects. In his study, Demers compared 8 different predictive strategies and eventually settled on the one that performed the best. He classified the performance of every NHL team from 2008-2014 as over-achieving, under-achieving, or expected, for each playoff round. Demers designated only two teams, the Penguins and Kings, as at least slightly over-achieving at each of the four playoff rounds. In other words, both teams were able to outperform Demers’ expectations across all first-round series they played in from 2008-2014, each second round series they played in from 2008-2014, etc. And since only two teams were able to separate themselves even marginally from the pack, Demers concluded that the NHL experiences high levels of parity. He notes nearly every team performed at about what would be expected of them over the 7-year period. In any given year, teams could be expected to perform at levels wildly different from their expectation, but these effects appeared to average out even over the relatively short time considered (Demers 2015).

Teams may also be interested in evaluating performance at a more specific level. One could consider results on a player-by-player basis, as a group of researchers Gramacy et al. (2013) did. They were dissatisfied with the plus/minus statistic, which measures the difference between goals scored when a player is on the ice and goals given up when a player is on the ice. In their opinion, plus/minus is too dependent on random chance and teammates to be a good individual measure. Their strategy allowed them to account for the context of a player’s situation, as a good team could mask poor players and vice versa. In developing a different measure, they were also able to assess the value of players based on their salary. Interestingly, they found that some high-paid players appeared to have little impact on their team, like Zdeno Chara, and Evgeni Malkin. Others, like Pavel Datsyuk, stood out even once his team was accounted for. They found only about 90 players had a significant effect on their team, either positively or negatively. The group also named “budget” players that their metric labeled as underrated. Teams could use the information the group provided to identify hidden sources of strength or weakness in their lineups (Gramacy et al. 2013).

Players with a knack for goal-scoring are valued for obvious reasons in the NHL. However, according to Chan et al. (2012), there are several other distinct types of players, some of whom also bring immediate value to a team. These researchers were interested in classifying players based on certain attributes, such as points, hits, and shutouts, while also reducing reliance on any one of these statistics. They could then identify which player groupings seemed to provide the most value to their team. The result was the classification of forwards, defensemen, and goalies into categories like “offensive”, “defensive”, “physical”, “elite”, etc. They denoted what an average player in one of these groupings looks like from a statistical perspective, as well as how many additional points such a player usually contributes to a team in the standings. These groups were also found to be differentiable by salary, so an individual type could also be classified as generally overpaid or underpaid. They found that goalies are the most valuable on a per-game basis, while the defensive forward type provides the best total value out of any classification. Their results also showed that defensemen as a whole are overpaid. The researchers meant for their results to act as a guide for general managers to evaluate trades, who could then compare the number of points expected to be gained or lost by a given deal (Chan et al. 2012).

These studies all tried their hand at measuring NHL performance, either by studying teams or players (Chan et al. 2012; Demers 2015; Gramacy et al. 2013). They also all used regular season data from these entities to inform their results. However, they all went about this process in quite different ways. Demers (2015) attempted to classify teams’ postseason performance based on their regular season statistics. Gramacy et al. (2013) analyzed player impact in a vacuum, independently of teammates, via a modification of the plus/minus statistic. Chan et al. (2012) established several broad player types who tend to exhibit certain characteristics. What all three papers concluded, however, is that few players or teams can do anything to separate themselves from the pack, even over the course of several seasons. Demers (2015) found only two teams who did barely did so over the course of seven seasons. Gramacy et al. (2013) found only about 90 players whose performances over four seasons significantly differed from that of an average player. Chan et al. (2012) were only able to make claims about their individual groupings, which average information from dozens of individuals. Consequently, it is paramount that a team exploit any advantage it has to gain an upper hand in such a competitive environment. Accordingly, two of the papers here present a sampling of players who stand out for one reason or another. One (Gramacy et al. 2013) named the players individually, whereas the other (Chan et al. 2012) points towards a position and a style of play, namely defensive forwards, as the most efficient. Both results were explicitly intended to be used by general managers, who make decisions about signing and trading players.

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