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Abstract

This paper investigates the time series properties of fighting and scoring in the National Hockey League from 1957-2013. The empirical analysis focuses on identifying structural breaks in the various time series and correlating these breaks with rule changes in the NHL, especially those that focus on fighting. We find that player behavior in the areas of fighting and scoring changed structurally before rule changes in the NHL that reduced the benefits and increased the costs of fighting. The data and empirical results suggest that the rise and fall of the enforcer was a function of changes in social norms within the NHL rather than legal changes by the league itself. The example suggests that other sports might also experience changes in social norms that lead to reduced violence and increased offense before formal rule changes are made by league officials.

JEL classification: Z22, D71, L83

Keywords: Social Norms, Cultural Change, Rule Changes, Structural Breaks

1. Introduction

Hockey is a physical game. Due to its physical nature both injuries and fights are common. To help regulate the game both formal rules and informal social norms have arisen to regulate play. Coincident with increasing evidence that head trauma has long-term health consequences, the number of fights in hockey have diminished over time. This leads to the question: did the players themselves change the culture of the game through changing social norms or was it necessary for the National Hockey League (NHL) to change the rules of the game in order to reduce fighting? To test our hypothesis, we utilize time series techniques to identify structural breaks in performance, penalty, and fight data from the NHL.

Time series provide a unique way to identify changes in the game that can provide insights to how hockey has changed over time. Sports historians and scholars have often assumed *exogenous* changes in the game based on particular historical events. In contrast, we make no prior judgments about the timing of eras. Instead, we let the data speak and utilize time series tests with structural breaks to *endogenously* identify eras. By doing so, we hope to identify the timing of eras in the NHL that may not have been apparent when focusing *a priori* on particular historical events.

Utilizing time series tests to analyze sports data has only recently become more popular in the literature and is most prominent in the works of Fort and Lee (2006, 2007), Lee and Fort (2005, 2008, 2012), and Mills and Fort (2014), who employ unit root and structural break tests to examine competitive balance in a number of sports.[1] In the present paper, we adopt a similar methodological approach in a different context and examine time series on the mean and standard deviation of four traditional NHL performance measures: goals, assists, points, and

[1] See also the works of Scully (1995), Palacios-Huerta (2004), Schmidt and Berri (2004), Nieswiadomy et al. (2012) and Groothuis et al. (2015).

penalty minutes, and four measures of fighting: the number of fights per game, the percentage of games with at least one fight, the percentage of games with more than one fight, and the percentage of players who fought during the season.

Our research question is whether culture changes rules or do rules change culture? To test this hypothesis, we use time series data on both the mean and standard deviation of each series from 1957-58 through 2012-13. We find that all but one of these time series are stationary around one or two structural breaks. Perhaps most noteworthy, we find two structural breaks in both the mean and standard deviation of penalty minutes and the percentage of games with fights in a season suggesting that there has been a rise and fall in the role of an enforcer on a team over time. In addition, because the break in fighting occurs before major rule changes, we conclude that changes in informal social norms predated changes in formal rules concerning fighting in the NHL. Therefore, in this case the causal link appears to be from social norms to formal rules.

2. NHL History and Literature Review

The NHL started in 1917 with three teams and has expanded over time to the current level of thirty teams.[2] In 1922, a five-minute penalty for fighting was established instead of expulsion for the remainder of the game. This made hockey unique because fighting became semi-legal and gave rise to what became known as the Enforcer. Rockerbie (2012) states: "[t]he new system encouraged each club to carry a few players that would act as "enforcers" on the ice, expected to deal with the other club's enforcers in a controlled battle of fisticuffs. This established a long-standing code of conduct in the NHL that still exists today. Skilled players are not expected or encouraged to fight in their own defense when rules are ignored, instead, an

[2] In June 2016, the NHL announced its intentions to have an expansion team playing in Las Vegas, Nevada, by the 2017-2018 season.

enforcer comes to the aid of the stricken skilled player, with the expectation of being met by the other club's enforcer. This system of on-ice détente worked well."[3]

Given that fighting and physical play are common in hockey, the economic literature has used hockey as an economic laboratory and two streams of literature have developed. The first focuses on the demand for hockey through the question of whether fighting and physical play generate higher revenue for owners or higher wages for players. The second focuses on the "law and economics" of the NHL and asks the question: How do rule changes and enforcement influence the semi-legal behavior of fighting?

As to the question of whether fighting and physical play pay, the literature on fan attendance and revenues finds that it does. Jones (1984), Jones et al. (1993), Jones et al. (1996), and Paul (2003) all find that fighting increases attendance at NHL games. Paul et al. (2013) finds this same relation for the American Hockey League, the main development league for the NHL. Stewart et al. (1992) and Coates et al. (2011) both find that fighting reduces the probability of winning games in the NHL but has the direct effect of increasing attendance. In addition, Coates et al. (2011) find weak evidence that highly penalized teams have higher revenues. Rockerbie (2014), using more recent data, finds that fighting slightly reduces attendance. Overall this stream of literature suggests that team owners at least in the past do not have financial incentives to reduce either fights or physical play in hockey.

As to the question of whether fighting and physical play pay, the literature on player salaries also suggests that it does. Both Jones et al. (1997) and Haisken-DeNew and Vorell

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[3] Rockerbie (2012) further states "Rule 47 (which replaced Rule 56) now even specifies the allowable behavior during a fight: the players must first drop their gloves and fight bare-knuckled; third-men are not allowed into a fight between two players (immediate expulsion from the game); kicking with skates is strictly forbidden and severely punished; players must end the fight at the instruction of the referee if they separate, and; pulling the opponent's sweater over his head is not permitted." This rule provides the case for the semi-legal nature of fighting in the NHL.

(2008) find a pay premium for unskilled wing players who fight. Haisken-DeNew and Vorell (2008) suggest, however, that the wage premium may be a compensating wage differential for the physical harm that fighting causes.

In the second strand of the literature the focus has been on the economics of crime. Given the semi-legal nature of fighting in the NHL both the changes in rules and enforcement has served as an economic laboratory. Most of the literature has focused on the natural experiment of the introduction of a second referee. Allen (2002) finds that the second referee did not reduce violent behavior but did increase the level of detection. Levitt (2002) found no effect on either behavior or detection. Depken and Wilson (2004) and Wilson (2005), however, both find that fighting is reduced and scoring increased. Allen (2005) uses the same natural experiment but asks whether the culture of violence will change behavior or does rule enforcement change behavior? The author finds that rules matter more than culture. This strand of literature suggests that rules and the enforcement of rules can change behavior and encourage less fighting. Rules of the game, however, are agreed upon by both team owners and players and the previous strand of literature suggests that both have financial incentives to allow fighting. On the other hand, players understand, with an increasing awareness, that there are health incentives to minimize fights. This leads to the question: Do rules change culture or does culture change rules?

3. Culture and Social Norms

The theoretical and empirical analysis of social norms has a long history in economics. On the theoretical side, Elster (1989) and Posner (1997) provide longer and shorter, respectively, discussions of how economists define social norms relative to legal norms, private norms, and group norms. Dequech (2009) distinguishes between moral and epistemic values which, in turn, generates different types of social norms. Muehlheusser and Roider (2008) investigate the phenomenon of certain team (societal) members to not report objectively bad behavior on the part of other team (societal) members. All of these studies provide interesting hypotheses that can be applied to real-world empirical applications such as the one investigated herein.[4]

Culture can be thought of as attitudes and values attributed to a group as a whole. Hockey has a tradition of a "tough guy" culture. For example, one norm that was slow to change was the wearing of a helmet. Wise and Scott (2012) analyze the changing norm of helmet use in the NHL. Although the health value of wearing a helmet was known as early as the 1930s, wide spread helmet usage did not begin until the 1970s. Wise and Scott (2012) suggest that the combination of rule changes and norm changes were the catalyst for helmet adoption. In particular, they suggest that "since new players were required to use helmets and players tend to have relatively short careers, the effect of this policy was to ensure that helmets would eventually be universally adopted. In effect, the NHL policy removed any stigma associated with helmet usage and encouraged adoption."

Posner and Rasmusen (1999) define a norm as "a social rule that does not depend on government for either promulgation or enforcement." They further suggest that "[n]orms are an attractive method of social control because a rule may be desirable but too costly a project for the state to undertake relative to the benefits." In the case of the NHL rules are enforced by the referee, which is costly. Posner and Rasmusen (1999) further suggest that, depending on which norms prevail, enforcement can occur in many ways. Enforcement can be automatic where violating a norm provides automatic sanctions such as driving on the right side of the road in the United States. Other enforcement mechanisms include guilt, shame, ostracism, and informational

[4] For instance, Morgulev et al (2014) investigate the social norm of flopping in professional basketball and Azar (2004) investigates the social norm of tipping.

sanctions. In hockey, the norm of not wearing a helmet might have been enforced by shame, thus the player, in his own mind, did not live up to the tough-guy culture. It could be informational, in that wearing a helmet suggests that the player is weak. This could explain why helmet use was slow to occur.

Posner also suggests that some norms are enforced by bilateral costly sanctions or multilateral costly sanctions. In hockey, we suggest that the role of the enforcer arose to sanction players on the other team who used too much physical force on star talent. For instance, when Wayne Gretzky was traded to the Los Angeles Kings, he required that Marty McSorley be included in the trade. McSorley served as his enforcer and is the fourth-most penalized player in NHL history with over 3,300 penalty minutes in his career. Given the nature of their job, enforcers provide costly sanctions and thus the quantity of penalty minutes for these players should be high.

However, over time the audience for NHL games might have sufficiently changed that the players might alter existing social norms so to maximize the internalized returns generated by their behaviors. Thus, if NHL fans began rewarding scoring and offense more than defense and fighting, the empirical question would seem to lie in which group of individuals notices this change first: the players or the league/team owners?

If the players themselves initiate a change in the social norms of hockey such that fighting is reduced and scoring and offense increased without formal rule changes by the league, this would suggest that we should see changes in player behavior *before* actions by the league. On the other hand, however, if the league or team owners discover that fan preferences are changing, they would be expected to introduce rule changes *before* changes in player behavior.

In both cases, players and team owners are hoping to simultaneously improve the game to the benefit of fans, and in both cases player behavior is expected to change, perhaps to the extent that a notable change or "structural break" is introduced into measurements of player behavior. The key difference is the timing of any changes in player behavior relative to formal rule changes. According to established definitions of social norms, if the change in behavior takes place *after* formal rule changes, then the change in behavior cannot be interpreted as a change in social norms. On the other hand, if the change in behavior takes place before any changes in formal rules then the behavioral change can be interpreted as a change in social norms.

4. Methodology and Data

Methodology

To create a time series to identify structural breaks in hockey, we calculate both the mean and standard deviation of performance and penalty data across players as well as various measures of fight data across players and games for each season from 1957-58 through 2012-13; each annual time series consists of 54 observations.[5] To determine if the time series are stationary (i.e., have a deterministic trend) or non-stationary (i.e., have a stochastic trend) and to identify structural breaks, we utilize the one- and two-break minimum LM unit root tests proposed by Lee and Strazicich (2003, 2013).

Following Perron (1989), it is well known that ignoring an existing structural break in unit root tests will reduce the ability to reject a false unit root null hypothesis.[6] To overcome this drawback, Perron proposed including dummy variables in the usual augmented Dickey-Fuller

[5] Data are not available for 2003-2004 because of the season-cancelling lock-out by team owners.
[6] By "structural break," we imply a significant but infrequent, permanent change in the level and/or trend of a time series. See Enders (2010) for additional background discussion on structural breaks and unit root tests.

unit root test (ADF test) to allow for one known, or "exogenous," structural break. In subsequent work, Zivot and Andrews (1992, ZA hereafter), among others, proposed unit root tests that allow for one unknown break to be determined "endogenously" from the data. The ZA test selects the break where the *t*-statistic testing the null of a unit root is minimized (i.e., the most negative). The ZA test, however, and other similar ADF-type endogenous break unit root tests derive their critical values assuming no break under the null hypothesis. Nunes, Newbold, and Kuan (1997) and Lee and Strazicich (2001), among others, show that this assumption can lead to spurious rejections of the unit root hypothesis in the presence of a unit root with break. As a result, when using these tests, researchers can incorrectly conclude that a time series is "trend-break stationary" when in fact the series has a unit root with break. To avoid these drawbacks, we utilize the one- and two-break minimum LM unit root tests developed by Lee and Strazicich (2003, 2013), which has the desirable property that its test statistic is not subject to spurious rejections. Thus, conclusions are more reliable since rejection of the null hypothesis unambiguously implies that the series is stationary around one or two breaks in the level and/or trend.

Our testing methodology can be summarized as follows.[7] According to the LM "score" principle, the test statistic for a unit root can be obtained from the following regression:

$$\Delta y_t = \delta'\Delta Z_t + \phi\widetilde{S}_{t-1} + \Sigma\gamma\Delta\widetilde{S}_{t-i} + \varepsilon_t, \qquad (1)$$

where $\widetilde{S}_t = y_t - \widetilde{\psi}_x - Z_t\widetilde{\delta}$, $t=2,..,T$; $\widetilde{\delta}$ are the coefficients from the regression of Δy_t on ΔZ_t and $\widetilde{\psi}_x$ is the restricted MLE of ψ_X $(\equiv\psi + X_0)$ given by $y_1 - Z_1\widetilde{\delta}$. The $\Delta\widetilde{S}_{t-i}$ terms are included, as necessary, to correct for serial correlation; ε_t is the contemporaneous error term assumed to be

[7] Gauss codes for the one- and two-break minimum LM unit root test are available on the web site https://sites.google.com/site/junsoolee/codes.

independent and identically distributed with zero mean and finite variance; Z_t is a vector of exogenous variables contained in the data generating process; Z_t is described by $[1, t, D_{1t}, D_{2t}, DT_{1t}^*, DT_{2t}^*]'$, where $D_{jt} = 1$ if $t \geq T_{Bj} + 1$, $j = 1,2$, and zero otherwise, $DT_{jt}^* = t$ if $t \geq T_{Bj} + 1$, and zero otherwise, and T_{Bj} is the time period of the structural break. Note that the testing regression (1) involves ΔZ_t instead of Z_t so that ΔZ_t is described by $[1, B_{1t}, B_{2t}, D_{1t}, D_{2t}]'$, where $B_{jt} = \Delta D_{jt}$ and $D_{jt} = \Delta DT_{jt}^*$, $j=1, 2$. Thus, B_{1t} and B_{2t}, and D_{1t} and D_{2t}, correspond to structural changes or breaks in the level and trend under the alternative, and to one period jumps and permanent changes in the drift under the null hypothesis, respectively. The unit root null hypothesis is described by $\phi = 0$ and the LM test statistic is defined by:

$$\tilde{\tau} \equiv t\text{-statistic testing the null hypothesis } \phi = 0. \qquad (2)$$

To endogenously determine the location of two breaks ($\lambda_j = T_{Bj}/T$, j=1, 2), the LM unit root test uses a grid search to determine the combination of two break points where the unit root test statistic is minimized. Since the critical values for the model with trend-break vary (somewhat) depending on the location of the breaks (λ_j), we employ critical values corresponding to the identified break points.

To determine the number of lagged augmented terms $\Delta\tilde{S}_{t-i}$, $i = 1,..,k$, that are included to correct for serial correlation, we employ the following sequential "general to specific" procedure. At each combination of two break points $\lambda = (\lambda_1, \lambda_2)'$ over the time interval [.1T, .9T] (to eliminate end points) we determine k as follows. We begin with a maximum number of k = 4 lagged terms and examine the last term to see if its t-statistic is significantly different from zero at the 10% level (critical value of 1.645 in an asymptotic normal distribution). If insignificant, the k = 4 term is dropped and the model is re-estimated using k = 3 terms, etc., until the maximum lagged term is found, or $k = 0$. Once the maximum number of lagged terms is found, all lower lags remain in the regression.[8] The process is repeated for each combination of two break points to jointly identify the breaks and the test statistic at the point where the unit root test statistic is minimized.

Data

The data employed in this study describe performance and fighting statistics for the NHL from the 1957-58 season through the 2012-13 seasons. The penalty and performance data were obtained from the Hockey Database version 9.0, which is a public-domain database of player-level and team-level data for several hockey leagues. We focus on the NHL as it is the oldest professional league in the Hockey Database. Our sample period begins in 1957 because this is the first year for which fight data are available. [9]

Table 1 reports the descriptive statistics for the variables investigated here. First, we describe the fight-related data. We use several different measures of how much fighting there was in a given NHL season: the average number of fights per game, the percentage of games with at least one fight, the percentage of games that had more than one fight, and the percentage of players who fought in a given year. As can be seen in Table 1, there is considerable variation over the sample period across these four variables suggesting that the level of fighting has not been static over the sample period.

The performance statistics include the following variables: mean and standard deviation in penalty minutes, the mean and standard deviation in goals scored, the mean and standard deviation in assists, and the mean and standard deviation in points. Unlike the fight data, which

[8] This type of method has been shown to perform better than other data-dependent procedures to select the optimal k (e.g., Ng and Perron, 1995).
[9] The NHL fight data was obtained from David M Singer at www.hockeyfights.com.

is measured across games within a given season, the performance variables are measured across players within a given season (as is the percentage of players who fought in a given season).

During the sample period the average fights per game was just over one half; in an average NHL season, thirty-seven percent of games had at least one fight and thirteen percent had more than one fight; and thirty-six percent of all players had at least one fight during the season. The average number of penalty minutes per player was 65 and the standard deviation in penalty minutes averaged 682, reflecting the wide dispersion of penalty minutes across players.

Among the performance measurements, the average number of goals per player (excluding goalies) was approximately 11, the average number of assists was just under 19, and the average number of total points was just under 29. We point out that the number of assists is greater than the number of goals because it is not uncommon for more than one assist to be granted on a given goal. Also, there are many players who do not score a single goal or have a single assist during an entire season; the mean values across all players is used to normalize the data by the number of games played and the number of teams in the league. The standard deviation of goals scored, assists, and total points average 12, 16, and 26, respectively, which reflects the dispersion of these variables across players in the league in a given year.

5. Empirical Results

The LM unit root test results are reported in Table 2 for the fight, penalty, and performance data. In each case, we begin by applying the two-break LM unit root test. If only one break is identified (at the 10% level of significance) in the two-break test, we re-examine the series using the one-break LM unit root test. We first consider the results for the fight and penalty series. We find that all fight and penalty series are stationary around two structural breaks. To more accurately examine the sign and significance of the breaks, in Table 3 we report results from simple regressions on the level and trend breaks.[10] To better visualize our results, in Figure 1 we additionally report plots of the actual and fitted values from the regressions. In the percentage of games with a fight and the percentage of players who fought, the first structural break occurs in 1966 and 1967, respectively. Moreover, in the percentage of games with a fight, the break shows an increase in the upward trend while the percentage of players who fought shows a downward trend changing to an upwards trend. In the other two series, fights per game and percentage of games with more than one fight, each has a structural break in 1974 and 1975, respectively. Both of these breaks indicate an upward shift and an increase in the trend towards more fighting after 1974 and 1975, respectively. Most interesting, all four fight measures have their second structural break in 1987 or 1988 with three of the series breaking in 1988. All four series show a downward shift and a trend that goes from positive to negative following the break in 1987 or 1988. In sum, all four of these series show that fighting in hockey increased to a peak in 1987-1988 and declined thereafter.

Turning next to penalty minutes, we observe that both the mean and standard deviation are stationary around two structural breaks. Again, to more accurately examine the sign and significance of the identified structural breaks, we report results from simple regressions on the level and trend breaks in Table 4 and plots of the actual and fitted values in Figure 3. We observe that the first structural break in the mean penalty minutes occurs in 1978 and in the standard deviation in 1985. Both series had an upward trend prior to the break and both trends shifted upwards after the break with the mean in penalty minutes continuing on the upward trend. The second structural break in both penalty minute measures occurs in 1993 where both trends

[10] Given that these series were found to be stationary around breaks, the spurious regression problem found when utilizing nonstationary times series can be avoided.

shifted downwards following the same similar downward trend as in the fight data. Perhaps most noteworthy is that the second break in the penalty minute measures occurred five years after the break in the fight series, suggesting that a change in the social norms of hockey occurred before the change in formal enforcement by referees. As in the fight measure series, the penalty minute measures peak in the late eighties and continue to fall thereafter until the end of our sample period in 2013.

We next consider the results from Table 2 for the performance series. Except for the mean goals series, we find that all performance series are stationary around one or two structural breaks. Again, to more accurately examine the sign and significance of the identified structural breaks, we report results from simple regressions on the level and trend breaks in Table 4 and plots of the actual and fitted values in Figure 3.[11] We observe that for the series with two breaks (Mean Goals, SD Assists, Mean Points, and SD Points) all of the first breaks occur in 1978 or 1979, and the one break in the standard deviation goals series occurs in 1980. All of these series were showing a slow upward trend that shifted upwards then the trend turned downwards.

The second structural break for the standard deviation of assists series and both the mean and standard deviation of points series occurs in 1995 or 1996 when the series shifts downward and then levels off or begins a slight upward trend. Perhaps most notable, our results show that the offense-related measures of points and assists peaked ten years before fighting peaked. Then both series showed a decline that bottomed out for offensive measures in 1996 but continued to decline for fighting. These findings suggest that there has been a rise and fall in the role of the

[11] We note that while the Mean Goals series could not reject a unit root (at the 10% level), it nearly does so and has two structural breaks similar to those identified in the other five performance series. Given this outcome, we include Mean Goals in the discussion that follows while some caution is warranted when interpreting the regressions and visual plots of this series.

enforcer in hockey and that this change came about through changing social norms within hockey rather than through formal rule changes, which occurred after the structural breaks.

6. Conclusion

Sometimes the culture changes before the rules change and sometimes rules change before culture. The empirical evidence presented herein suggests that in hockey the culture of fighting changed before the rules ostensibly aimed at reducing fighting were changed; thus, changes in fighting were actually a reflection of changing social norms within the game. Hockey is noted to be a violent game; it is the only sport where fighting is not an automatic rejection. In hockey an on-ice fight results in a major penalty resulting in a five-minute penalty. An enforcer sometimes called a “goon” or “fighter” is part of the culture in ice hockey. An enforcer's job is to deter and respond to dirty or violent play by the opposition. When such play occurs, the enforcer is expected to respond aggressively, by fighting or checking the offender. Enforcers are expected to react particularly harshly to violence against star players or goalies. We find that all of the time series measuring fighting demonstrate a structural break in 1987 or1988, suggesting that the role of the enforcer peaked in the late 1980s.

Given that enforcers have more penalty minutes than other players, we suggest that the break in both the mean and standard deviation in penalty minutes captures a change in culture regarding the importance of the enforcer. Penalty minutes peaked in 1988 and then started to decline prior to rule changes. This suggests that the culture of hockey was changing, perhaps reflecting growing concerns over head injuries or other social norms (such as a possible decreased preference for violence) that were changing off-ice. One of the first major rule changes focusing on safety was in 1992 when a player received a game misconduct penalty for instigating a fight. In 1997-1998, a two referee system was added to detect more potential penalties. However, there changes all occurred *after* the structural break in fighting, suggesting that cultural changes preceded rule changes.

While we cannot say anything about the social norms in other sports, it is clear that the methodology suggested here can be applied to other sports. Interesting insight into other areas of social norms within sport such as hit batsmen in professional baseball, unnecessary roughness penalties in American football, and flagrant and technical fouls in professional basketball can potentially all be addressed using the same methodology employed herein.

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Table 1: Descriptive Statistics of the Data

Variable	Mean	Std. Dev.	Min	Max
FIGHTSPERGAME	0.57	0.26	0.14	1.12
PERCENTGAMESWFIGHT	0.37	0.13	0.12	0.61
PERCENTGAMESWMOREONEFIGHT	0.13	0.07	0.01	0.28
PERCENTPLAYERSWHOFOUGHT	36.30	7.78	22.47	53.60
MEANPENALTYMINUTES	65.28	17.19	42.78	104.04
SDPENALTYMINUTES	682.2	327.42	148	1128
MEANGOALS	10.90	2.30	14.62	23.74
SDGOALS	12.16	1.30	9.63	14.87
MEANASSISTS	18.67	2.30	14.62	23.74
SDASSISTS	16.64	1.68	13.79	20.04
MEANPOINTS	29.58	3.69	23.21	37.39
SDPOINTS	25.92	2.62	21.31	31.52

Notes: Data obtained from the Hockey Database version 9.0. The sample period includes the 1957-58 through 2012-13 NHL seasons.

Table 2. LM Unit Root Test Results for NHL Fight, Penalty, and Performance Data, 1957-1958 through 2012-2013

Time Series	*k*	*Breaks*	*Test Statistic*	*Break Points*
FIGHTSPERGAME	0	1975, 1988	-5.402*	λ = (.4, .6)
PERCENTGAMESWFIGHT	0	1966, 1988	-5.737**	λ = (.2, .6)
PERCENTGAMESWMOREONEFIGHT	0	1974, 1988	-5.368*	λ = (.4, .6)
PERCENTPLAYERSWHOFOUGHT	0	1967, 1987	-5.409**	λ = (.2, .6)
MEANPENALTYMINUTES	1	1978, 1993	-6.190**	λ = (.4, .6)
SDPENALTYMINUTES	2	1985, 1993	-7.255***	λ = (.4, .6)
MEANGOALS	0	1978, 1997	-5.256	λ = (.4, .8)
SDGOALS	0	1980	-6.320***	λ = (.4)
MEANASSISTS	0	1984	-4.222*	λ = (.6)
SDASSISTS	0	1979, 1995	-6.860***	λ = (.4, .8)
MEANPOINTS	0	1979, 1996	-5.535*	λ = (.4, .8)
SDPOINTS	0	1979, 1996	-7.007***	λ = (.4, .8)

Notes: *FIGHTSPERGAME, PERCENTGAMESWFIGHT, PERCENTGAMESWMOREONEFIGHT, PERCENTPLAYERSWHOFOUGHT, MEANPENALTYMINUTES, SDPENALTYMINUTES, MEANGOALS, SDGOALS, MEANASSISTS, SDASSISTS, MEANPOINTS, and SDPOINTS* denote the number of fights per game, percentage of games with fights, percentage of games with more than one fight, percentage of players who fought, mean penalty minutes, standard deviation of penalty minutes, mean number of goals per player, standard deviation of goals per player, mean number of assists per player, standard deviation of assists per player, mean number of points per player, and standard deviation of points per player per season, respectively. The Test Statistic tests the null hypothesis of a unit root, where rejection of the null implies a trend-break stationary series. *k* is the number of lagged first-differenced terms included to correct for serial correlation. The critical values for the one- and two-break LM unit root tests come from Lee and Strazicich (2003, 2013). The critical values depend on the location of the breaks, $\lambda = (T_{B1}/T, T_{B2}/T)$, and are symmetric around λ and (1-λ). *, **, and *** denote significant at the 10%, 5%, and 1% levels, respectively.

Table 3. OLS Regressions on Level and Trend Breaks of NHL Fight and Penalty Data, 1957-1958 – 2012-2013

$FIGHTSPERGAME_t = 0.073 + 0.389D_{1975} + 0.580D_{1988} + 0.015Trend + 0.026T_{1975} – 0.015T_{1988} + lags(1) + e_t$

(2.276)** (5.061)*** (5.749)*** (4.589)*** (2.925)*** (-4.557)***

$\bar{R}^2 = 0.890$ SER = 0.086

$PERCENTGAMESWFIGHT_t = 15.745 + 4.472D_{1966} + 36.322D_{1988} + 0.211Trend + 1.769T_{1966} – 0.825T_{1988} + lags(0) + e_t$

(11.760)*** (1.921)* (16.585)*** (0.939) (11.543)*** (-6.554)***

$\bar{R}^2 = 0.904$ SER = 4.048

$PERCENTGAMESWMOREONEFIGHT_t = 0.495 + 8.324D_{1974} + 15.936D_{1988} + 0.363Trend + 0.886T_{1974} – 0.465T_{1988} + lags(1) + e_t$

(0.577) (4.615)*** (5.847)*** (4.224)*** (3.537)*** (-4.142)***

$\bar{R}^2 = 0.871$ SER = 2.683

$PERCENTPLAYERSWHOFOUGHT_t = 34.142 + 2.513D_{1967} + 4.563D_{1987} - 0.795Trend + 0.718T_{1967} – 0.465T_{1987} + lags(0) + e_t$

(16.297)*** (0.974) (1.802)* (-2.685)*** (5.276)*** (-4.884)***

$\bar{R}^2 = 0.813$ SER = 3.364

$MEANPENALTYMINUTES_t = 28.585 + 12.652D_{1978} + 11.511D_{1993} + 0.308Trend + 0.744T_{1978} – 0.786T_{1993} + lags(0) + e_t$

(23.185)*** (4.045)*** (3.098)*** (3.623)*** (2.462)** (-2.517)**

$\bar{R}^2 = 0.759$ SER = 4.104

$SDPENALTYMINUTES_t = 43.637 + 48.220D_{1985} + 34.290D_{1993} + 1.314Trend + 0.274T_{1985} – 1.870T_{1993} + lags(3) + e_t$

(4.802)*** (4.824)*** (4.602)*** (4.745)*** (0.332) (-4.530)***

$\bar{R}^2 = 0.848$ SER = 4.101

Notes: Dependent variable is the number of fights per game, percentage of games with a fight, percentage of games with more than one fight, percentage of players who fought, mean penalty minutes, and standard deviation of penalty minutes in season t, respectively. t-statistics are shown in parentheses. D and T represent dummy variables for the identified intercept and trend breaks respectively. TREND denotes a common trend. White's robust standard errors were utilized to control for heteroscedasticity. Lagged values of the dependent variable were included to correct for serial correlation as described in Section 3. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

Table 4. OLS Regressions on Level and Trend Breaks of NHL Performance Data, 1957-1958 – 2012-2013

$MEANGOALS_t = 7.474 + 2.338D_{1978} - 1.177D_{1997} + 0.048Trend - 0.157T_{1978} + 0.016T_{1997} + lags(1) + e_t$

(4.090)*** (2.583)** (-2.742)*** (2.075)** (-2.852)*** (0.916)

$\bar{R}^2 = 0.841$ SER = 0.575

$SDGOALS_t = 11.968 + 2.267D_{1980} + 0.044Trend - 0.152T_{1980} + lags(0) + e_t$

(32.058)***(5.484)*** (1.663) (-13.129)***

$\bar{R}^2 = 0.686$ SER = 0.738

$MEANASSISTS_t = 6.482 + 0.842D_{1984} + 0.078Trend - 0.064T_{1984} + lags(2) + e_t$

(3.048)*** (0.951) (1.998)* (-1.892)*

$\bar{R}^2 = 0.775$ SER = 1.127

$SDASSISTS_t = 16.318 + 2.713D_{1979} - 1.958D_{1995} + 0.020Trend - 0.074T_{1979} + 0.038T_{1995} + lags(0) + e_t$

(45.618)*** (4.671)*** (-4.336)*** (0.728) (-1.263) (1.338)***

$\bar{R}^2 = 0.686$ SER = 0.961

$MEANPOINTS_t = 29.002 + 8.846D_{1979} - 4.848D_{1996} + 0.148Trend - 0.605T_{1979} + 0.105T_{1996} + lags(0) + e_t$

(42.120)*** (10.453)*** (-6.014)*** (3.328)*** (-9.986)*** (2.374)**

$\bar{R}^2 = 0.860$ SER = 1.398

$SDPOINTS_t = 25.699 + 5.149D_{1979} - 3.072D_{1996} + 0.050Trend - 0.274T_{1979} + 0.004T_{1996} + lags(0) + e_t$

(52.932)*** (6.153)*** (-4.508)*** (1.360) (-3.295)*** (0.096)

$\bar{R}^2 = 0.759$ SER = 1.309

Notes: Dependent variable is the number of mean number of goals per player, standard deviation of goals per player, mean number of assists per player, standard deviation of assists per player, mean number of points per player, and standard deviation of points per player per season, respectively. t-statistics are shown in parentheses. D and T represent dummy variables for the identified intercept and trend breaks respectively. TREND denotes a common trend. White's robust standard errors were utilized to control for heteroscedasticity. Lagged values of the dependent variable were included to correct for serial correlation as described in Section 3. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

Figure 1. OLS Regressions of Fight and Penalty Data on Level and Trend Breaks

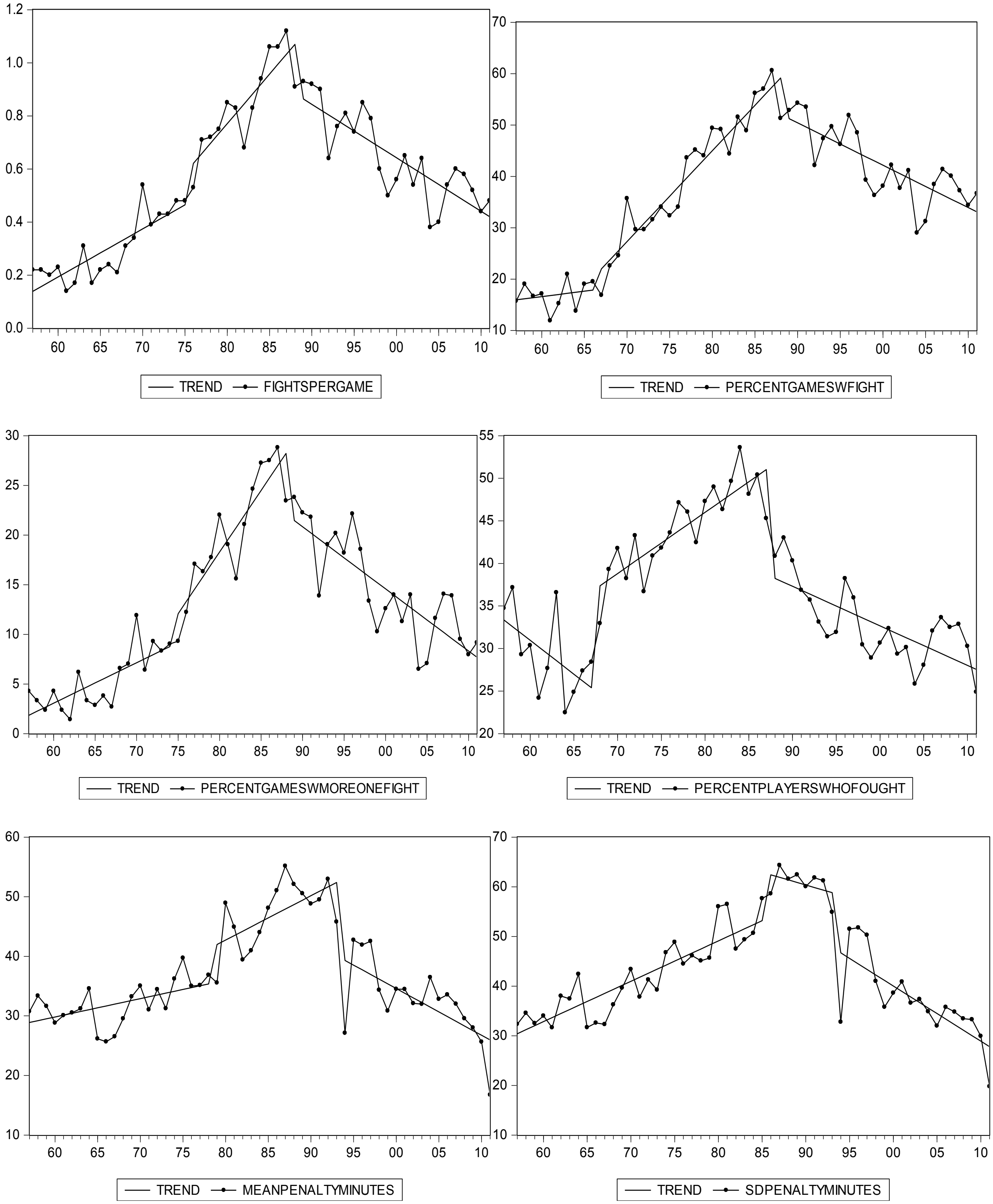

Figure 2. OLS Regressions of Performance Data on Level and Trend Breaks