The effect of absenteeism in the workplace: An example of NFL injuries and team performance

Strategy Economics Thesis

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Table of Contents

1. Introduction:

1.1 Overview, Relevance, and Contribution

Businesses increasingly rely on teams. Drew et al. (1996) survey 100 U.K. firms and provide evidence of team-based organizations becoming the norm in modern companies. Current business activities often rely on group efforts. For example, product launching in a specific region or quality management for an R&D prototype. Hamilton et al. (2003) identify the effect of teams on productivity. Their findings point to an increase in productivity by 14% in a garment plant after team adoption. Workers are able to utilize collaborative skills that would be wasted if no team work happens, like intrateam bargaining or mutual team learning. Given the importance of teams in the workplace, absenteeism may potentially affect firm productivity, leading me to the research question: 'Does absenteeism in the workplace influence group performance?'.

Absenteeism in the workplace refers to the absence of a worker in his/her job for a prolonged period of time due to reasons different than personal time or holidays, that is, unplanned leaves. The concept of absenteeism is a key aspect of an operational business since it heavily impacts the production function. The economic consequences of absenteeism should not be underestimated. Stewart et. al. (2003) reveal that the productivity loss of absenteeism costs the United States around $226 billion or $1635 per worker every year. Hoey et al. (2023) expand on the influential role absenteeism plays in the workplace using a sports setup. My paper aims to fill in the gaps that Hoey et al. (2023) started covering and broaden the understanding of the implications of absences. The research's ambition is to provide measurable effects of sudden nonparticipation of employees in setups where collaboration and synergies among individuals help consummate the objective and expand the knowledge on production complementarities within teams.

Existing research suggests absenteeism may be an important factor in group performance at work. Bartel et al. (2014) use panel data from hospital nurses' experience level to prove how exits of experienced nurses and the consequent replacement by a temporary nurse harm nurse team performance, suggesting workers' productivity is dependent on peers. Finding equally productive replacement workers after a worker departure remains a challenge for employers, potentially harming team workflow (Herrmann and Rockoff, 2012).

1.2 Hypothesis and Research Structure:

The hypothesis tested on this paper is:

Hypothesis: 'The absence of coworkers has an impact on group performance and outcomes'

To test this hypothesis I will make use of the NFL data from the regular season of 2022 and run OLS regressions on the performance outcome variable in the form of points and yards conceded/achieved on the number of injuries a team sustains throughout the season, after controlling for variables of interest. Moreover, different roles of workers may have different impacts on the final team outcome. To account for this, I run the OLS models on two subsets of data to distinguish between defense and offense players. I take this approach because there are parallels between the sport and a traditional work environment. The context of the NFL allows these similarities as the value output metrics for performance are easily measured, the independent variable for injuries is identifiable, and being injured has direct consequences on the players' pool, and lastly, because it is a team activity where the outcome depends on the complementarities of production from peers. Additionally, absences in this study refer to unplanned leaves of employees, the same way injuries in sports have a quasi-random variation property causing exogenous sudden leaves. By means of the OLS models, I obtain point estimates that hint at the extent of injured players causing an effect on the group outcome. Yet, obstacles and limitations may unveil when exercising these models. Limitations are discussed in Section 6.

I divide this study in different sections; Section 2 is a literature review where I discuss previous research related to this paper's topic, Section 3 describes the data and settings for this research, Section 4 explains the theoretical background and methodology of the experiment, Section 5 presents the results, and Section 6 wraps up the results and concludes the paper.

2. Literature Review:

Returning to this paper's motivation, teamwork can benefit individual and group performance. Mas and Moretti (2009) explain how production functions of workers are codependent with one another. They use data from a large grocery chain to provide evidence of low productivity workers benefiting from the presence of high productivity workers, leading to an optimal production function of the group. Falk & Ichino (2006) show how peer effects favorably influence an individual's performance in simple tasks like putting letters in an envelope, implying a positive relationship between the performance of two individuals. Bringing these findings to a larger scale indicate that a grouped team with the optimal mix of workers should yield better productivity relative to individual working cells. Similarly, Mailranta et al. (2009) provide evidence that inter-company labor mobility has positive spillover effects that boost productivity and profitability, mainly when job reallocating from a technical to a non-technical role. However, this is still a debated topic for two reasons. Dahl et. al. (2014) evaluate that the peer effects are more substantial as more individuals become part of a group as a causal chain makes the direct influence of the original peer amplify by intervening coworkers; the so-called 'snowball effect'. Alternatively, they also become aware of the decaying influence of the original peer over time. Yet, peer effects are affecting individual performance and their effects are not limited to one single individual, hence it can be argued that peer effects do have an impact on team production output and performance.

Knowing that teamwork is desirable for employers, the effects of absenteeism in the work environment are profoundly significant. Most of the contemporary papers about absenteeism discuss the various sources of absenteeism. Some researchers link absenteeism to the consumption of demerit goods like alcohol (Bacharach et al., 2010) and source absenteeism from the individual decision to binge drink. Others, like Halpern et al. (2001), argue that micro-absences from smoke breaks during working hours also lead to impoverished productivity. Further explanations about the sources for absenteeism are self-reported illnesses (Jacobson et al., 1996), peer attendance and organizational commitment (Hassan et al., 2014), or changes in government policies regarding paid leaves (De Paola et al., 2014).

While many researchers discuss this topic and its origin in different setups, this research aspires to shed light on the implications of labor force voids in team performance and outcomes. Mollerman & Slomp (1999) investigate the impact of the distribution of workforce flexibility on team performance. They measure performance in various ways, but the total cumulative production time is the most related to this thesis. Findings from their research suggest that absenteeism has a strong negative effect on cumulative production time, regardless of the distribution of flexibility, and that the workload of the bottleneck worker is greater relative to the other workers.

The most related paper to the current study is Hoey et al. (2023). In their paper, they propose two channels for absenteeism influencing team productivity. A direct channel causes a direct loss of production as the employer fails to find a replacement for the absentee, and an indirect channel causes coworkers to produce less because their productivity depends on the absentee. They also use the sports context to analyze absenteeism effects by measuring an ex-ante effect of injuries on individual and team performance. They find that when absences occur, the group experiences disarray in the coworker network and a decrease in coworker skills, harming group productivity. Berman et al. (2002) use the sports setup to build a bridge between shared team experience and favorable team performance. They find that share team experience extends to tacit knowledge, and consequently becomes a resource for comparative advantage, but has diminishing returns even turning the effect on team performance negative at some point.

3. Setting, Background, and Data:

In this section, I discuss why the selected setting for studying absenteeism in the workplace is valid and adequate. I briefly review the NFL structure and describe the dataset I use for this research.

3.1 Setting:

In this paper, I use the NFL workplace setting during season 2022 to explore further the effect of voids in the labor force on team productivity, using players' injuries as a proxy for absenteeism. The NFL setting is adequate to monitor the production function of a team because it has both team size constraints (i.e., the team units cannot be larger than what the rules specify) and time constraints. The game is played in 4 x 15-minute quarters for a combined playing time of 60 minutes. The highest score at the end of 60 minutes wins. This allows for testing productivity as the outcome spreads over a predefined period. Ties are rare in American Football, and overtime periods occur if necessary to determine a winner. Overtime periods are not frequent, so I exclude them from this analysis.

Highly inspired by Hoey et al. (2023), I address endogenous staffing changes in football teams during the 2022 season by exploiting quasi-random coworker injuries in NFL team members as a source of temporary. These 'replacement' players are expected to have lower productivity than the injured players, for they would be part of the original line-up for all games if they could generate a better output for the team. Furthermore, I find compatibilities between a company's labor economics and a football team. As a business owner, an efficient production function that properly executes operations is a key enabler to reaching the ultimate goal, profit maximization. In other words, in a setting where the size of the workforce cannot increase when a worker is absent, coworkers may have to work additional time to make up for the productivity loss. This can lead to sub-optimal individual and team performance in producing outputs. However, not all coworkers can compensate for the absence of a peer, for not all of them have the skills to carry out the activity of the absent peer.

Similarly, in the NFL setup, the team's goal is to beat their rivals to secure a high standing by the end of the season. A team needs to maximize points compared to their opponent to win the game. If a player gets injured, productivity loss in terms of the (in)ability of the team to not concede (or score) points might occur and the path to victory becomes hazy. Moreover, the nature of the game requires some degree of specialty of the players. Defensive players may have different characteristics than offensive players. This means that not all players can compensate for the absence of a team member, since not all of them have similar skills that can substitute absentee's tasks.

3.2 Background Knowledge of American Football:

The objective of an NFL game is for a team to score more points than the opposing team. Teams are formed by 46 players in the NFL, with 11 players taking the field at any time. The field is 100 yards long by 53 yards wide, with two 10-yard endzones at each end. The game starts with a kickoff; the team with possession of the ball is the offense, and the team without the ball is the defense. The distinction between these two sub-teams is crucial for this paper. The offense's job is to move the ball up the field and score points. This can be done by rushing forward with the ball or passing it up the field for a teammate to catch. The offense is given four chances (or four downs) to make at least 10 yards. If the offense manages to move the ball 10 yards or more, they will retain possession of the ball while given another four downs to make an additional 10 yards.

The defense's job is to stop the offense from moving the ball forward by tackling, stopping them from moving forward, or forcing them off the field. If the offense fails to move the ball 10 yards within four downs, the ball is given to the defending team at that point. The defending team will then bring on their offensive players and try and move the ball in the opposite direction so that they can score.

The teams will usually have three different units of 11 players that come on the field at different times. They include: i) the offense, ii) the defense, and iii) special teams. Special teams are specialist players that come on the field when there is a kick involved. Within the special teams is a mix of offensive and defensive players mixed with either a punter or kicker for offense or a punt returner for defense. For the scope of this study, I will exclude the special team since their participation needs measurement mechanisms in the dataset.

There are four different ways of scoring: 1. Touchdown, 2. Extra points (Conversion), 3. Field Goal, 4. Safety. The scope of this research applies total points scored/conceded, only distinguishing the source of points for touchdowns.

3.3 Dataset

The datasets of this study come from the same source, www.pro-football-reference.com. I use this website's data alone to dodge potential mismatches across datasets. Data pertains to the NFL 2022 regular season, excluding Wild Card games, Divisional playoffs, and the well-known Super Bowl game. There are 18 weeks in the regular season, where all teams play 17 games and have one bye week. The NFL consists of 2 conferences, the AFC and the NFC, with 16 teams each, adding up to 32 teams. For the scope of this paper, the data sample represents 25% of the NFL teams, specifically from the four teams in the NFC North Division – Chicago Bears, Detroit Lions, Green Bay Packers, and Minnesota Vikings – and the four teams in the NFC East Division – Dallas Cowboys, New York Giants, Philadelphia Eagles, and Washington Commanders[1].

Two primary datasets are of interest. First, the team game-by-game data, where there is a split between defensive and offensive plays for every game a team played throughout the regular season. Here, data pertaining to the points scored/received, yards scored/received, tackles, passes, and further specifications on the nature of these result variables are found. Although some players are present exclusively during defensive/offensive plays, others may have data for both types of plays. That is, even if there is a clear distinction between defensive/offensive teams, some players are able to play for both teams if the coach requires them to do so. Second, the injury data at the individual level comes in the form of a weekly report, where all players who have suffered injuries are displayed. This report categorizes players by the graveness of their injuries and gives the probability of a player missing the next game due to the injury. The scope of this paper is absenteeism in the workplace, resembled by player injuries that disallow them to play a game in the NFL context. Thus, I move forward with the dataset exclusively considering players that missed next game; that is, those players with probability of missing next game being 100%. I follow this identification of injuries structure because it's the structure the official website of the

[1] See Appendix 1 for team codes.

NFL (nfl.com/injuries) follows[2]. After data cleaning, I merge these two datasets into a single dataset to perform the STATA Software analysis. The final number of observations is 271, spread across the 18 weeks observed during the analysis.

Table 1: Descriptive statistics of main variables of interest:

	Obs	*Mean*	*Std. dev.*	*Min*	*Max*	% of total
Weeks played	271	9.46	5.30	1	18	-
% injured per team	271	.084	.061	0	.26	-
Number of injured per team	271	2.52	2.18	0	11	-
Offensive players	136	-	-	-	-	50.18
Defensive players	135	-	-	-	-	49.82
Team points	271	23.55	9.95	0	54	-
Opponent points	271	22.69	9.45	-49	-3	-
Team achieved yards	271	349.65	74.74	182	520	-
Opponent achieved yards	271	348.74	81.72	148	570	-

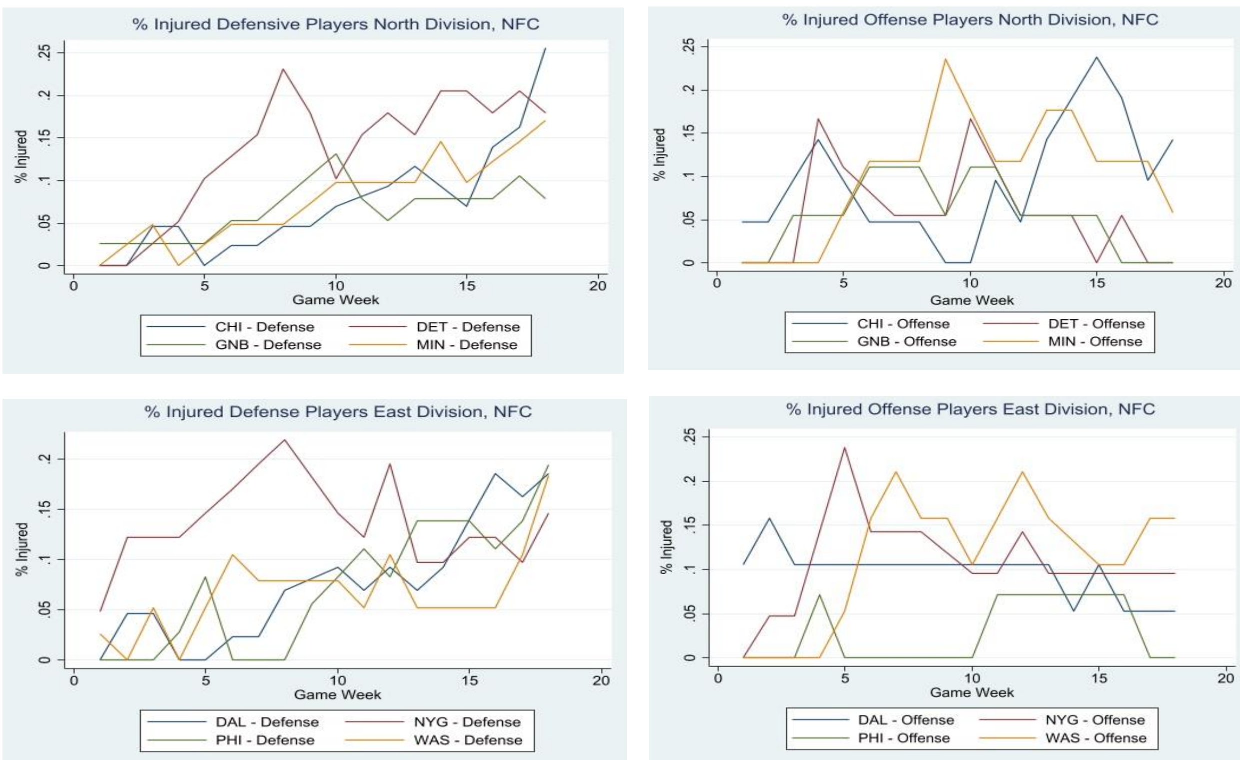
Notes: These descriptive statistics belong to the merged dataset. All injury and individual-level data belongs to the 8 teams studied: CHI, DET, DAL, GNB, MIN, NYG, PHI, and WAS. Team data belongs to the studied teams. Opponent team data belongs to studied teams, for they play against each other, and to the following teams: ARI, ATL, BAL, BUF, CAR, CIN, CLE, HOU, IND, JAX, LAR, NEW, NOR, NYJ, MIA, PIT, SEA, SFO TAM, and TEN. All data from this table pertains to the regular NFL season 2022.

Table 1 displays the summary statistics of the most relevant variables for this study. The split between defensive and offensive players is nearly symmetric. The average percent of injured players for a team during a particular game is 8.4%. Total points scored by a studied team are

[2] See Appendix 2 for detailed examples on how the injury report works and how I define an injured player for a specific week.

marginally higher than total points conceded. Similarly, yards achieved by a studied team are also slightly above yards achieved by opponent teams. This may hint at a moderate superiority of the teams subject to this research relative to their opponents[3], only 2 of the 8 observed teams finished the season below the (median) 16th standing. Not all teams have the same level, thus, their performance varies.

Figure 1: Trend of % of injured players throughout the season:



Notes: These figures belong to the merged dataset. They display the trends of percent injured players over the 18 weeks that the regular season lasts by matching the. Figures to the right show data for offense players and to the left for defense players, segmented into the two divisions from the NFC, North and East.

Figure 1 helps explain the trend in the percentage of injured players across teams throughout the season. On the left side, I display the trend data for offense players, and on the right, defense players. I expect an upward trend in the percentage of injuries because the likelihood of injury

[3] Standings of observed teams: PHI (2nd), MIN (4th), DAL (7th), NYG (10th), DET (11th), WAS (16th), GNB (17th), CHI (32th).

increases after each game slightly (Ekstrand et al., 2011). While defense players seem to follow this trend, offense players have a hazy trend, with teams like PHI carrying 0 percent injuries during a period of time.

4. Identification Strategy:

To estimate the effect of injury-driven absences in American Football teams and thus quantify the effect of absenteeism in the workplace, I will use an OLS regression equation of the following sort:

$$Y_{jt} = \beta_0 + \beta_1 * INJ_{jt} + \delta_{jt} + \rho_{jt} + \tau_j + \varphi_{jt} + \varepsilon_{jt} \qquad (1)$$

The outcome variable Y_{pjt} serves as a measurement of production output or performance. In this case, it takes values for both performance indicators – points and yards achieved/conceded – for team j in game t. Points scored and conceded are not solely derived from offensive and defensive plays, but also can be the result of a converted kick, a safety or a field goal from one of the two teams in a game. Conversely, yards obtained and allowed exclusively stem from offensive and defensive plays. Since the dataset only contains data on the team-game level for offensive and defensive plays, the preferred output metric is yards in favor and against a team.

The focal explanatory variable for variation in output is INJ_{jt}, resembling the injuries a team j sustains during a specific game t and relative to the injury level, or in a conventional workplace, the number of absent workers j during a specific day t relative to the rate of absent coworkers. During the analysis, injuries were evaluated in 2 dimensions. First, injuries were perceived as the percent of injured players a team sustained for a particular game. This calculation was done by simply dividing the number of injured players by the total size of the squad - either attacking or defending. Second, injuries are represented by the number of injured players of a team j during game t.

I consider the fixed effects (FEs) of some that may influence team performance by including them as control variables to absorb these effects. δ_{jt} contains the FE of an observed team j during game t and ρ_{jt} contains the FE of the opponent team for team j during game t. These effects are included because not all teams perform in the same way; some teams are better than others, so including fixed effects for teams and their respective opponents is necessary. τ_j absorbs the FE for the week in which team j plays a given game t, and is included in the equation since the time factor might play a role in team performance; teams learn from their own and rivals' capabilities throughout the season, allowing for strategic performance. Lastly, φ_{jt} captures the FE of the psychological effect of playing at home since it may influence game outcomes (Legaz-Arrese et al. 2013). Naturally, this OLS regression equation could include more possible control variables to avoid Omitted Variable Bias and bypass endogeneity. The error term ε_{jt} captures all the unaccounted noise of equation (1).

A second regression equation (2) is formulated, where I categorize the percent of injured players into five quantiles and represent them as dummies. Description of these quantiles are found in **Table 2**. I categorize percent of injured to have detailed information about injuries without treating them as a continuous variable.

$$Y_{jt} = \beta_0 + \beta_1 * INJ_{jt,1} + \beta_2 * INJ_{jt,2} + \beta_3 * INJ_{jt,3} + \beta_4 * INJ_{jt,4} + \beta_5 * INJ_{jt,5} + \omega_{tj} + \varepsilon_{jt} \qquad (2)$$

Equation (2) explains the same regression as equation (1), but now the explanatory variable percent of injured players for team j during game t is categorized into five different quantiles, represented by five dummies with structure $\beta_n * INJ_{jt,n}$. Note that $INJ_{jt,n}$ only represents percent of injured players and not number of injured players and that Y_{jt} represents performance in the form of points or yards. The estimates regression tables that use this categorized measure for absences are benchmarked against the first group of injured players. Let ω_{tj} capture all the FEs considered in equation (1) - δ_{jt}, ρ_{jt}, τ_j, φ_{jt} – and ε_{jt} be the error term. In the results section, Tables 3 and 5 display the injury estimates of equation (1) and Tables 4 and 6 of equation (2).

Table 2: Description of categorized percent of injuries per team in quantiles:

	DEFENSE PLAYERS			*OFFENSE PLAYERS*		
	Range of % injured	% Players in group	Players in group	**Range of % injured**	Players in group	Players in group
INJURED GROUP 1	**0%-2.3%**	15.56	21	**0%**	25.53	32
INJURED GROUP 2	**2.3%-5.5%**	22.96	31	**0%-5.3%**	19.85	27
INJURED GROUP 3	**5.5%-9.7%**	22.96	31	**5.3%-9.5%**	15.44	21
INJURED GROUP 4	**9.7%-13.9%**	17.78	24	**9.5%-11.8%**	21.32	29
INJURED GROUP 5	**13.9%-25.6%**	20.74	28	**11.8%-23.8%**	19.85	27

Notes: The bold percentages are crucial for understanding tables in the Results section of this paper. The 5 injured groups resemble the 5 quantiles in which observations are categorized and they aim to find the best distribution of injury data depending on the frequency and injury value. However, sometimes group size may differ by many observations, threatening the internal validity of the study as treatment groups have different sizing.

There are several limitations to this identification strategy. A threat to this study's internal and external validity could be that the relatively small sample size implies high p-values on the results, meaning that the models have low explanatory power. Moreover, data might be incomplete as various control variables are not included in equation (1), for example, individual-player-level data or time series data potentially explaining the trend a team might be following. Data may also contain measurement errors corresponding to errors made by the measurer (website) when retrieving the data from the official final scores. Another threat to internal validity could be the different measures for outcomes and the sub-sampling split between defense and offense players. When looking at scored/received points, notice that not all points come from defensive/offensive plays (e.g., conversions), so the data sample will ignore these points and will not attribute them to either defense or offense teams.

5. Results

In this section, results from the analysis are displayed. Note that the structure of the results distinguishes between offense and defense players for each team. Tables 3 to 6 show the estimates of injuries on the team-level performance for both subcategories of teams – defense and offense - after controlling for the opponent team's performance, the week in which the game takes place, and whether the game is played at home or away. The performance indicators, brought into a traditional workplace setup, may refer to 2 routes of measuring outcomes. Points scored/conceded are interpreted as the end result of the input workers bring, the final product. Yards obtained/allowed are interpreted as the means towards the end result, the path towards the final product.

5.1 Defense Team Results:

Table 3 presents regression results for the defense team's performance, measured by points (Model 1 and 3) or yards (Model 2 and 4) conceived to rival teams. Here, the treatment variable injuries for a given team j in a given match t and is measured by either the percentage of injured players on team j found on the first row or by the number of injured players on team j in the second row, during game t. Because players may greatly differ in their skill at the individual level, consider solely Models 1 and 2, where the percent of injured players is the injury variable. This will allow a more adequate interpretation of the results.

It is observed how points conceived against rivals should decrease as the percent of injured players in a team increases (1) while the number of yards allowed to the rival team seems to increase as the percent of injured players in a team increases (2). More precisely, if 10 percent of defense players in a team are injured for a game, the team is expected to concede 3.175 fewer points and 18.16 more yards. Such behavior of variables is surprising as one would expect that if a team, conditioned by injured defense players, is conceding more yards, they would also allow the opponent team to score more points. This is not the case for these models. Yet, the coefficients are not significant at any significance level, implying that injuries have no effect on team performance in these models supposing a threat to their external validity.

Table 3: The effect of absent defense team players on team performance, uncategorized injuries:

	(1) Points conceived vs opponent	(2) Yards conceived vs opponent	(3) Points conceived vs opponent	(4) Yards conceived vs opponent
Percentage of injured	-31.75 (27.43)	181.6 (191.9)		
Number of injured			-0.629 (0.706)	5.183 (4.909)
Constant	25.69*** (2.432)	334.0*** (17.01)	25.10*** (2.497)	331.8*** (17.37)
Observations	130	130	130	130
R-squared	0.502	0.468	0.498	0.470

Notes: robust standard errors in parentheses. The percentage of injured refers to the average % number of players who were injured for a team throughout the season games; The % of injured ranges between 0 - 25.6%. The number of injured refers to the average number of players injured for a team throughout the season. The number of injured ranges between 0 – 11. Data belongs to the North and East division teams from the NFC, during NHL 2022 regular season. P-values: *** p<0.01, ** p<0.05, * p<0.1

Under the premise that replacement players should perform worse than injured players who would have played if they were not injured, one can presume that the performance of the team will worsen. **Table 4** showcases injuries in a different way than Table 3. Here, injuries are categorized into 5 quantiles, each containing roughly 20 percent of observations for the subsample, and using quantile 1 as a benchmark, the reference quantile. Note that when categorizing the percent of injured players into these 5 groups, the response of team performance becomes more logical to the percent of absent workers. Model 5 statistically proves that there is a significant increase of 7 points conceded by a team when the percent of absent workers pertains to the group 2 interval [2.2 , 5.5], compared to quantile 1. However, in Model 5, allowed points to the rivals appear to become less negative as the quantile of percent of injured players for a game increases relative to group 1, even turning the coefficient positive when reaching the highest injury rate quantile. A possible interpretation of this would be that the team or business reacts to workforce losses and starts adapting to these absences, thus they suffer less from absenteeism in later periods of time when the employer or team manager is able to foresee leaves in the labor pool and is able to strategize upon it. As described in Figure 1, there is a upward trend in the percent of injured as the weeks pass by and the season approaches the end.

Model 6 follows a similar line of reasoning as Model 5. Models 7 and 8 assess the source of conceiving yards against opponents and aim to provide more information regarding what defensive actions have a larger impact on yards lost by a team, but the interpretation of their coefficients is rather ambiguous. While Model 7 states that 12.2 fewer yards are conceded due to missed interceptions for injured group 2, Model 8 states that 36.0 additional yards are lost due to missed tackles, compared to the reference group. Missed interceptions or tackles refer to the yards that the opponent team is able to obtain by either passing the ball or rushing. This effect of injured group 2 in Model 8 is statistically significant at the 5% level. However, when looking at injured group 3, the point estimate of absent workers has the same sign and (almost) the same magnitude as the estimate for group 3 in Model 7. Lost yards stemming from missed interceptions have a negative effect (14.6 additional yards lost, Model 7), and yards lost stemming from missed tackles have a negative effect (14.5 additional yards lost, Model 8). It appears that the effect and magnitude of intercepting and tackling exchange signs depend on the percent of injured players.

Table 4: The effect of absent defense team players on team performance, categorized injuries:

	(1) Points lost vs opponent	(2) Yards lost vs opponent	(3) Yards conceived due to interceptions	(4) Yards conceived due to tackles
2. Injured type	7.895***	23.81	-12.20	36.01**
	(2.019)	(18.96)	(29.14)	(13.49)
3. Injured type	3.036	29.00	14.55	14.95
	(3.277)	(37.40)	(24.66)	(23.94)
4. Injured type	0.888	34.79	9.186	25.60
	(3.757)	(31.14)	(19.89)	(21.67)
5. Injured type	-2.575	20.64	31.40	-10.76
	(2.894)	(36.15)	(22.70)	(22.40)
Constant	20.72***	327.6***	207.8***	119.6***
	(1.793)	(24.37)	(17.63)	(12.26)
Observations	130	130	130	130
R-squared	0.557	0.470	0.525	0.508

Notes: Robust standard errors in parentheses. The types of injuries refer to the different quantiles of the % of players injured in one team. Each quantile contains roughly 20% of observations. Let X be the variable for % of injured, then quantiles range as follows: Type 2: $0.023 < X < 0.055$; Type 3: $0.055 < X < 0.097$; Type 4: $0.097 < X < 0.139$; Type 5: $0.139 < X < 0.256$. Data belongs to the North and East division teams from the NFC, during NHL 2022 regular season. P-values: *** p<0.01, ** p<0.05, * p<0.1.

Yet, note that the magnitudes of the coefficients for injuries on performance sub-indicators vary among Models 7 and 8, especially for groups 2, 4, and 5. Taken into a more conventional workplace environment, such as retail companies or production plants, and given the restricted sample, these results imply that there is no clear ranking or guideline to argue what type of play in a game/role of a worker in a company sustains a greater impact on how production is achieved[4]. Nevertheless, there is significant evidence that, when the percent of absentees is not too high (between ~2% and ~5%), the end product, points against, increases substantially (Model 5), and one of ways the end

[4] Here I discuss whether a specific defensive play, intercepting or tackling, has greater or lower impact on how team performance varies.

product is defined, yards allowed due to missed tackles/opponents rushing yards, also increase accordingly (Model 8). However, I want to make clear that, except for the coefficients for quantile 2 in Models 5 & 8, my coefficients are statistical zeros, meaning that injuries have no effect on team performance.

5.2 Attack Team Results:

Pursuing a similar analytical path as Tables 3 & 4, **Table 5** presents the results of offensive players' absences, uncategorized, and their effect on team performance. Models 9 and 10 exhibit logical estimates of injuries on team performance. A 10 percent of injuries on the offensive team should yield a decrease of 0.163 points per game and a decrease of 16.3 yards per game. Again, estimates for Models 9-12 are not significant at any level, so there is no evidence of causal effect of attacking players' injuries on team performance.

Table 5: The effect of absent offense team players on team performance, uncategorized injuries:

	(9) Points scored vs opponent	(10) Yards earned vs opponent	(11) Points scored vs opponent	(12) Yards earned vs opponent
Percentage of Injured	-1.625 (23.54)	-163.0 (252.5)		
Number of Injured			-0.199 (1.270)	-10.05 (13.02)
Constant	23.72*** (1.871)	363.6*** (20.07)	23.89*** (1.905)	365.7*** (19.53)
Observations	132	132	132	132
R-squared	0.456	0.449	0.456	0.451

Notes: robust standard errors in parentheses. The percentage of injured refers to the average % number of players who were injured for a team throughout the season games; The % of injured ranges between 0 - 25.6%. The number of injured refers to the average number of players injured for a team throughout the season. The number of injured ranges between 0 – 11. Data belongs to the North and East division teams from the NFC, during NHL 2022 regular season. P-values: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The effect of absent offense team players on team performance, categorized injuries:

	(13) Points scored vs opponent	(14) Yards gained vs opponent	(15) Yards obtained due to passing	(16) Yards obtained due to rushing
Injured type 2	-5.421	-11.57	18.03	-29.60
	(3.753)	(33.70)	(23.74)	(21.10)
Injured type 3	-0.286	12.95	8.94	4.012
	(3.956)	(43.74)	(38.99)	(34.11)
Injured type 4	-2.732	-18.99	-9.55	-9.441
	(4.757)	(48.43)	(36.32)	(24.44)
Injured type 5	-3.216	-26.42	-0.036	-26.39
	(4.898)	(46.19)	(28.62)	(31.40)
Constant	-20.72***	-327.6***	211.29***	148.6***
	(1.793)	(24.37)	(21.75)	(17.44)
Observations	132	132	132	132
R-squared	0.475	0.456	0.558	0.527

Notes: Robust standard errors in parentheses. The types of injuries refer to the different quantiles of the % of players injured in one team. Each quantile contains roughly 20% of observations. Let X be the variable for % of injured, then quantiles range as follows: Type 2: $0.000 < X < 0.053$; Type 3: $0.053 < X < 0.095$; Type 4: $0.095 < X < 0.118$; Type 5: $0.118 < X < 0.238$. Data belongs to the North and East division teams from the NFC, during NHL 2022 regular season. P-values: *** p<0.01, ** p<0.05, * p<0.1.

Table 6 displays the results for the offensive team players' injuries, categorized in the same way as in Table 4. Injuries do not have an effect on the attacking performance of a team, however, it is worth mentioning some incongruencies in this table. Again, under the premise of expecting injuries to have a negative influence performance, it seems that, in some cases, injuries can take a positive coefficient on production (Model 15, injured group 2) relative to the reference injury group. Despite that, Models 13, 14, and 16 appear to have a more predictable behavior for injured group 2, with performance indicators dropping as injuries take place. Nonetheless, the noticeable variation of estimates' sign and magnitude when benchmarked against group 1, becoming dependent on which bracket of the injured percent is analyzed together with the non-significance of point estimates, make these models inconclusive.

6. Discussion, Conclusion, and Limitations:

6.1 Discussion

I investigate how absenteeism affects holistic team productivity in the context of the National Football League. In this setting, I perform three main analyses. First, even if there is evidence of positive spillover effects, I evaluate the possibility that defensive and offensive players might have different abilities or specializations that are untransferable. This implies that measuring their productivity altogether can be misleading, as different roles in the team might have different sizeable impacts on the final outcome. To solve this, I divide the dataset into defensive and offensive groups. Second, I categorize injuries into quantiles to create a more realistic scenario since some teams sustained absences of >15 percent of the players' pool for a game. Third, I explore two different outcome measures, points scored/conceded and yards achieved/conceded, to resemble two ways of measuring team performance – the final outcome (points or end product) and how the final outcome is achieved (yards or means towards end product).

The main results from this investigation point out several interesting implications of absenteeism, the most important of them being the value of the estimates. Although all 16 models present point estimates different than zero, hinting at a possible effect of absenteeism in team performance. Nonetheless, only two estimates are not statistical zeros, meaning no statistically significant effect of absences in team productivity for most cases. Next, note that nearly all eight models with categorized injuries present a negative estimates of absences in group performance. This supports the idea that collective efforts can yield beneficial outcomes and that a disruption of the coworker network may lead to inferior productivity.

Nevertheless, we must pay attention to the two main drawbacks to the presented models; i) lack of significant coefficients at the 5% level, and ii) inconsistencies in coefficient signs as the percentage of injured players changes. With that in mind, the only Models that provide significant estimates are Models 5 & 8. Model 5 proves that any team that sustains between 2.3% and 5.5% of defensive injured players in a given game will allow opponents to score seven additional points, on average, and Model 8 indicates that a team with these very same characteristics on injuries will concede 36.0 yards to opponents due to missed tackles, on average. I also underline the difference in the size of coefficients for both defensive and offensive teams. When comparing points conceded/scored (Models 5 & 13) and yards conceded/obtained (Models 6 & 14), I observe that injured defensive players have a larger impact on team performance than injured offensive players. This suggests that the operational roles of employees affect productivity heterogeneously. Another divergence between defense and offense is the source of yards conceded/achieved. Defensive players allow fewer yards due to failed tackles, while the offensive counterpart achieves more yards from passing the ball, insinuating a larger difference in how each player performs.

In line with the findings of Mollerman & Slomps (1999), I find adverse effects of absenteeism in the production function of a team independent of the distribution of the workers' roles. Negative impacts on group performance are noticeable regardless of the player's position. While Hoey et al. (2023) find that a disruption caused by absences in the work environment leads to a marginal decrease in the team's productivity, even when a replacement covers the vacancy, my estimates cannot provide enough support for this statement in most cases. Potential mechanisms for this drop in efficiency are working complementarities that may arise between workers when collaborating toward an end result, such as spillover or positive peer effects, and the inability of the employer to find a replacement that fits the job and matches the productivity of the absentee.

6.2 Limitations:

This paper has limitations and threats to both internal and external validity. The research does not find estimates statistically different form zero, meaning no effect of injuries on team performance is can be supported and internal validity is threatened. Because of the small number of observations of my sample I can potentially suffer from low explanatory power, which decreases my ability to find an effect, should it exist. Additionally, even if the paper's aim is not to explain all variation in team performance, models suffer from poor goodness of fit (<0.56 r-squared value). There is still room for improvement in this field, adding more control variables might explain the performance variation better.

Concerning external validity, I chose the eight selected teams for the analysis fully arbitrarily, indicating a non-random sample selection. A substantial threat to external validity is my small number of observations. This implies a risk of incapability to extrapolate my results to other setups or larger samples. Due to my sample characteristics and the player specific sporting-laboral conditions, generalization of findings to other non-sporting settings or different contexts is not possible. The NFL setting is restricted by specific working hours of players, which is an advantage when measuring productivity, but it is not in line with the modern work environment where workers might work more or less than what their contract stipulates. Also, the NFL assumes that replacements must be available for the next game (working day) so workforce size is constant. Again, this is favorable to measure productivity, but the reality is that companies do not replace absentees within one day, making the size of the workforce vary Furthermore, the study only considers a single season of the NFL. Teams may change over time and so their expected performance, exposing my paper to temporal validity. Replication of this research on the full population of the NFL context for several seasons could bring cleaner external validity. Because of the above reasons, it is erroneous to apply these findings to the labor market in general.

6.3 Conclusion

The broader economic implications of this analysis must be treated carefully. While I find two coefficients causing a significant negative impact of (defensive) injuries on team outcomes, most of my estimates are not significant and don't show any significant effects. Still, due to existing literature on absenteeism in teamwork the environment (Bartel et al., 2014, Herrmann and Rockoff, 2012, and Stewart et al., 2003, among others) and their statistically significant findings, there are reasons to believe that absenteeism has a negative effect on group performance. This negative causal relationship can be found in sporting contexts (Hoey et al., 2023) like the one I study in this paper. Therefore, despite not showing any significant effects with my results, potentially due to the limitations of my data sample or research setting, we can get an idea of what the consequences of absenteeism in the workplace are; a decrease in group productivity.

Managers should try to overcome the plausible adversities of the negative effects of absenteeism and think strategically. That is, to have an available, high-quality labor pool where they can source replacement workers that can sufficiently (or exceedingly) fulfill the absentee's tasks and maintain (or improve) the level of team productivity. This is food for thought for companies when strategizing their recruitment processes and might serve as a motivator to boost their agility to maintain the team dynamic when absences take place. The challenge remains for businesses and implies performing profile screening adequately to minimize unforeseen absences or storing unselected applicants efficiently in case they are needed to cover an unexpected vacancy. Finally, three avenues for further research are i) the analysis of absenteeism in a different non-sporting context, ii) the investigation of the seasonality of absenteeism, essentially whether the timing of the absence has any implications for production outcomes, and iii) the effects of an alternative behavior to absenteeism that is very common in the post-pandemic era, working remotely.

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Appendix 1:Ways of scoring points in the NFL in detail:

There are four different ways of scoring: *1. Touchdown:* if the ball is carried into the endzone area, or thrown and caught in the endzone, this is a touchdown and is worth 6 points. *2. Extra points (Conversion):* once a touchdown has been scored, the offense has the option of kicking the ball through the uprights for an extra point (15 yards from the endzone), or trying to pass or run the ball into the endzone again for an extra two points (2 yards from the endzone). *3. Field Goal:* At any time, the team with the ball can kick the ball between the posts and over the crossbar. To do this, they must hand it to a teammate who will hold it on the ground ready for a kicker to make the kick. A successful kick scores 3 points. *4. Safety:* if the defense tackles an offensive player behind his own goal line, the defending team scores two points.

Appendix 2: Example of injury report:

In the official injury report from the NFL website, nfl.com/injuries, each week injured players get categorized into: Probable, Questionable, Doubtful, and Out. The reading of these is:

Probable	75% chance of playing next game
Questionable	50% chance of playing next game
Doubtful	25% chance of playing next game
Out	The player is out for next game

For this analysis, I only use players who fall under the 'Out' category and take them as injured. More information can be found on the cited dataset website:

https://www.pro-football-reference.com/teams/kan/2022_injuries.htm

Appendix 3: Team codes & standings NFL season 2022:

TEAM	CODE	AFC/NFC	STANDING IN REGULAR SEASON
Chiefs	KC	AFC	1
Eagles	PHI	NFC	2
Bills	BUF	AFC	3
Vikings	MIN	NFC	4
49ers	SFO	NFC	5
Bengals	CIN	AFC	6
Cowboys	DAL	NFC	7
Ravens	BAL	AFC	8
Chargers	LAC	AFC	9
Giants	NYG	NFC	10
Lions	DET	NFC	11
Jaguars	JAX	AFC	12
Dolphins	MIA	AFC	13
Steelers	PIT	AFC	14
Seahawks	SEA	NFC	15
Commanders	WAS	NFC	16
Packers	GNB	NFC	17
Patriots	NEW	AFC	18
Buccaneers	TAM	NFC	19
Falcons	ATL	NFC	20
Panthers	CAR	NFC	21
Browns	CLV	AFC	22
Saints	NOR	NFC	23
Jets	NYJ	AFC	24
Titans	TEN	AFC	25
Raiders	LV	AFC	26
Broncos	DEN	AFC	27
Rams	LAR	NFC	28
Colts	IND	AFC	29
Cardinals	ARI	NFC	30
Texans	HOU	AFC	31
Bears	CHI	NFC	32