**Monograph:**
Gregory-Smith, I. (2019) Wages and labor productivity. Evidence from injuries in the National Football League. Working Paper. Sheffield Economic Research Paper Series, 2019018 (2019018). Department of Economics, University of Sheffield ISSN 1749-8368

The University Of Sheffield.

Department Of Economics.

# Sheffield Economic Research Paper Series.

## Wages and Labor Productivity. Evidence from injuries in The National Football League

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ISSN 1749-8368

SERPS no. 2019018

June 2019

www.sheffield.ac.uk/economics

# Wages and labor productivity. Evidence from injuries in the National Football League

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June 2019

Studies in labor economics face severe difficulties when identifying the relationship between wages and labor productivity. This paper presents a novel identification strategy and demonstrates that the connection between wages and labor productivity is remarkably robust even when institutional constraints serve to distort the relationship. Identification is achieved by considering injuries to professional football players as an exogenous shock to labor productivity. This is an ideal empirical setting because injured players in the NFL can not be replaced easily because franchises are constrained by the salary cap. Injuries are shown to play a major role in franchise success and a tight connection between wages and marginal productivity emerges. This is in spite of regulatory frictions that serve to hold down wages for some workers.

JEL codes: J31, Z22

Key Words: Wages, labor, productivity, injuries, sports

## 1 Introduction

In textbook labor markets wages are exactly equal to the employee's marginal contribution to the firm's revenue, known as marginal revenue product ($W = MRP$). If the firm is tempted to pay less than this, competition ensures that the worker can always find alternative work at $W = MRP$ and the firm can always find another worker willing to work at $W = MRP$ in the event that the employee demands more. This result is found in economic models across the discipline. In macroeconomic models with microeconomic foundations it is often assumed explicitly that workers are paid their marginal product (Romer, 2011). In modern models of the labor market the competitive labor market is often working in the background. For example, in bilateral bargaining, wages may deviate from marginal revenue product according to how surpluses from production are split, but the employee's participation constraint is defined by their outside option, which is assumed to be equal to their marginal product in alternative employment (Binmore, 2007; Ashenfelter and Card, 2011).

Despite the equality between wages and marginal product being a fundamental result in the discipline, modern empirical studies tend to avoid testing the relationship. This is because observing and measuring the marginal productivity of labor is usually not possible. Instead, the literature typically uses secondary datasets of matched workers and firms to examine differences in earnings and uses panel data methods to control for heterogeneity in labor productivity. These studies have provided indirect evidence that wages may depart from

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marginal productivity for particular groups such as women (Goldin et al., 2017; Hellerstein et al., 1999) and black men and women (Charles and Guryan, 2008). Other studies find that competitive market forces dominate pay-setting concerns even in controversial settings such as the executive labor market (Gabaix and Landier, 2008; Kaplan and Rauh, 2013). However, none of these studies actually measures worker productivity because they do not assess the individual's marginal contribution to the firm's revenue.

A small body of work has tried to measure marginal productivity directly. The approach requires observations of firm's output, the assignment of a production function so that the individual contribution to the output can be plausibly determined as well as wages paid to the individual workers. For example, Scully (1974) estimates marginal productivity of baseball players by assessing the effect of their performance on the probability of winning and the elasticity of the franchise's revenue to winning. Frank (1984) estimates the marginal productivity of salesmen in 13 automobile dealerships based on the number of sales and the piece rate paid to each salesmen to infer the relationship between wages and productivity. Frank (1984) finds that wages are far more compressed than the variation in marginal productivity estimates would imply. Lazear (2000) uses individual data on auto glass installers to demonstrate the productivity gains associated with moving from hourly wages to piece rates and notes that workers on average see their pay rise by less than the productivity gains. However, confirming the relationship between individual productivity and individual wages is difficult because of standard identification issues such as omitted variable bias and reserve causality. It is unlikely that all relevant variables determining marginal revenue product can be measured without error and in Lazear (2000) there is clear evidence that the structure of wages impacts worker productivity. Therefore, a source of exogenous variation in productivity, together with individual data on wages and productivity is necessary to identify the relationship between wages and labor productivity.

This paper uses injuries to professional American Football players in the National Football League (NFL) to establish a direct link between wages and marginal productivity. The NFL offers an exceptional opportunity to identify the relationship between wages and marginal productivity. Injuries occur frequently in the NFL and team franchises are unable to replace injured players easily because the NFL operates a hard salary cap for every franchise in the league. The marginal dollar value of talent to the franchise is equal to the marginal change in win probability from employing the talent multiplied by the dollar value of a win (Szymanski, 2006). Therefore, the financial impact of an injury is the expected value lost from the reduced probability of winning. If the equality between wages and marginal product holds, the financial loss should be equal to the injured player's wage; *a dollar of injured talent is a dollar of productivity lost.*

Identification of the relationship between wages and productivity is possible because injuries do not fall evenly upon franchises. In fact, franchises experience significant variation in terms of the injuries they receive. Even a single injury to a star player can have a major impact on a season. Consider the 2011 Indianapolis Colts, who lost 14 out of a total of 16 games when their star quarterback Peyton Manning missed the season with a neck injury. In that year, Manning was paid \$26.4M or 13% of the salary cap for no on field productivity. If Manning's wages were equal to his marginal revenue product one would expect the franchise to lose an equivalent amount of revenue from having their worst season in 20 years.

An alternative approach to identification has been undertaken by Nguyen and Nielsen (2014).

Therein, stock price reactions to the unexpected deaths[2] of top executives are used to estimate the relationship between executive compensation and their contribution to the firm's market capitalisation. The authors find that higher paid CEOs do indeed have higher contributions to shareholder value. This is a strong result but the NFL setting employed in this paper offers some advantages in terms of identification. First, the incidence of sudden deaths to the CEO is rare, only 81 CEOs died at US firms unexpectedly between 1991 and 2008. Second, and perhaps more significantly, the CEO's value must be estimated with reference to the expected cost and benefits of the incoming replacement. For example, if the market believes that the incoming CEO is, in expectation, just as good value as the deceased CEO, the market reaction should be zero. The NFL setting does not suffer from this complication because the hard salary cap prevents highly paid injured players being replaced with like-for-like players[3]. Third, the stock market reaction must reflect only expected productivity differences between the deceased and incoming CEO. This is perhaps a strong assumption if the market negatively prices the uncertainty introduced when the CEO suddenly dies. For example, might other key employees now take the opportunity to leave the company? Therefore, while shocks to productivity can occur in other employment settings it is the high frequency of injuries, together with variation in player wages and the hard salary cap in the NFL offers specific advantages in terms of identification. Additionally, unlike some empirical settings, all data necessary for analysis are in the public domain including: player wages, contracts and precise statistical measures of performance, and the market's expectation of performance is captured by the betting odds prior to kickoff.

The following section outlines the relevant economic theory associated with the wages of professional sportsmen. One complication is that institutional features of the NFL, including the salary cap itself, may affect the market clearing wage rate for talent. In section 2.1, the possibility of injury is added to the baseline model and it is shown that the prospect of injury does not impact upon the market clearing wage of talent. However, whether player wages are actually below, equal to, or above marginal product is ultimately matter for empirical examination. Section 3 introduces the data and presents descriptive statistics, before the econometric estimation of whether $W = MRP$ in section 4. Section 5 concludes.

# 2 Wages and productivity in the NFL

Fort and Quirk (1995) is a well known model in the literature that captures the essential features of the NFL labor market. The problem for team $i$ is to choose a level of talent $t_i$ to maximise profits[4] $\pi_i$.

[2]The use of unexpected deaths in post as an identification strategy has been used in other empirical settings such as Jones and Olken (2005) who use unexpected deaths of country leaders to explain country growth rates.

[3]Even if a franchise is able to reorganise its team in the event of an injury to, for example the starting quarterback (QB), with an equally talented QB, it can only free up the salary cap space to do this by releasing talent from elsewhere in the team, thereby suffering a loss of productivity from those players. In practice, when starting QBs get injured it is almost always the job of the substantially lower paid backup QB to take the field until the starting QB recovers.

[4]Profit maximisation is the objective typically assumed in the literature for NFL franchises (Vrooman, 1995). Another possibility is that franchises maximise wins (Késenne, 2000b) subject to a profit constraint (which could be negative if the owner is willing to bankroll the franchise). While win maximisation is thought to be more appropriate in some European sports (Garcia-del Barrio and Szymanski, 2009), profit maximisation is a reasonable approximation for North American sports (Zimbalist, 2003)

$$\pi_i \quad = \quad R_i(w_i(t_i)) - ct_i \tag{1}$$

The share of talent $\frac{t_i}{T}$, generates a share of wins $w_i = \frac{t_i}{T}$ in a season. The share of wins generates revenue $R_i$. Each unit of talent costs $c$ in wages so team $i$'s wage bill is $ct_i$. There are no fixed costs. Total talent in the league is fixed at $T$ units of talent[5]. With each team in the league simultaneously maximising profits, the *laissez-faire* equilibrium condition is:

$$\frac{\partial R}{\partial t_i} = \frac{\partial R}{\partial w_i}\frac{\partial w}{\partial t_i} = \frac{\partial R}{\partial t_j} = c^* \tag{2}$$

Each team in the league increases their share of the talent until the marginal revenues from talent are equal and equal to the marginal cost of talent[6]. Consequently players receive their marginal product in wages. Note this does not imply equal talent shares. In Fort and Quirk (1995), team $i$ is able to leverage its talent stock to produce more revenue than team $j$ because it draws from a larger fan base. A strong-drawing team will continue to increase their talent stock from weak-drawing teams until marginal revenues are equalised. This is the 'dominant team' problem or the problem of 'unbalanced contests' (See Borland and Macdonald (2003) for a review). A desire for more balanced contests and less certain outcomes is the basis for regulations such as the salary cap.

The NFL salary cap constrains choices over talent with a view to restoring a more equal distribution of talent. Each team's annual wage bill must be below a limit[7] determined by a fraction $k$ of total league revenues $\Sigma R$:

$$ct_i \leq \bar{C} \quad hence \quad c \leq \frac{\bar{C}}{t_i} \tag{3}$$

where $\bar{C} = k\Sigma R; \;\; k < 1$

With $c = \frac{\bar{C}}{t_i}$ equilibrium wages clear below the marginal revenue of talent $\frac{\partial R}{\partial t} > c = \frac{\bar{C}}{t_i}$. If the cap $\bar{C}$ binds on both franchises then talent and wins are distributed evenly with $\frac{w_i}{w_j} =$

[5]It is argued that this is the appropriate assumption for a domestic league, such as the NFL, that is effectively closed to international talent (Késenne, 2014). This assumption implies that a when a team hires new talent it takes it away from another team in the league. This assumption is not appropriate for leagues open to international labor such as Association Football in the English Premier League where talent can be easily hired from Europe.

[6]An alternative equilibrium condition is discussed by Symanski (2006). Therein a strong argument is made that the choice made by teams in most professional sports is one over budget for talent and that because choices over budget are made simultaneously and independently by the teams (*à* la Nash-Cournot), teams do not internalise the externality that increasing their budget imposes on the other team. The result is that budget choices act as strategic substitutes and marginal revenues from talent are not equalised. However, for our purposes the simpler 'Walrasian' equilibrium (Késenne, 2014) is appropriate as talent supply in the NFL is fixed making teams much more aware of the externalities that their hiring choices impose. Additionally, budgets are actually fixed by the salary cap.

[7]The cap is actually a window as NFL franchises must satisfy $ct_i > \underline{C}; \underline{C} = l\Sigma R, l < k$. While theoretically, a team could desire to spend less on talent than allowed by the lower limit, more often than not, it is the upper limit that binds on NFL franchises.

$\frac{t_i}{t_j} = \frac{t_j}{t_i} = 1$. The impact of the cap on franchise profits is theoretically mixed. Since wages are held lower, profits increase (especially for the smaller franchises) but, since talent is not always able to move to where it is most profitable, franchises (particularly larger ones) lose profits to misallocation (Késenne, 2000a, 2014).

The other main regulations with the claimed intention of promoting competitive balance currently in operation in the NFL are the reverse order of finish college draft system and revenue sharing. Under the draft, the worst performing teams from the prior year get the first choice from the pool of graduating college students entering the league. However, the literature has emphasised the 'invariance principle' (Rottenberg, 1956), which, in the spirit of the Coase theorem, argues that the initial allocation of talent does not affect final distribution of talent when talent can be traded easily between teams (though it is debateable whether this is in fact the case). Additionally, franchises in the NFL share approximately 60% of their revenue. Quirk and Fort (1992) show that revenue sharing in the standard model reduces demand for talent therefore lowers the market clearing wage relative to what would occur under profit maximisation and no revenue sharing but does not affect competitive balance[8]. Therefore, it is the salary cap in the NFL which potentially plays the most important role in affecting competitive balance and the extent to which players' wages are tied to the players' marginal products.

## 2.1 Injuries

In Fort and Quirk (1995) the choices over talent map one-to-one with wins. I now extend their baseline model to consider the uncertainty that is introduced when injuries shock the talent stock. This section also considers the assumption underpinning the identification strategy that will be used when estimating the relation between wages and marginal productivity.

Let team $i$ experience a talent shock due to injury $\mu_i \sim N(0, \sigma)$. Ex ante, teams can not forsee injuries to their talent or their rival's talent so the expectation of the shock is normalised to zero. Positive realisations of $\hat{\mu}$ can be interpreted as injuries to the opposing team ($\hat{\mu_i}+\hat{\mu_j} = 0$). In the NFL, talent is distributed unevenly between players within a team so an injury to a single star player could be enough to change the sign of $\hat{\mu}$. A team is unable to replenish its talent stock after the injury shock until the next season because of the salary cap. The wages of injured players must be honoured and count towards the cap in the NFL.

When $i$ plays $j$, the probability $p$ that $i$ wins is affected by the realisation of shock. Talent stock $T$ in the league (after all injuries are realised) is fixed and normalised to 1. At the start of the season spending on talent by the teams is equal as determined by the salary cap $t_i = t_j = \frac{\bar{C}}{c}$.

$$Prob(win_i = 1) = p = \frac{t_i + \hat{\mu_i}}{T} \tag{4}$$

Injury shocks reduce the probability of winning and because wins generate revenue, expected revenue falls. If talent earns its marginal product, the total injury bill (holding $j's$ injuries constant) equals the expected loss in revenue $L$:

[8]Alternative models of franchise behaviour such as win maximisation as presented by Késenne (2014) show that revenue sharing increases the clearing rate for wages and could promote balance.

$$c^*\hat{\mu} = \frac{\partial R}{\partial t_i}.\hat{\mu} = \frac{\partial R}{\partial w_i}.\frac{\partial w_i}{\partial t_i}\hat{\mu} = L \tag{5}$$

Equation 5 is the key equality that this paper wishes to test. With data on injuries and player wages, the dollar value sitting out due to injury $c^*\hat{\mu}$ can be observed. While it is not possible to observe directly the franchise revenue lost to injury $\frac{\partial R}{\partial t_i}.\hat{\mu}$ it can be calculated by estimating the reduction in win probability from injured players $\frac{\partial w_i}{\partial t_i}.\hat{\mu}$ together with the marginal revenue from winning $\frac{\partial R}{\partial w_i}$. This task is conducted in section 4.

The crucial identifying assumption for an unbiased estimate of $\frac{\partial R}{\partial w_i}.\frac{\partial w_i}{\partial t_i}\hat{\mu}$ is that the expectation of the injury shock is zero and remains zero after conditioning upon the choice of talent by franchise $i$, that is $E(\mu_i|t_i) = 0$. In other words, injuries are assumed to be exogenous to talent choice. What are the threats to this identifying assumption? First, because the collisions that occur on the field of play are deliberate actions one may reasonably question whether injuries are not also a part of deliberate strategy by opposing teams. Moreover, it will be seen below that injuries during the game, particularly to key players such as the starting quarterback significantly impact the likelihood of winning that game. This provides an incentive to injure opponents and an incentive to take actions that mitigate the injury risk. Of course, targeting players for injury is illegal and heavy penalties are imposed for any team caught doing it, thereby reducing the incentive. However, there is sufficient ambiguity in tackling that a policy of targeting players for injury could go undetected and anecdotal evidence suggests that 'bounties', small bonuses for a knock-out hit on an opponent, was a historical practice. This was brought to light in the case of the New Orleans Saints who were heavily penalised for allegedly offering bounties for players between 2009 and 2011. Coaches and players involved were given suspensions and the franchise was fined \$0.5m and, more significantly, forfeited their draft selections for 2012 and 2013. An issue emerges if high earning players are more likely to be targeted than regular players[9]. This potentially introduces a correlation between talent $t_i$ and the injury shock $\mu_i$. The pool of injured players from which lost productivity is being estimated could then over represent highly paid star players.

To indicate whether or not this is a likely problem affecting the estimates, two tests are provided in the appendix. Table A1 performs a balance test on the control variables, according to whether an injury occurred to the starting quarterback during the game. If such injuries occur randomly, there should be no significant differences in the means of the observable variables. All the monetary variables are calculated net of the opposition so should be zero in expectation, irrespective of whether or not an injury occurs to the starting quarterback. This is indeed the case, for the total amount of injured money sitting on the bench, the gini coefficient, the ratio of starting wages to non-starting wages and the total wage bill. Additionally, the both in the injured and non-injured groups, the team plays Away from home 50% of the time and there is no difference in the number of rest days prior to the match. Crucially, the market is unable to predict within game injuries as the difference in the vegas spread is also approximately zero for the two groups. The table also shows the importance of the injury to the quarterback. The backup quarterback's passing rating is 16 points less than the starting quarterback's passing rating at the mean.

[9] Although the main identifying specification is restricted to the quarterback position only.

The second test is reported in Table A2 and explores the relationship between injuries and player wages in more detail. Supporting the identifying assumption that injuries are exogenous to talent choices, Table A2 finds no robust relationship between injuries and player wages. There are several plausible reasons why injuries remain exogenous despite apparent incentives to injure star players. First, many injuries simply occur off the field or are triggered during training and therefore are not the result of a single deliberate collision by an opponent. Second, to the extent that opponents may seek to injure talented players more than non-talented players there is an equal incentive for teams to protect their talented players[10]. Third, it is well known that there exists an informal code whereby players taking 'dirty shots' can expect retaliation by the more physical players on the field and sometimes a rebuke from their own teammates. Fourth, players often continue to play through knocks received during a game and are only diagnosed with a serious injury after the game. This means the beneficiaries of an injury to a star player could be the teams who have yet to play against the injured player, rather than the team responsible for the injury. Given that any player can pick up an injury at any time, both on and off the field and even after a serious collision with an opposing player it is very difficult to predict whether or not an injure will occur, what the nature of that injury would be and the likely duration of the injury. Since the market cannot predict injuries, it is argued that there always remains a substantial stochastic element to any footballer's injury.

Section 4 tests whether equation 5 holds, although it can be noted here that are reasons to suspect departures from this equality. In particular, with the salary cap binding, the total injury bill equals $\frac{\bar{C}}{c}\hat{\mu} < c^*\hat{\mu} = L$. If wages are constrained below the market clearing equilibrium due to the salary cap the dollar value sitting out due to injury will be less than the franchise revenue lost due to injury. Players may be willing to accept with such terms if playing for an NFL franchise affords outside earnings such as lucrative deals for product endorsements. On the other hand, since entry to the league through the draft is controlled by the existing player's union, it is possible that wages are held up above their market clearing rate for some players, for example, in favour of veteran players at the expense of rookies. Therefore, whether players earn their marginal product is ultimately an empirical question [11].

# 3 Data

An advantage of the NFL setting is that most of the data necessary for analysis is located in the public domain. Detailed information on player wages and bonuses from 2011-2015 was collected from *spotsrac.com*. Richard Borghesi provided the author with data on salaries from 1995-2001 which had been collected from USAToday[12]. While a player's compensation can exhibit complicating features such as singing on bonuses and performance incentives the

[10]The reason that the position of Left Tackle is the second highest paid position is because their job is to protect the Quarterback. This is described in detail by Lewis (2007).

[11]The extent to which competition is balanced in a season is also affected by the realisation of the injury shock in a similar way $\frac{w_i}{w_j} = \frac{t_i+\hat{\mu_i}}{t_j+\hat{\mu_j}}$. Since the expectation of the shock is zero, competitive balance ex-ante is unchanged. However, the variance of the shock will influence the realisation of the distribution of wins. If teams are closely balanced ex ante, the prospect of injury is likely to reduce balance as injuries are realised unevenly between teams. If teams are unbalanced ex ante, the prospect of irreplaceable injured talent could increase balance ex post as the dominant team has more talent to lose. However, the focus in this paper is on wages and productivity rather than competitive balance.

[12]Unfortunately, USAToday has withdrawn their salary data from the public domain.

bottom line is a 'CAP number' which is assigned to each year of the player's contract for the purposes of monitoring the franchise's compliance with the annual Salary Cap. It is the CAP number which represents the opportunity cost of the player and is essentially sunk by the franchise at the start of the season. If the player is injured, and can not play, the CAP number remains unchanged for the duration of the season.

Performance data was hand collected from *sports-reference.com*. The data is at a high level of disaggregation. In addition to a large number of variables which captures team performance in each game, performance statistics for each player is available on a game by game basis. For each season, each player is assigned a performance rating and for each game the Quarter Back, the highest paid and most important position in the NFL is assigned a passing rating based on each play that the player made during the game. Additionally, information from betting markets can be incorporated to capture the expectation of a franchise's performance in each game.

Data on injuries, games missed and substitution of starting players for backup players is obtained from *sports-reference.com* and *mangameslost.com*. Caporale and Collier (2015) calculate the number of man-games lost over the course of the season due to injuries and use the variable as a control in a regression of win percentage over an NFL season, exploring the impact of rebalancing mechanisms such as the college draft. This paper adopts a fundamentally different approach by exploiting data on injuries to individual players both over the course of a season and during individual games, with a view to matching this information to each player's wage. This permits an analysis of injuries at the team-season level, the team-game level and, in respect of the quarterback position, within games.

### 3.1 Descriptive Statistics

A large degree of variation in player wages will assist the identification of the causal impact of a dollar lost to injury on the probability of winning. Table 1 shows mean payments by key positions between 2011 and 2015. Panel A provides a breakdown of the different elements compensation by position. In addition, to salary, players receive additional payments when signing the contract *Singing* and making the playing squad *Roster*. There is substantial variation between positions. The Quarter Back (QB) commands a salary that is, on average, twice that of the running back. Panel A also shows that QBs receive more supplements to their salary. The final column in Panel A labelled 'Dead Money' records the amount charged to the Cap in the event that the player is cut in that year. Dead money indicates that the franchise has committed to paying the player an amount which can not be recovered if the player is cut before the end of their contract.

As well as substantial variation between positions there is substantial variation within positions. Panel B shows the breakdown by year of the Cap hit (all elements of pay charged to the Cap for each year) within team franchises. The standard deviation on the QBs Cap hit implies is $5m, more than twice the mean salary with larger variation at the top end of the distribution. Consistent with Rosen's 1981 'superstar' theory of wages, the 90th percentile QB is paid 10 times more than the median QB, with the 99th percentile paid a further 1.5 times the 90th percentile QB. Within the same position *and team*, variation is even greater. The starting QB is paid, on average, 10 times more than the backup QB. If the starting QB is injured, one can expect a substantial reduction in the probability that the team wins the

Table 1: Player Wages 2011-2015

Panel A: Mean wages by position

| Position | N | Salary | Signing | Roster | Dead Money |
|---|---|---|---|---|---|
| *Offense* | | | | | |
| Quarter Back | 467 | $2,094k | $1,006k | $248k | $4,953k |
| | | | | | |
| Left Tackle | 283 | $2,044k | $629k | $162k | $3,504k |
| Running Back | 697 | $1,019k | $295k | $96k | $1,044k |
| Wide Receiver | 1,091 | $1,133k | $416k | $106k | $1,786k |
| | | | | | |
| *Defence* | | | | | |
| Defensive line | | | | | |
| Line Backer | 738 | $1,221k | $515k | $134k | $2,001k |
| Corner back | 973 | $1,217k | $402k | $124k | $1,556k |

'Dead money' is charge to the cap if the player is cut.
Signing bonuses are paid upon signing.
Roster bonuses are conditional upon making the active roster.

Panel B: Cap hit Inequality Measures

| Year | Team Cap | Mean | S.D | Gini | 99by90 | 90by50 | 75by25 |
|---|---|---|---|---|---|---|---|
| 2011 | $120.0m | $1,806k | $2,410k | 0.5679 | 2.566 | 6.744 | 4.659 |
| 2012 | $120.6m | $1,719k | $2,441k | 0.5818 | 2.582 | 7.156 | 4.036 |
| 2013 | $123.0m | $1,791k | $2,513k | 0.5885 | 2.550 | 7.301 | 4.167 |
| 2014 | $133.0m | $1,900k | $2,704k | 0.5927 | 2.566 | 7.170 | 4.444 |
| 2015 | $143.3m | $2,009k | $2,842k | 0.5984 | 2.757 | 7.369 | 4.620 |
| | | | | | | | |
| Pooled | | $1,843k | $2,587k | 0.5870 | 2.665 | 7.070 | 4.352 |
| | | | | | | | |
| Pooled QB | | $3,744k | $5,075k | 0.6352 | 1.501 | 10.427 | 8.519 |

All wages in nominal values.
90by50 Divides wages at the 90th percentile by the 50th percentile.

Table 2: Player Injuries

Panel A: 1995-2001

| Position | N | N injured | Missed 16 | Injury Frequency<br>Missed 7-15 | Missed 1-6 | Missed 0 |
|---|---|---|---|---|---|---|
| *Offense* | | | | | | |
| *Quarterback* | 522 | 142 | 0.029 | 0.081 | 0.163 | 0.728 |
| *Running Back* | 1,051 | 187 | 0.021 | 0.031 | 0.126 | 0.822 |
| *Wide Receiver* | 1,102 | 190 | 0.018 | 0.038 | 0.116 | 0.828 |
| *O Line* | 2,423 | 503 | 0.022 | 0.043 | 0.144 | 0.791 |
| *Defence* | | | | | | |
| *D Line* | 1,717 | 312 | 0.019 | 0.026 | 0.137 | 0.818 |
| *Line Backer* | 1,431 | 237 | 0.018 | 0.030 | 0.117 | 0.836 |
| *Cover* | 1,958 | 335 | 0.018 | 0.030 | 0.122 | 0.829 |
| *Special Teams* | 261 | 5 | 0.019 | 0.000 | 0.000 | 0.981 |

Panel B: 2011-2015

| Position | N | N injured | Missed 16 | Injury Frequency<br>Missed 7-15 | Missed 1-6 | Missed 0 |
|---|---|---|---|---|---|---|
| *Offense* | | | | | | |
| *Quarterback* | 349 | 92 | 0.049 | 0.106 | 0.109 | 0.736 |
| *Running Back* | 574 | 115 | 0.017 | 0.052 | 0.130 | 0.801 |
| *Wide Receiver* | 796 | 167 | 0.013 | 0.053 | 0.145 | 0.790 |
| *O Line* | 1,635 | 439 | 0.026 | 0.072 | 0.174 | 0.731 |
| *Defence* | | | | | | |
| *D Line* | 1,144 | 227 | 0.013 | 0.047 | 0.140 | 0.801 |
| *Line Backer* | 991 | 230 | 0.019 | 0.052 | 0.159 | 0.770 |
| *Cover* | 1,384 | 328 | 0.017 | 0.062 | 0.160 | 0.762 |
| *Special Teams* | 163 | 1 | 0.006 | 0.000 | 0.000 | 0.994 |

Notes:
1. N counts the number of player-seasons at each position.
2. N injured counts the number of player-seasons with any injury of any duration.
3. Injury frequency is the proportion of players who missed any part of X number of games that year. For example, in panel A, only 2.9% of QBs missed the entire season but only 72.8% of QBs went the entire season without missing any playing time due to injury.
4. *O Line* comprises Guards, Centers, Tackles and Tight Ends. *D Line* comprises and Defensive Ends and Tackles. *Cover* comprises Safeties and Corners and Defensive Backs. *Special Teams* comprises Kickers, Punters and Long Snappers.

game. Further descriptives are provided in the appendix that demonstrate the high degree of wage variation between NFL players.

Table 1 also shows inflation in nominal wages at the mean over a relatively short sample period. There are small increases in the Gini coefficient over the same period, implying that the increase has gone to paying the higher paid players a little more. This has occurred alongside increases in the overall team cap. The overall cap is determined each year by a formula based on approximately 48% of total league revenues. If the salary cap is increasing, it implies aggregate franchise revenues are increasing. The Cap has increased substantially since its introduction in 1994 at $34.6m.

Panel A of Table 2 introduces the second time period for which data is available and shows the incidence of injury over the season by position for the years 1995-2001. Season long injuries occur relatively infrequently, with only 2.9% of QBs missing the entire season due to injury. However, injuries frequently cause players to miss part of the season. Only 72.8% of QBs manage the entire season without any injury at all. Injury rates at other positions are lower, with 79% of Offensive Linesmen to 83.6% of Linebackers going the whole season uninjured. Injuries to Punters and Kickers in the *Special Teams* are very rare.

How has the incidence of injury changed over time? The NFL has become more conscious of 'player safety' over the sample period. In April 2016, a federal appeals court upheld an out of court settlement between the NFL and multiple concussion lawsuits filed by former players. The settlement is thought to be worth approximately US$1 billion and will cover approximately 20,000 players. Since 2009, the NFL has introduced a 'concussion protocol' and tightened its rules on concussions. However, it is unclear whether this will increase or decrease the number of observed cases of injury in the data. While the true injury risk is likely to be reduced, the recorded number of injuries might increase because the ability to diagnose this type of injury has improved[13]. Other restrictions on blocking and tackling have also been introduced to decrease the likelihood of an injury occurring. For example, in 2016, the 'chop block', where a player blocks another high on the body, while a teammate hits the same player low, became illegal due to risk of knee injuries.

Referring to panel B of Table 2 which pools data across the years 2011-2015, the incidence of being injured for the whole season is 2 percentage points higher for Quarterbacks compared to the 1995-2001 period. While a small increase in absolute terms, this is two-thirds higher than the prior period. It appears the reduced injury risk has been offset by the increased rate of injury detection (and perhaps an increased fear of litigation) between the two periods. However, the likelihood of the Quarterback going the entire season uninjured is marginally higher in the later period. Together, these descriptive statistics are consistent with increased protection of the Quarterback position so that minor injuries occur less often, but when major injuries do occur they are treated more seriously and force longer absences from the field of play.

The differences between the time periods at other positions are not so clear. The rates of season long injury are broadly similar in the second period and marginally fewer players go the entire season uninjured. It would appear that it has been the Quarterbacks who have been the main beneficiaries of the rule changes that have targeted player safety. It is clear

[13] As of 2016, whenever a potential concussion is identified the player is removed from the game and an independent Neurotrauma consultant will examine the player.

Table 3: Injury Types 2011:2015

| Injury | N | Percent | Duration (weeks) | St. Dev |
|---|---|---|---|---|
| Knee | 1,224 | 21.22% | 8.85 | 13.08 |
| Ankle | 710 | 12.31% | 4.45 | 6.71 |
| Hamstring | 668 | 11.58% | 3.22 | 4.44 |
| Leg | 408 | 7.07% | 5.48 | 11.37 |
| Shoulder | 380 | 6.59% | 5.96 | 8.55 |
| Concussion | 377 | 6.54% | 3.27 | 6.07 |
| Foot | 375 | 6.50% | 7.25 | 9.60 |
| Groin | 240 | 4.16% | 2.81 | 3.01 |
| Hand | 203 | 3.52% | 4.72 | 4.92 |
| Back | 174 | 3.02% | 5.24 | 9.04 |
| Chest | 158 | 2.74% | 5.24 | 7.50 |
| Hip | 132 | 2.29% | 7.15 | 12.09 |
| Illness | 132 | 2.29% | 4.98 | 12.19 |
| Neck | 103 | 1.79% | 6.22 | 10.64 |
| Undisclosed | 99 | 1.72% | 12.70 | 10.48 |
| Achilles | 96 | 1.66% | 14.11 | 11.57 |
| Arm | 85 | 1.47% | 9.44 | 5.75 |
| Head | 84 | 1.46% | 2.57 | 3.51 |
| Elbow | 60 | 1.04% | 4.41 | 5.12 |
| Other | 60 | 1.04% | 3.33 | 3.26 |
| Total | 5,768 | 100.00% | 5.95 | 9.58 |

Notes:
1. N counts the number of unique injuries to players in the NFL between 2011 and 2015
2. Percent is the percentage of all injuries accounted for by the injury type
3. In 2.7% of cases, two body parts were identified as injured. To avoid double counting, the injury was assigned to the first recorded category. E.g. "Knee/ankle" was classified as a knee injury, whereas "Ankle/knee" was classified as an ankle injury

then that the Quarterbacks, are not only paid very differently to other players but experience injuries differently as well. This motivates a separate analysis of injuries and wages to QBs below.

Table 3 uses more detailed data on injuries from *mangameslost.com* for the period 2011-2015. Here, injuries are classified to all NFL players on a game by game basis. Duration is calculated by taking the number of days from being declared injured until the date of the next game when the player was available for selection and the mean number of weeks is reported. Duration is right censored at seven days after end of the regular season. Knee injuries are the most common injuries and keep players out for a relatively long period of time, almost 9 weeks on average. Only 6.5% of injuries were due to concussions and these players were rested for an average of 3 weeks.

### 3.2 Injuries and the probability of winning: Season and Game level

The data allow estimation of the impact of injuries on the probability of willing at different levels of aggregation: at level of the season, the game and within the game itself. For the purposes of identification, injuries that occur to Quarterbacks within the game itself represents

Table 4: Injuries on the probability of winning: season level 1995:2001

| | OLS | | FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Ln Injured money | -0.24*** | -0.24*** | -0.23*** | -0.23*** |
| | (-3.39) | (-3.39) | (-3.05) | (-3.05) |
| *Control Variables* | | | | |
| Ln(Wage bill) | 1.93*** | 1.93*** | 2.56*** | 2.56*** |
| | (3.79) | (3.79) | (4.81) | (4.81) |
| Ln(Wage bill standard deviation) | | -1.39*** | | -1.83*** |
| | | (-3.59) | | (-4.71) |
| Year dummies | Yes | Yes | Yes | Yes |
| Observations | 213 | 213 | 213 | 213 |
| Number of teams | | | 31 | 31 |
| R-squared | 0.119 | 0.119 | 0.153 | 0.153 |

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the tightest specification. Prior to this, let it be shown that total injuries that occur over a season are important enough to affect franchise's record over that season and that injuries prior to match day also have an impact on the likelihood of winning that particular match. Using data aggregated at the season level analysis for the period 1995-2001, the dependent variable in Table 4 is the percentage of games won by team $i$ in season $t$ expressed in log odds $w_{it} = ln(w_{it}/1 - w_{it})$. Estimation is by OLS and fixed effects (FE). The FE estimator controls for unobserved team level fixed effects. Given that it is likely there are unobserved factors that could contribute to the winning record, the FE estimates are preferred, alebit in practice the estimated coefficients are similar.

The main explanatory variable of interest is *Ln Injured money* and is defined as the natural log of the total amount spent on player wages while the players were injured. For example, a player who misses eight games out of the sixteen games in the regular season due to injury, would add 50% of their total compensation to *Injured money*. Total compensation in this dataset is the sum of salary and bonuses received during the year. Controlling for team's wage bill for the season, the total amount spent on players, the impact of *Injured money* on the franchise's playing record over the regular season is explored. Since not all teams qualify for the small number of games that occur postseason the analysis is restricted to the regular season only. The median team wins and loses 8 games in the season (an 8-8 record). The estimated coefficients on *LnInjured money* show that injured money is important for a franchise's success in that season. The standard deviation of *Ln Injured money* is close is 1.05, making interpretation of the effect size relatively straightforward. Taking the FE estimate in column (4), a one standard deviation change in Injured money changes the log odds of winning by 0.23. This implies a team with an 8-8 record who experiences a one standard deviation injury shock sees their record fall on average by one game, to 7-9. Likewise, a two standard deviation injury decrease in Injured money implies the median team would improve to 10-6 which is typically required to qualify for the post-season games with the prospect of playing in the Super Bowl.

$Ln(Wage\ bill)$ is the natural log of the total amount spent by the franchise on player wages during the season. If every team spent exactly the same on player wages as implied by the theoretical version of the cap in Section 2, then this variable would not be identified. However, in practice, there is significant variation between teams spending and within team-years. Smaller franchises may not wish to spend the full amount permitted by the cap, although they must spend at least 90% of the cap. Additionally, since the cap permits certain elements of pay, such as signing bonuses to be charged over the life of the cap (see appendix) teams can strategically vary the amount charged to the cap in any one year. For these, reasons the wage bill does vary and as expected, teams that pay more in a season, win more games on average in that season. From the FE estimate of column 4, a 10% increase in franchise spending in that season implies approximately 0.25 increase in the logodds, which is close to the same effect size as a one standard deviation injury shock.

Table 4 also reports another interesting control variable. It has been argued in the literature that wage inequality within teams diminishes team performance (Borghesi, 2008) perhaps due to a withdrawal of effort among relatively low-paid players. $Ln(Wage\ bill\ standard\ deviation)$ measures the within team wage spread in each year and estimated coefficients are negative. From the FE result, a 10% increase in the standard deviation of the wage bill, holding the total bill constant, reduces the median team's record by approximately 0.7 of a win. However, care is required when interpreting this estimate. A team that spends more typically does so by recruiting more star players, or by paying more for star players. This inevitably increases the standard deviation of wages within the team. Indeed, the Pearson's correlation coefficient between the wage bill and its standard deviation is 0.889, highly collinear. Since it is unlikely that significantly reducing the inequality of wages within the team is feasible without also reducing the total talent in the team one should caution against a strategy focused solely on wage equality without regard to total team spend.

While analysis at the season level provides a broad overview of the impact of injuries, a limitation of the analysis is that it aggregates information across all the games in the season. Important determinants of match outcomes, such as who the team is playing, the market odds prior to kick off, whether or not the team is playing at home can only be controlled for on a game by game basis. Therefore a more precise analysis is offered with data in Table 5, which reports the game level analysis where each of the 32 NFL franchises play 16 games over 5 regular seasons 2011-2015. Additionally, the wage data available in the period 2011-2015 is more detailed than that from 1995-2001 because the data records the official 'cap number' that represents the charge to the salary cap for the franchise over that season.

For each game, the dependent variable takes the value of 1 if a win is recorded and zero otherwise. Estimation is by logit and a conditional logit which controls for team level fixed effects. Controlling for fixed effects over a five year period should be a reasonably tight specification because unobservables such as training facilities and franchise culture should not vary a great deal over this time period. $Ln\ Injured\ Money\ (net)$ is the natural log of total wages for players who were unable to play that game net of their opposition's injured wages. This variable mirrors the injury shock $c.\mu_i$ outlined in the theory section above. Table 5 reports the estimated coefficients and marginal effects for the main variables of interest are interpreted below.

The estimated coefficient of the raw effect of $Ln\ Injured\ Money\ (net)$ in column (1) implies an average marginal effect (AME) of -0.07. A one standard deviation change in this variable

Table 5: Injuries on the probability of winning: game level 2011:2015

| | Logit | | | Logit FE | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln Injured Money (net) | -0.29*** | -0.18*** | -0.13** | -0.29*** | -0.19*** | -0.12* |
| | (-5.18) | (-2.93) | (-2.01) | (-4.88) | (-2.88) | (-1.73) |
| *Control Variables* | | | | | | |
| Starter Gini (net) | | -0.20 | 0.33 | | -0.51 | 0.23 |
| | | (-0.42) | (0.68) | | (-0.92) | (0.40) |
| Starter/Non-Starter (net) | | -0.041 | -0.037 | | 0.011 | -0.045 |
| | | (-0.32) | (-0.28) | | (0.081) | (-0.31) |
| Away | | -0.55*** | 0.036 | | -0.59*** | -0.038 |
| | | (-6.79) | (0.39) | | (-7.02) | (-0.40) |
| Ln Wage Bill (net) | | 1.40*** | -0.013 | | 1.21*** | 0.12 |
| | | (4.58) | (-0.040) | | (3.62) | (0.33) |
| Rest Days (net) | | -0.00030 | -0.013 | | -0.00077 | -0.013 |
| | | (-0.018) | (-0.77) | | (-0.046) | (-0.75) |
| Vegas Spread | | | 0.14*** | | | 0.13*** |
| | | | (16.9) | | | (13.4) |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,529 | 2,528 | 2,528 | 2,529 | 2,528 | 2,528 |
| Number of teams | 32 | 32 | 32 | 32 | 32 | 32 |

Estimated coefficients reported not marginal effects.
The estimated coefficient of *Ln Injured Money (net)* in column (1) implies a marginal effect of -0.07.
Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

implies an extra win over the course of the season consistent with the result found at the season level above. When converted to dollars (in millions) the AME is -0.006. A one standard deviation injury shock is approximately \$15.25M in player wages. This implies a one standard deviation increase in this variable implies a 9 percentage point reduction in the probability of winning that game (unconditional). With 16 games in the season, the one standard deviation injury shock implies losing 1.47 games in the season. To equate wages with marginal revenue product a single win for the franchise would need to be equal to \$10.4M.

The control variables that play an important role in win probability include $Away$, a dummy which equals 1 for an Away fixture (AME 0.13) and the total wage bill of the franchise net of the opponent (AME 0.28) in the relevant year. Two measures on inequality within the franchise are included; the Gini coefficient among starting players and the ratio of the starters wage bill to non-starters. However, nether of these variables are statistically significant. The inconsistency between this result and that obtained at the season level, could be explained by the tighter specification permitted by the game level analysis. In particular, the measures of wage inequality of at the level of the game now control for the opposition's inequality and wage bill as well. Once these variables are included, the measures of wage inequality do not have a major impact.

The most important control variable for the analysis is the Vegas Spread for each game which is included in columns (3) and (6). This provides the market's expectation of the probability of winning. For each game, an under/over spread is offered on either team. If A plays B and the Vegas spread is +7, then the market is predicting that A has a 50% chance of winning by 7 or more points and that B has a 50% chance of winning or losing by 7 or less. Card and Dahl (2011) show this variable is an unbiased predictor of match outcomes and a replication of their test with this more recent data period is shown in the appendix. The estimated coefficient in column (6) implies an extra point on the spread is worth 3% in win probability. Since all the control variables in Table 5 are known to the market prior to kick off, one would expect them to be priced in to the Vegas Spread, otherwise it would imply outstanding arbitrage opportunities, such as betting just on away teams. However, as shown in columns (3) and (6), the control these variables are no longer predictive of the match outcome once the Vegas Spread is accounted for. However, there remains an effect on the margin of statistical significance for the main variable of interest $Ln\ Injured\ Money$ ($net$). This is likely due to some uncertainty prior to kick off surrounding the extent of injury to some players. Whether a player misses a game due to injury is coded retrospectively as a one or zero and it is not known whether the market gave an a player who is coded injured some chance of playing prior to kick off. In other words, the market is unable to price in all injuries perfectly prior to kick off. The following section presents a more precise analysis using injuries to quarterbacks during the game itself but even at the broader levels of aggregation presented above, injuries play a role in winning games.

# 4 Main Results

## 4.1 Injuries and the probability of winning: Within game analysis

The most critical position in the NFL is the Quarterback (QB). They are the highest paid (see above) and play a unique role in the side as they are responsible for play selection as well as play execution[14]. More so than a captain in Association Football or a Point Guard in Basketball, Quarterbacks have a major bearing on the outcome of the game. In their 53 man squad (roster), a team will employ a starting QB and at least one and sometimes two or three backup QBs in case of an injury to the starting QB. As such an injury within game to the starting Quarterback represents the cleanest shock to labor productivity in the NFL.

For the period 2011 to 2015, it is observed in the data from *sports-reference.com* whether the starting QB was replaced by the backup QB during any game. One advantage with the data from this period is that the replacement can be cross-referenced to data on injuries from *mangameslost.com*, where the specific nature of the injury, whether it is to the head or other part of the body, is observed. This means one is able to verify the seriousness of the injury, so that instances of 'tactical substitutions', where the starting QB is not really injured but replaced by the backup QB for performance reasons can be correctly excluded. On occasions, QBs are substituted late in the game when the contest is already won and these can also be excluded. Furthermore, historical match reports were cross-referenced from *nfl.com* to ensure the in-game QB substitutions represented genuine injury shocks.

Table 6 shows the results. When the backup QB is required to take the field the team is more likely to lose by 28 percentage points (average marginal effect 'Injured QB' col(1)). Likewise if the opponent's QB steps in the team is more likely to win by 28 percentage points. These estimated effects are equivalent to giving the other team 9.5 points on the spread. Column (2) confirms that this injury is not predicted by the market prior to kick-off and column (3) shows this is unaltered by unobserved franchise fixed effects. An injury to the starting QB is clearly a major shock to the franchise.

Most starting QBs experience variation in form over their career and therefore their contribution relative to a backup QB is likely to vary. It is possible to control for how well a QB played during the game with their official 'passing rating'. Passing rating is measured on a scale from zero to 158.3 points for a perfect game[15]. The estimated coefficient on passing rating in column (4) shows how important the QB's performance is to the probability of winning. A one standard deviation increase in the passing rating corresponds to a 19% point increase in the likelihood of winning. Backup QBs replacing injured QBs on average have 16 fewer points in passing rating per game, which equates to 12 fewer percentage points in the likelihood of winning each game. Passing rating is capturing approximately half of the effect of substituting in the Backup QB. Of course, in any one game a Backup QBs can play well and help their team win[16]. However, given the same passing rating in the game, an injury to the starting QB further reduces the likelihood of winning. It is likely that the weaker passing game of the backup QB allows the opposition defence to line up against running plays with greater certainty, rendering non-passing plays less effective. Additionally, to the extent that the starting QB's may possess superior leadership skills, are better at changing the play at the line of scrimmage or are better at running the ball themselves, franchises may benefit from

[14] Plays are also designed and selected by the Head Coach and Offensive Coordinator

[15] Four categories are used as a basis for compiling a rating: Percentage of completions per attempt, Average yards gained per attempt, Percentage of touchdown passes per attempt and Percentage of interceptions per attempt. A passing rating of over 100 is considered a very good performance *http://www.nfl.com/help/quarterbackratingformula*

[16] Nick Foles won the Most Valuable Player award in his winning Super Bowl appearance in 2017 as a backup QB with an excellent passing rating of 106.1, 15 points above the average for a starting QB and 26 points above the average for a backup QB.

these attributes.

There is considerable variation between franchises in the difference in wages between starting and backup QBs and therefore the shock of losing the starting QB to injury is also expected to vary. Column (5) examines '$\Delta$ Injured-Backup QB wage' which interacts an injury to the starting QB during the game with the wage differential between the starting QB and backup QB who replaced them. The estimated coefficient for this variable implies a one standard deviation increase in the wage differential is associated with a loss of 7 percentage points in the likelihood of winning, conditional upon the starting QB getting injured during the game. For illustrative purposes, a one standard deviation in wage differential is approximately \$11M at the median. Therefore, the implied marginal productivity for \$10M of QB wages would equal approximately 6.6 percentage points in the likelihood of winning each game , or approximately 1 game over the course of the regular season. Therefore, a win would need to be worth approximately \$10M to the franchise in order to equate median QB wages with their marginal revenue product. This is almost exactly the same as the estimates obtained above when adding up the wage bill of injuries at all playing positions, albeit the identification on QB injuries is much more precise.

As expected, the effects sizes in Table 6 are symmetric for the opposition variables (none of the differences in magnitude of the estimated coefficients are statistically significant). The control variables act upon the match outcome in a similar way as in Table 5. The Vegas Spread remains the most important predictor of the match outcome, albeit the magnitude, conditional on what the QB achieved the game, is reduced in columns (4) and (5). This is expected as the market can not predict perfectly how a QB will perform in any one game. After controlling for $Vegas\ Spread$, none of the control variables are expected to be statistically significant as all these variables are public information prior to kickoff. However, a negative coefficient on *Away* emerges because the specification requires passing rating (which is not known prior to kick off) to be held constant. Since passing rating is systematically lower when QBs play away from home, holding this constant introduces collinearity with *Away*. If passing rating is omitted, then the coefficient on *Away* returns to being statistically insignificant from zero.

Altogether, these estimates imply that an injury to the starting QB has a major bearing on the outcome of the match and the impact and the size of the effect is proportional to the wage differential between the starting QB and backup QB. Note that the impact of the amount of injured money $Ln\ Injured\ Money(net)$ is no longer statistically significant after conditioning on the QB's performance during the game and the Vegas Spread. Therefore, the most relevant identifier of a shock to labor productivity among NFL players, appears to be an injury to the starting QB. As stated above, the estimates imply that a win will need to be worth approximately \$10M to justify the marginal difference in wages between the starting and backup QBs. The next section seeks to determine whether or not this is the case.

## 4.2 How much is a win worth?

Starting Quarterbacks are paid on average approximately 10 times the amount of the backup Quarterback. However, it has been seen that the team is not 10 times less likely to win, rather approximately 28 percentage points less likely to win each game. If the median 8-8 team was forced to go the entire season with the backup quarterback they would still be predicted to win at least 3 or 4 games in the season. Such a team would not make the postseason playoffs

Table 6: Injuries on the probability of winning: Within game quarterbacks 2011:2015

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Injured QB | -1.18*** | -1.28*** | -1.24*** | -0.72*** | |
| | (-6.69) | (-6.83) | (-6.53) | (-2.95) | |
| Injured QB (opp) | 1.19*** | 1.31*** | 1.34*** | 0.84*** | |
| | (6.80) | (7.02) | (7.14) | (3.45) | |
| Vegas Spread | | 0.15*** | 0.14*** | 0.095*** | 0.095*** |
| | | (18.6) | (16.0) | (7.74) | (7.77) |
| Passing rating | | | | 0.056*** | 0.056*** |
| | | | | (19.3) | (19.3) |
| Passing rating (opp) | | | | -0.058*** | -0.058*** |
| | | | | (-19.2) | (-19.2) |
| Δ Injured-Backup QB wage | | | | | -0.048*** |
| | | | | | (-2.98) |
| Δ Injured-Backup QB Δ wage (opp) | | | | | 0.055*** |
| | | | | | (3.48) |
| *Control variables* | | | | | |
| Ln Injured Money (net) | | | | -0.028 | -0.029 |
| | | | | (-0.33) | (-0.34) |
| Starter Gini (net) | | | | 0.95 | 0.98 |
| | | | | (1.21) | (1.25) |
| Starter/Non-Starter (net) | | | | 0.034 | 0.034 |
| | | | | (0.19) | (0.19) |
| Away | | | | -0.25** | -0.25** |
| | | | | (-2.01) | (-2.00) |
| Ln Wage Bill (net) | | | | 0.41 | 0.41 |
| | | | | (0.65) | (0.64) |
| Rest Days (net) | | | | 0.0012 | 0.00095 |
| | | | | (0.055) | (0.043) |
| Year dummies | No | No | No | Yes | Yes |
| Fixed effects | No | No | Yes | Yes | Yes |
| Observations | 2,555 | 2,555 | 2,555 | 2,555 | 2,555 |
| Teams | 32 | 32 | 32 | 32 | 32 |

Estimated Coefficients after logit (conditional logit for FE) reported.
Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7: Franchise Revenues and Income

| | | Revenue | | Book Value | | Operating Income | | |
|---|---|---|---|---|---|---|---|---|
| Year | N | Mean | St.Dev | Mean | St.Dev | Mean | St.Dev | Salary Cap |
| 2000 | 31 | $116.20m | 19.61 | $423.45m | 107.45 | $15.54m | 15.20 | $62.17m |
| 2005 | 32 | $188.41m | 26.41 | $818.97m | 134.61 | $32.43m | 13.14 | $85.50m |
| 2008 | 32 | $221.56m | 26.73 | $1040.00m | 177.92 | $24.66m | 12.30 | $116.00m |
| 2009 | 32 | $236.66m | 27.60 | $1042.50m | 188.63 | $32.26m | 20.54 | $123.00m |
| 2010 | 32 | $250.50m | 41.34 | $1022.44m | 223.83 | $33.31m | 29.57 | - |
| 2011 | 32 | $260.78m | 39.06 | $1036.31m | 237.50 | $30.60m | 23.30 | $120.00m |
| 2012 | 32 | $275.72m | 55.13 | $1106.72m | 284.43 | $41.11m | 44.50 | $120.60m |
| 2013 | 32 | $286.47m | 60.85 | $1165.47m | 316.56 | $44.03m | 48.18 | $123.00m |
| 2014 | 32 | $299.22m | 63.46 | $1427.81m | 532.47 | $53.32m | 50.35 | $133.00m |
| 2015 | 32 | $346.59m | 69.52 | $1966.96m | 628.05 | $76.21m | 50.45 | $143.28m |
| 2016 | 32 | $379.91m | 75.98 | $2338.44m | 570.12 | $91.53m | 52.51 | $155.27m |
| 2017 | 32 | $411.13m | 92.76 | $2522.03m | 626.20 | $101.38m | 58.96 | $167.00m |
| % Change | | 254% | | 496% | | 483% | | 169% |

Notes:
1. Source: Forbes
2. NFL franchises owners opted out of the collective bargaining agreement in 2010 that provides for the salary cap.
3. There is a mechanical relationship between league wide revenues and the salary cap under the NFL's collective bargaining agreement between the NFL franchises and the player's union the NFLPA. Under the current agreement, the salary cap is approximately 48.5% of total league revenues.

but how much does winning matter for the revenue of the team? If wages are, on average, equal to marginal product, the prediction is that the four to five win difference over the season is worth the difference in wages between the backup and starting QB.

To estimate the impact of winning of franchise finances, data on franchise performance was merged with data on franchise finances from Forbes. Forbes provided the author with franchise book values for the years 1995-2017 and franchise revenues for the years 2000 and 2005. Additionally, revenues and operating income are currently publicly available on the Forbes website for the years 2008-2017. Table 7 shows the large increase in mean revenues and book values experienced NFL franchises by between 2000 and 2017 alongside the increase in the salary cap.

One complication in estimating the elasticity of revenue to a win, is that approximately 60% of franchise revenues are pooled and then redistributed. This is principally through a collective arrangement to share media revenue. The increase in revenues observed in Table 7 are predominately driven by media revenue and the growth in book values is heavily influenced by the public subsidisation of new NFL venues. Franchises earn approximately 20% of their revenue from their venue which is unshared (Vrooman, 2012). Since there are only 16 games in the regular season, the elasticity of game day attendance to winning is somewhat muted in the short run (see table A4 appendix). It would appear then, that the majority of revenue and even the growth in revenues are insensitive to a franchise's win rate in the short run.

Over a longer period of time, a franchise can generate additional revenues steadily building up its core support. This raises revenue through game-day gate receipts and merchandise. Additionally, as the NFL has increased its market reach over the sample period, with regular season games occurring internationally, in the UK and Mexico, the more sucessful teams are the better positioned teams to attract new international support. Additionally, support for the public subsidisation of NFL infrastructure and franchise stadia is arguably related to the intensity of local support. But to what extent is winning important in this revenue development? Vrooman (1995) estimates a three-year win elasticity over the period 1990-1992 of .12, which implies if the average win rate doubles over these three years franchise revenues would increase by 12%. Vrooman (1995) also shows that NFL revenues are considerably less win elastic than the other major US sports. However, if measured over a longer period of time, the arguments laid out in (Vrooman, 2012) would imply a higher win elasticities.

Table 8 shows the impact of winning on franchise book values and revenues as measured by a rolling average of the franchise's win percentage between 2000 and 2017. Column 1 reports the unconditional coefficient suggesting a 10 percentage point increase in the rolling win rate is associated with approximately \$50m in the annual book value over the sample period. A 10% point increase is equal to the median 8-8 team improving to 9.6 wins on average period season, which is coincidentally almost exactly 1 standard deviation improvement. Thus a 2 standard deviation improvement is broadly equivalent to an 11-5 season on average and worth approximately \$100m in book value and \$30m in revenue per annum. Therefore, a single win in the regular season would be worth c.\$10m per annum, on average in the long run. Recall, from the estimates in section 4.1, a win would need to be worth approximately \$10m for the median QB wages to be equal to their marginal revenue product. Even allowing for a degree of imprecision in these sample estimates it is remarkable that such a tight connection between wages and marginal revenue product has emerged.

The set of control variables in Table 8 are also interesting. The set of year dummies capture the growth in both book values and revenues and contribute to the high R-squared values for the model's fit. Indeed, there is more growth in the dependent variables over time than there is variation between franchises so even the worst performing franchise will have made money over the period. Nevertheless, the observable controls that capture variation between franchises are also important. A set of controls for the initial conditions of the franchise in 1995 are included to capture long term legacy effects. The total number of historical wins and the age of the franchise do not impact book value or revenue but a historical Super Bowl win is worth approximately \$63M (\$13M in revenue). The stadium variables are statistically and economically significant. An extra 1,000 in capacity is associated with \$10M in value and \$3M in revenue. More expensive stadia raise revenues and book values (a 10% increase in build cost is associated with \$7M in book value and any stadia related debt is excluded from the book values). Building a new stadium in the franchise period is associated with \$252M of value on average for that franchise (FE estimate) and each year the stadia is not renewed costs the franchise \$3.6M in book value. Turning to the Metropolian area controls: a 10% increase in local population is associated with c.\$5M in franchise value albeit the growth rate of the local area does not impact franchise values. Holding a monopoly over the local metropolitan area is worth \$295M relative to secondary franchises in the area (e.g. the New York Jets) and \$177M more than primary franchises (e.g. the New York Giants). The number of substitute franchises from the other three main sports, Baseball, Basketball and Hockey is positively associated with NFL franchise values and revenues. This reflects the fact that franchise location is endogenous in the US and there are several examples of NFL franchises relocating to higher demand local areas. In sports outside of the US, such as the English Premier League, team location is more plausibly exogenous and one might expect a inverse correlation between revenues and the number of substitute sporting events in the local area.

Table 8: Sensitivity of winning to revenues and book values

| | Book Value | | | Revenue | | |
|---|---|---|---|---|---|---|
| | OLS (1) | OLS (2) | FE (3) | OLS (4) | OLS (5) | FE (6) |
| Rolling win percentage | 498*** | 352*** | 377*** | 152*** | 85.8*** | 147*** |
| | (4.52) | (3.67) | (2.69) | (4.65) | (3.58) | (3.18) |
| *Initial conditions in 1995* | | | | | | |
| No. Wins | | 0.33 | | | -0.059 | |
| | | (0.77) | | | (-0.64) | |
| No. Super Bowls | | 63.0*** | | | 13.6*** | |
| | | (7.14) | | | (7.11) | |
| No. Post season years | | 1.94 | | | 1.28* | |
| | | (0.55) | | | (1.70) | |
| Franchise age | | -4.25* | | | -0.43 | |
| | | (-1.93) | | | (-0.91) | |
| *Stadium variables* | | | | | | |
| Capacity | | 10.00*** | | | 2.96*** | |
| | | (8.06) | | | (10.5) | |
| Ln (total build cost) | | 71.0*** | | | 15.9*** | |
| | | (6.50) | | | (5.67) | |
| New stadium | | 108*** | 252*** | | 21.8*** | 45.3*** |
| | | (4.68) | (8.99) | | (3.95) | (7.15) |
| Yrs since expansion | | -3.66** | | | -0.36 | |
| | | (-2.31) | | | (-0.86) | |
| *Metropolitan Area controls* | | | | | | |
| Ln population | | 49.5*** | | | 7.44** | |
| | | (3.31) | | | (2.37) | |
| Population growth rate | | -4.16 | | | -3.52 | |
| | | (-0.27) | | | (-1.05) | |
| Only franchise | | 295*** | | | 72.0*** | |
| | | (7.41) | | | (8.31) | |
| Main franchise | | 118** | | | 12.5 | |
| | | (2.20) | | | (1.08) | |
| No. substitutes | | 60.6*** | | | 16.2*** | |
| | | (4.20) | | | (5.14) | |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 721 | 721 | 721 | 383 | 383 | 383 |
| R-squared | 0.835 | 0.899 | 0.912 | 0.694 | 0.867 | 0.905 |
| No. teams | 32 | 32 | 32 | 32 | 32 | 32 |

Notes:
1. Book values available 1995-2017. Revenues available for 2000, 2005, 2008-2017.
2. All monetary variables in Dec 2017 prices.
3. The estimated coefficient in column (3) and (6) implies 10 percentage point increase in the rolling win rate increases book values by $50M and revenues by $15M respectively.
4. The R-squareds range between 69.4% and 91.2%. These high values are due to the large growth in franchise book values and revenues that occurred over the sample period. This this growth is captured by the set of year dummies. Excluding the year dummies reduces the R-squareds to between 0.4% and 46.2%.

After conditioning upon the set of observable controls in columns (2) and (5) the estimates in row 1 for win percentage reduce by approximately one third. The fixed effects estimate in column (3) is close to that of column (2) reflecting the fact that most of the observable controls relevant for book values do not change much over the sample period. The fixed effect estimate for revenue in column (6) however is closer to the unconditional estimate that of column (4). This is likely because the relevant controls for revenue do in fact vary within franchises over the sample period. In particular, a new stadium is built in the sample period is worth \$45.3M in new revenue.

### 4.3 Wages and Productivity: Heterogeneity between Rookies and Veterans

From the estimates in section 4.1, a win needed to be worth approximately c.\$10m for the median QB wages to be equal to their marginal revenue product and the section above appear to confirm that this is indeed the case. However, it is important to note that the estimates of marginal productivity are derived from point estimates at the mean. As such, it can be stated with reasonable confidence that quarterbacks close to the mean of the wage distribution appear to be paid their close to their marginal revenue product. However, this result may mask heterogeneity in the relationship between wages and productivity elsewhere in the distribution. As shown in section 3, there is a wide distribution of wages both within the quarterback position and between quarterbacks and other positions. To what extent can these differences be explained by differences in productivity?

There are reasons to suspect that some players represent better value for money than others. In particular, an important institutional friction of the NFL is a player's eligibility for free agency. Newly drafted players out of college, known as 'rookies', are not free to leave the franchise to which they are drafted within the first four years of their career. The franchise however can cut a player at any time. Only after four years do rookies become unrestricted 'free agents'[17]. Hence there is a considerable difference in bargaining power between rookies and veteran players. For example, Patrick Mahomes is a second year rookie who was promoted to the starting QB for the Kansas City Chiefs at the beginning of the 2018 season and was paid \$3.7M in 2018, whereas the outgoing veteran QB Alex Smith was paid \$13.4M in 2017 and secured a 4-year deal with the Washington Redskins worth \$94M in 2018. Mahomes' 2018 passing rating (to date) is 113.8 which is outperforming Smith's rating 85.7 by a considerable margin. Further, veterans are in short supply because many rookies will leave the NFL before being eligible for free agency, either because they have a career ending injury or, more likely, because they fail to make the roster of their franchise. This has been highlighted by Vrooman (2012, p.8) who argues 'It is common for veteran players to coalesce with management to bargain away the rights of future generations of disenfranchised rookies and forgotten former players. This creates a twisted bilateral monopoly where veteran players are often overpaid because of upper-tier monopoly power, while rookies are exploited because of owners lower-tier monopsony power'.

Table 9 shows the impact of being a rookie on wages. Rookies are paid 55%-56% less on average than veteran players. It is important to note that this difference remains after controlling for individual productivity and team level fixed effects. Productivity up to the season in which wages are determined is captured by the 'approximate value' (AV) metric. This metric is supplied by *sports-reference.com* and accounts for the points achieved (conceded) per drive

[17] Under current rules, franchises are also allowed to restrict the movement of one free agent known as the 'franchise tag'.

Table 9: Wages: Rookies vs Veterans

| | OLS | | FE | |
|---|---|---|---|---|
| | Coeff. | $t-stat$ | Coeff. | $t-stat$ |
| Rookie | -0.56*** | (-16.1) | -0.55*** | (-16.0) |
| Age | 0.012 | (1.50) | 0.017* | (1.96) |
| $ApproximateValue_t - 1$ | 0.12*** | (15.8) | 0.12*** | (15.3) |
| $ProBowl_t - 1$ | 0.32*** | (6.49) | 0.32*** | (6.54) |
| $No.games_t - 1$ | 0.020*** | (7.78) | 0.019*** | (7.46) |
| Injury Reserve | 0.015 | (0.59) | 0.016 | (0.60) |
| Draft Round (1st round omitted) | | | | |
| 2nd round | -0.38*** | (-8.64) | -0.38*** | (-8.94) |
| 3rd round | -0.60*** | (-12.0) | -0.60*** | (-11.9) |
| 4th round | -0.61*** | (-10.4) | -0.61*** | (-10.5) |
| 5th round | -0.75*** | (-10.5) | -0.75*** | (-10.5) |
| 6th round | -0.77*** | (-13.6) | -0.77*** | (-13.9) |
| 7th round | -0.84*** | (-15.7) | -0.85*** | (-15.5) |
| Position (Quarterback omitted) | | | | |
| Defensive line | -0.15 | (-1.58) | -0.13 | (-1.41) |
| Defensive cover | -0.099 | (-0.99) | -0.088 | (-0.90) |
| Linebacker | -0.26** | (-2.59) | -0.24** | (-2.47) |
| Offensive line | -0.14 | (-1.68) | -0.13 | (-1.59) |
| Running back | -0.34*** | (-3.89) | -0.33*** | (-3.78) |
| Special teams | -0.0100 | (-0.088) | -0.0059 | (-0.052) |
| Wide Receiver | -0.18* | (-2.04) | -0.16* | (-1.88) |
| Year dummies | Yes | | Yes | |
| Fixed Effects | No | | Yes | |
| Observations | 3,941 | | 3,941 | |
| Number Teams | 32 | | 32 | |
| R-squared | 0.540 | | 0.545 | |

Cluster Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
1. The dependent variable is the natural log of the variable 'CAPHIT' which is the official amount of wages charged to the franchise's salary cap for the year. Column 1 are OLS estimates and column 2 controls for team-level fixed effects.
2. Rookie is a dummy identifying players on restricted contracts which typically last 4 or 5 years. Most players enter the league at 21/22 years old and so players are typically 25/26 when they enter free agency. The estimates imply that rookies are paid c.55% less than veterans for the same level of performance as measured by their approximate value. Approximate value is supplied by sportsrefence.com and combines detailed information about on the field performances of players at all positions. *Probowl* identifies players who were invited to the Pro Bowl which celebrates the best players in the two leagues (AFC and NFC) in that season.
3. There is a tight relationship between draft pick order and rookie wages because initial wages in the first year out of the draft are set by collective bargaining. Undrafted players are excluded from the analysis above because they immediately become free agents but have failed to make the draft selection.

and distributes these points based on the contribution of the player, in their position, to those points. The AV metric for every player is recorded for every season on a scale of 0-26, with the mean of 4 and a standard deviation of 3.72. Therefore a one standard deviation in productivity results in an increase in wages of approximately 44%. It is also noteworthy that there is no impact of being placed on injured reserve ($IR$). This shows that the wages of injured players are indeed honoured for the year and that the exclusion restriction requiring that wages do not predict injuries appears to hold. Overall, the large differences in rookie and veterans wages can not be solely explained by differences in their productivity. Given that it was argued above that the median player is being paid close to their net marginal revenue product, it is highly likely that rookies, (on average), are below their marginal product and veterans above it. This is consistent with monopsonistic exploitation of rookies as advanced by Vrooman (2012).

Alternatively, underpayment relative to marginal revenue product for rookies and overpayment for veterans could reflect an non-exploitative model of deferred compensation as in (Lazear, 1979). One possible view of the large increase to player wages that occurs when players become free agents is as an incentive mechanism for players to exert full effort both before and after free agency. As rookies, players exert effort to maximise their marketability when they enter free agency. If less than full effort is supplied the rookie risks dropping out of the league before their big pay day. After entering free agency, veterans will also exert full effort because pay at their franchise would exceed their outside option of their marginal product and so do not want to risk being traded. Rookies are not exploited in this model because the optional value of deferred compensation offsets the underpayment in wages. However, deferred compensation contracts are more readily applicable to working environments where monitoring productivity is prohibitively costly (Huck et al., 2011). Since rookie performances are easily observed and under-performing rookies easily dismissed, it is hard to explain why a franchise would need to adopt this incentive mechanism. Moreover, deferred compensation contracts are expensive. Given the high degree of uncertainty associated with surviving until free agency rookies will discount the optional value of the free agency pay-day by a considerable amount. A precise estimate of the option value is difficult because survival rates vary significantly by player quality and will be distorted by idiosyncratic risk preferences. However, using the draft pick as a proxy for player quality, 77.4% of first round picks survive four years, while only 21.7% of 7th round picks survive. 34.3% of the median draft pick survives 4 years in the league[18]. Therefore the c.55% wage premium that veterans enjoy on average relative to rookies will be discounted by average rookie by approximately 65% (assuming risk neutrality). As such it is safe to conclude that most rookies are underpaid relative to their marginal product even considering the option value of the free agency payday. Additionally, it is observed that players move regularly between franchises when they enter free agency implying that their current franchise is not prepared to offer them a veteran contract above their outside option, as expected under the deferred compensation model.

# 5 Conclusion

The estimates obtained here for the marginal productivity of NFL players suggests that, notwithstanding heterogeneity between rookies and veteran players, sportsmen in the NFL are paid, on average, at a rate which is very close to their marginal contribution to the franchise's revenue. This was identified by observing the lost value from the reduction in win probability

[18]See *https://www.milehighreport.com/2014/5/13/5713996/how-long-does-the-average-draft-pick-stick-around*

from injured players being approximately equal to the wages earned by those injured players on average. *A dollar of injured talent is a dollar of productivity lost.* This result provides empirical support for models of sporting leagues such as (Fort and Quirk, 1995) where talent is hired at a market clearing rate which is also equal to the firm's marginal revenue of talent. More generally, it provides evidence for a tight connection between wages and productivity even when specific institutional constraints, in this case a salary cap and restricted rookie contracts, act to hold down wages for some workers. The broad connection between wages and marginal revenue product appears remarkably robust despite these frictions.

An opportunity to extend the research here is to build a dataset that links the timing of an on-field injury to the real time movement of in-play betting odds. While historical in-play odds are not currently publicly available, private betting companies own datasets containing such information. This would provide an unambiguous connection between the injury to the player and the change in the probability of winning the game. If access to such data was opened up to academics for research purposes, this would allow one to more precisely identify the immediate impact of injury on the probability of winning by using the market reaction as a close proxy for the change in probability. These movements could then be compared the player's wages[19].

A second opportunity to build upon the research here would be to explore the role of non-productivity related characteristics such as the race of the player. Although race is not identified in this data, the NFLPA collects self-identified demographic information on NFL players. If access to this data was made available to academics, given the detailed individual level data on productivity already in the public domain, it would be possible to determine the extent to which race played or continues to play a role in the wages of NFL players and the success of NFL franchises.

[19] This was suggested by David Forrest at the European Sports Economics Association 2018.

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## Appendix

Note to Editor: The following is not intended for print but can be made available on-line. It is included here for the referees. If some of the material below is regarded as central to the paper I am happy to include and discuss in the paper. Likewise, I'm happy to move more material to the appendix if deemed necessary.

### Evidence supporting Exclusion Restriction

Table A1: Balance test for within game injuries to starting Quarterbacks

| | No QB injury mean | Injury to QB mean | Difference | p |
|---|---|---|---|---|
| Passing Rating | 88.99 | 72.47 | 16.52 | 0.00 |
| | | | | |
| Ln Injured Money (net) | -0.00 | 0.03 | -0.03 | 0.59 |
| Starter Gini (net) | 0.00 | -0.00 | 0.00 | 0.77 |
| Starter/Non-Starter (net) | 0.00 | -0.01 | 0.01 | 0.67 |
| Away | 0.50 | 0.48 | 0.02 | 0.60 |
| Ln Wage Bill (net) | 0.00 | -0.01 | 0.01 | 0.16 |
| Rest Days (net) | 0.01 | -0.07 | 0.07 | 0.70 |
| Vegas Spread | 0.02 | -0.24 | 0.26 | 0.58 |
| N | 2369 | 192 | 2561 | |

Notes:
1. As expected, starting QB have significantly higher average passing rating that backup QBs
2. Crucially, there are no significant difference in means between other observable variables. This is consistent with the exclusion restriction that requires injuries to occur randomly. In particular, teams with higher or lower wage bills do not experience injuries more often and crucially, the market is unable to predict a within-game injury to the starting QB.

Table A2: Do wages predict injuries?

| | No games missed | | | Season long injury | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln wages | 0.017 | -0.021** | -0.0046 | -0.0047 | 0.0046* | 0.0072* |
| | -1.44 | (-2.14) | (-0.32) | (-0.88) | -1.84 | -1.95 |
| Age | | 0.019 | -0.077 | | 0.0033 | 0.0018 |
| | | -0.78 | (-1.52) | | -0.64 | -0.17 |
| Age squared | | -0.00024 | 0.0013 | | -0.000066 | 0.000065 |
| | | (-0.57) | -1.5 | | (-0.73) | -0.36 |
| Starter | | -0.037* | -0.015 | | -0.0095** | -0.0049 |
| | | (-1.85) | (-0.56) | | (-1.98) | (-0.75) |
| Approximate Value | | 0.074*** | 0.079*** | | -0.0061*** | -0.0045*** |
| | | -33.4 | -26.6 | | (-8.89) | (-5.66) |
| Pro Bowl | | -0.18*** | -0.13*** | | 0.031*** | 0.020*** |
| | | (-6.05) | (-4.08) | | -8.32 | -4.97 |
| Ln Wage bill | | 0.03 | -0.00067 | | 0.0069 | 0.009 |
| | | -0.55 | (-0.0100) | | -0.52 | -0.63 |
| Year dummies | yes | yes | yes | yes | yes | yes |
| Position dummies | no | yes | no | no | yes | no |
| Player FE | yes | no | yes | yes | no | yes |
| Observations | 6,795 | 6,103 | 6,103 | 6,795 | 6,103 | 6,103 |
| R-squared | 0.001 | 0.248 | 0.176 | 0.001 | 0.078 | 0.058 |

Notes:
1. Linear probability model where the dependent variable takes the value of 1 if no games are missed due to injury in columns (1)-(3) and if all games are missed in columns (4)-(6). Standard errors are clustered at the player level.
2. Column 2 indicates a marginal impact of wages on injury propensity. A player is 2 percentage points more likely to miss no games in the season if their wages double. However, this is not robust to player fixed effects. Likewise column 5 suggests a weak correlation between season long injuries and wage but again not robust to player fixed effects
3. Approximate Value is a performance metric calculated by sports-reference.com and Pro Bowl indicates whether the player was selected to the Pro Bowl. Unsurprisingly, these variables reflect the fact that non-injured players are more likely to perform well during the season
4. Interestingly, there is no robust relationship between starting and injury which is surprising given a starting player would be expected to play more minutes than squad players. This suggests a large part of injury risk occurs away from match day (e.g. during training)

## Additional Tables

The regression analysis of injuries and wins at season level in section 3.2 returns estimates on the conditional mean. However, it is possible the impact of injuries could vary within the distribution. To explore this, a quantile regression was run and the table of results is shown below. The effect sizes are larger at the extremes in the distribution, at the 90th and 10th percentile, relative to the middle of the distribution. There is not definitive reason for this, but one might speculate that top teams need to avoid injuries to star players to remain at the top, while weak teams do not have the squad depth to replace their starting players. Teams in the middle might have a more balanced squad where injured starters can be replaced by strong backup players.

Table A3: Injuries and wins: Season level quantile regression

| | (1) q10 | (2) q25 | (3) q50 | (4) q75 | (5) q90 |
|---|---|---|---|---|---|
| Ln Injured money | -0.36*** | -0.19* | -0.11 | -0.21* | -0.40*** |
| | (-3.28) | (-1.66) | (-1.10) | (-1.71) | (-2.83) |
| Ln Wage bill | 0.16 | 1.48* | 2.06*** | 2.14* | 2.82** |
| | (0.12) | (1.67) | (2.78) | (1.96) | (2.37) |
| Ln Wage bill SD | -0.12 | -1.28 | -1.63*** | -1.09 | -1.65* |
| | (-0.087) | (-1.57) | (-3.23) | (-1.19) | (-1.84) |
| Observations | 213 | 213 | 213 | 213 | 213 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
1. This table presents quantile regression results of the total injured money incurred by a franchise during the season upon the proportion of wins in a season. The dependent variable is the percentage of games won $w_i$ in the season $t$ expressed in log odds: $w_{it} = ln(w_{it}/(1 - w_{it}))$
2. The sign on injured money indicates a negative relationship at each percentile. While column (5) suggests a slightly stronger unconditional impact at the 90th percentile there is no significance difference between the 90th percentile and the 10th percentile. The effect sizes in the middle of the distribution are more modest.

Table A4: Impact of winning on finances: short run

| | OLS | | | FE | | |
|---|---|---|---|---|---|---|
| | Value (1) | Revenue (2) | Income (3) | Value (4) | Revenue (5) | Income (6) |
| $Winpc_{t-1}$ | 187* | 31.7* | 10.1 | -2.93 | -16.6 | -15.0* |
| | (1.80) | (1.89) | (0.85) | (-0.29) | (-0.22) | (-1.72) |
| $PostseasonWin_{t-1}$ | 37.7 | 6.47 | 10.3 | 6.52 | 43.1 | 11.2** |
| | (0.69) | (0.73) | (1.63) | (1.29) | (1.16) | (2.57) |
| $ChampionshipWin_{t-1}$ | -42.1 | -7.66 | -14.2 | -4.52 | -12.6 | -12.3 |
| | (-0.40) | (-0.44) | (-1.15) | (-0.46) | (-0.18) | (-1.45) |
| $SuperBowlWin_{t-1}$ | 202 | 28.1 | 24.8 | 12.1 | 49.9 | 16.6 |
| | (1.50) | (1.27) | (1.57) | (0.97) | (0.54) | (1.54) |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 445 | 383 | 383 | 383 | 445 | 383 |
| R-squared | 0.762 | 0.686 | 0.337 | 0.887 | 0.887 | 0.548 |
| Teams | 32 | 32 | 32 | 32 | 32 | 32 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
1. This table estimates the elasticity of winning in the season prior on the book value, revenue and operating income of NFL franchises over the sample period. The sample period begins in 2000 and ends 2017 omitting the years 2001-2004 and 2006-2007 as financial data was not available on NFL franchises in these years. Columns (1) to (3) report OLS regression and columns (4) through (6) the fixed effects estimates.
2. While there has been a large appreciation in book values, revenues and income of NFL franchises over the sample period there is no robust relationship between winning and any of the financial variables in the short run. This result is consistent with the arguments laid out in Vrooman (2012).

## Example Contracts

Panel A of Table A5 shows the structure of Andrew Luck's contract which he signed in 2016. Luck was the starting QB for the Indianpollis Colts. Media reports will typically headline the total value of the contract when it is signed, in this case "$140m" [20]. However, this amount is spread over six years and while Luck received $\$47m$ guaranteed on signing (a $\$12m$ salary plus $\$32m$ signing bonus plus $\$3m$ roaster bonus) these amounts can be spread over the duration of the contract to even out the Cap Hit. While the player can be cut at any time, monies guaranteed on signing would hit the cap immediately in the year that the player is cut. The 'Dead Money' in the final column records the amount charged to the Cap in the event that the player is cut in that year.

Table A5: Andrew Luck's contract vs Scott Tolzien

Panel A: Starting Quarter Back

| Year | Salary | Signing | Roster | Cap Hit | Dead Money |
|---|---|---|---|---|---|
| 2016 | 12m | 6.4m | 0 | 18.4m | 47m |
| 2017 | 7m | 6.4m | 6m | 19.4m | 28.6m |
| 2018 | 12m | 6.4m | 6m | 24.4m | 19.2m |
| 2019 | 9.125m | 6.4m | 12m | 27.525m | 12.8m |
| 2020 | 11m | 6.4m | 11m | 28.4m | 6.4m |
| 2021 | 11m | 0 | 10m | 21m | 0 |

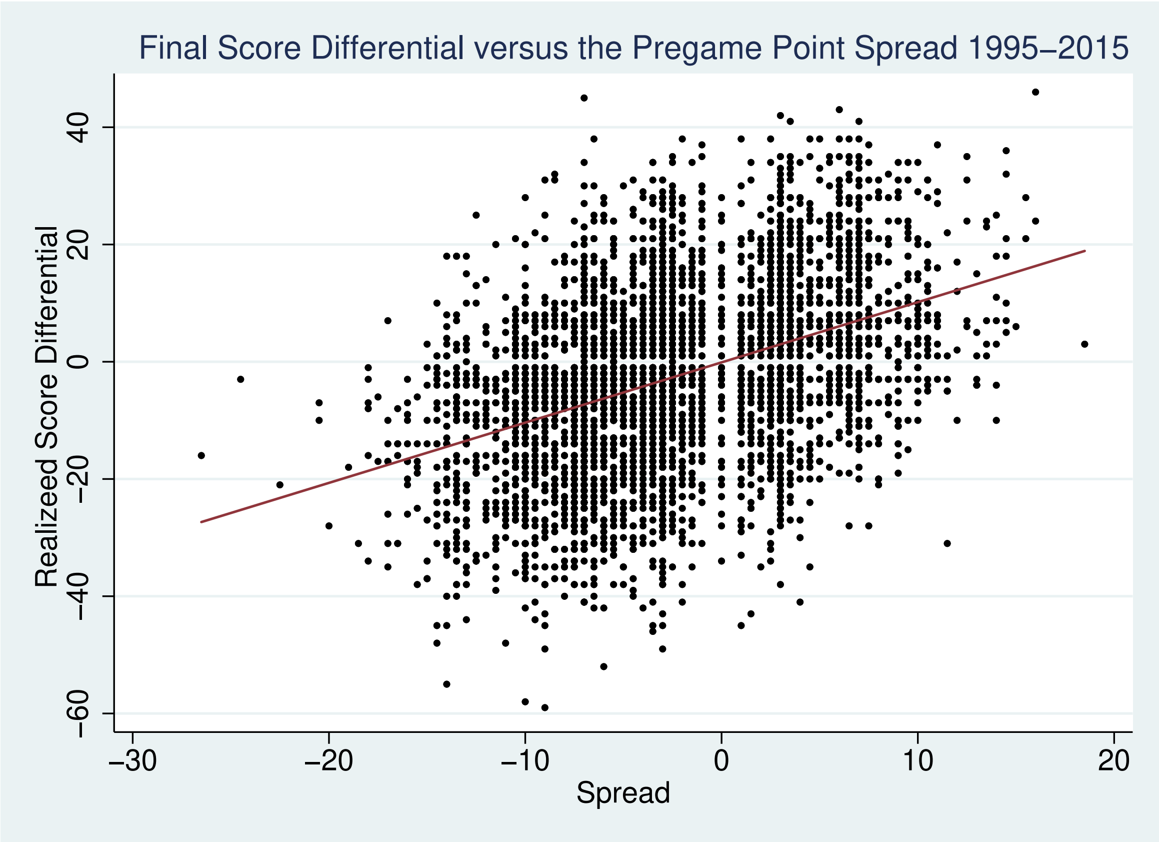
Panel B: Back up Quarter Back

| Year | Salary | Signing | Roster | Cap Hit | Dead Money |
|---|---|---|---|---|---|
| 2016 | 1.25m | 0.25m | 0 | 1.5m | 0.5m |
| 2017 | 1.75m | 0.25m | 0 | 2.0m | 0.25m |

By contrast, panel B details the Colt's backup QB, Scott Tolzien's contract. Tolzien signed a 2 year contract with $\$0.5m$ guaranteed on signing and none of salary guaranteed. As a result Tolzien could be cut at the end of 2016 with only a $0.25M charge to the 2017 cap.

[20]See *http://www.nfl.com/news/story/0ap3000000672131/article/andrew-luck-signs-sixyear-140-million-colts-contract*

Fig. 1: Replication of Card & Dahl 2011 showing the pre-match Vegas Spread is an unbiased predictor of the final score




Realized score differential is opponents minus home team's final score. An increase in one point on the spread implies the opposition will get one more point over the home team on average. The plotted regression line has an intercept of -0.11 (s.e. 0.20), a slope of 1.02 (s.e. 0.03) and a R-squared of 0.17. Card & Dahl (2011, p121) with data 1996-2005 find an intercept of -0.17 (s.e. = 0.21) and slope 1.01 (s.e. = 0.03) and a R-squared of 0.20.

Table A6: Variable Definitions

| Variable | Description |
|---|---|
| *Player wage variables* | |
| Salary | Annual salary in nominal dollars |
| Signing | Signing bonus in nominal dollars |
| Roster | Roster bonus in nominal dollars |
| Dead Money | The outstanding charge in nominal dollars to the franchise's salary cap in the event that the player is cut before the contract expires |
| Ln wages | The official charge to the salary cap for the player in year $t$ |
| *Injury variables: Season level* | |
| Ln Injured money | Natural log of the sum of all player wages * x/16, where x is the number of games of the regular season in year $t$ the player missed due to injury |
| Ln(Wage bill) | Natural log of the total wage bill of the franchise in year $t$ |
| Ln(Wage bill standard deviation) | Natural log of the standard deviation of the wage bill of the franchise in year $t$ |
| *Injury variables: Game level* | |
| Ln Injured money (net) | Natural log of the sum of all player wages who are injured in that game minus the same figure for the opposition |
| Starter Gini (net) | The gini coefficient of the wages of starting players net of the opposition |
| Starter/Non-Starter (net) | The ratio of the starting wages to non-starting wages net of the figure for the opposition |
| Away | Dummy variable taking the value of one if the game is an away fixture* |
| Ln Wage Bill (net) | Natural log of the total wage bill of the franchise in year $t$ net of the figure for the opposition |
| Rest Days (net) | Number of days since the last fixture, net of the figure for the opposition |
| Vegas Spread | Number of points on the pre-kickoff spread |
| *Injury variables: Within game quarterbacks (QBs)* | |
| Injured QB | Dummy variable taking the value of 1 if the starting QB is injured during the game |
| Injured QB opponent | Dummy variable taking the value of 1 if the opposition's starting QB is injured during the game |
| Backup QB wage diff. | The difference in natural log of wages between the starting and backup QB when the starting QB is injured during the game |
| Backup QB opponent wage diff. | The difference in natural log of wages between the opposition's starting and backup QB when the opposition's starting QB is injured during the game |
| Passing Rating | The official passing rating of the QB for the game |
| Passing Rating opponent | The official passing rating of the opposition's QB for the game |
| *Franchise value dependent variables* | |
| Revenue | Revenue in nominal dollars (millions) as recorded by Forbes.com |
| Book Value | Book value in nominal dollars (millions) of franchise based on current stadium deal at time $t$ deducting stadium debt (Forbes.com) |
| Operating Income | Earnings before interest, taxes, deprecation and amortization in nominal dollars (millions) (Forbes.com) |
| *Franchise Value Control Variables* | |
| Rolling win percentage | Rolling average of the percentage of wins in the regular season |
| *Initial conditions in 1995* | |
| No. Wins | Number of wins in the regular season up to 1995 |
| No. Super Bowls | Number of Super Bowl wins up to 1995 |
| No. Post season years | Number of seasons up to 1995 when the team qualified for the post season playoffs |
| Franchise age | 1995 - the original year the franchise was founded |
| *Stadium variables* | |
| Capacity | Capacity of the stadium at time $t$ |
| Ln (total build cost) | Natural log of total build cost of stadium at time $t$ in 2017 prices |
| New stadium | Dummy variable taking the value of 1 if a new stadium was built between 1995 and 2017 |
| Yrs since expansion | Number of years at time $t$ since the last increase in stadium capacity |
| *Metropolitan Area controls* | |
| Ln population | Natural log the population in the metro area |
| Population growth rate | Percentage change in population between 2016 and 2010 |
| Only franchise | Dummy variable taking the value of 1 if franchise $i$ is the only NFL franchise in the metropolitan area |
| Main franchise | Dummy variable taking the value of 1 if franchise $i$ is the largest NFL franchise in the metropolitan area (e.g. New York Giants) |
| No. substitutes | Number of National Basketball Association, Major League Baseball or National Hockey League franchises in the metropolitan area |
| *Wage determinants* | |
| Rookie | Dummy variable taking the value of 1 if player is on their first contract |
| Age | Player's age as recorded by $sports-reference.com$ |
| Approximate Value | Player's Approximate value as recorded by $sports-reference.com$ |
| Pro Bowl | Dummy variable taking the value of 1 if player played in the season's pro bowl |
| No. games | Number of games where the player featured in at least one play in the season |
| Injury Reserve | Dummy variable taking the value of 1 if the player was on injury reserve |
| Draft Round 2nd-7th | Set of dummy variables taking the value of 1 according to where the player drafted. 1st round draft picks are the baseline category |
| *Short run franchise performance variables* | |
| Winpc | Percentage of wins in the regular season of 16 games |
| Postseason Win | Dummy variable taking the value of 1 if the franchise won a game in the postseason |
| Championship Win | Dummy variable taking the value of 1 if the franchise won their championship game in the postseason |
| Super Bowl Win | Dummy variable taking the value of 1 if the franchise won the Super Bowl in the postseason |