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Bachelor Thesis Behavioural and Health Economics

The Effect of a COVID-19 Infection on Work Performance: Evidence from Professional Football

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Abstract

This paper examines the effect of a COVID-19 infection on an individual's work performance through data of football players. Infection and performance data of English Premier League players of season 2020/2021 were analysed. Staggered difference-in-difference design shows that a player's likelihood to play drops with fifteen percentage points after a COVID-19 infection compared to the pre-infection period. An event study shows that the drop in likelihood to play is still significant five months after the infection. There was no significant effect found of a COVID-19 infection on a player's performance. The expectation is that this is because players that got infected and that would have performed worse, did not get the chance to play. Because the performance of footballers who have not played cannot be observed, more research will be needed to confirm this. If the expectation turns out to be true, it confirms that COVID-19 has lasting economic effects by lowering the performance of workers. This would be an extra incentive for governments, companies, and individuals to take measures against the virus and prevent decreases in work performance.

Introduction

The COVID-19 pandemic has had a huge economic impact worldwide. Companies adapted to the pandemic by encouraging remote working, and governments instituted lockdowns and started vaccination campaigns to contain the spread of the virus. Around the world there has been controversy regarding the effectiveness of COVID measures. For example, Goldstein et al. (2021) argue that lockdowns significantly reduce the spread of COVID-19 and its related deaths. This effect becomes insignificant after 120 days. On the other hand, Allen (2022) argues that lockdowns were not efficient in dealing with the pandemic and had marginal effect on the deaths due to COVID-19. The question is whether the benefits of policies outweigh the social and economic costs.

A central difficulty in weighing the costs and benefits of these policies is the sparse evidence on the economic costs of a COVID-19 infection, especially in the long-term. If - for instance - there are large or long-term health consequences from a COVID-19 infection that prevent workers from returning to work at full capacity, then the benefits of lockdowns and other COVID measures may be understated. The benefits of COVID-19 measures are often not immediately observable, while the costs often have a major and visible impact on society (Hsiang et al., 2020). When more is known about the effects of a COVID-19 infection, it can be better assessed whether measures against the virus were useful, and the consequences of future policy can be better estimated.

To fill this gap in the literature, this paper investigates the effect of COVID-19 infections on performance at work. This is done by looking at the "work performance" of players during matches in the English Premier League (EPL). Why the focus on football, rather than an arguably more generalizable setting? Firstly, football had a relatively low disruption in the individual output of workers due to COVID-19, as the output of players is driven more by physical and mental performance than capital and technology (Fischer et al., 2021). Where most jobs had to do with major adjustments by, for example, remote working, keeping distance or even temporarily suspending work, the changes regarding football matches were small. Furthermore, it is often not easy to measure productivity in most settings and especially among knowledge workers (Jensen & van der Voordt, 2016). Football is a sport in which the labour output can be measured objectively and to measure the productivity this paper uses work performance as a proxy. Football also receives a lot of media attention. Information about players is regularly measured and a large amount of information is publicly available. Professional sport is one of the only settings where the identity and performance of every player and coach is known and is therefore suitable for researching the labor market (Kahn, 2000). This offers a unique situation where data on both COVID-19 infections and employee performance is available, which makes football a suitable setting to investigate the effect of COVID-19 on work performance.

The question this paper addresses is: What is the effect of a COVID-19 infection on the performance of a football player in the English Premier League season 2020/2021?
To answer this research question, this research analyses player performance data of the 2020/2021 English premier league season, using staggered difference-in-difference design and event studies. The performance data under study include passes, touches, and interceptions.

Recent studies were mostly focused on the immediate effects of a COVID-19 infection, but there is not much research done on the lasting economic effects of an infection (Fischer et al., 2021). If the effect turns out to be bigger than only the immediate effects (e.g., having symptoms and being contagious), then that means that the costs of getting a COVID-19 infection are even greater than previously thought. This could change the decision making of individuals, companies, governments, and policymakers. This includes, for instance, companies making investments to fight the virus, governments announcing lockdowns and other COVID measures, and individuals contemplating to take a vaccine.

One of the ways in which this paper contributes to existing literature, is that it investigates whether the findings of Fischer et al. (2021) can be replicated in the English Premier league. Fischer et al. (2021) found that COVID infections had a negative impact on the performance of footballers in the Bundesliga and Serie A and an effect was found even half a year after the infection. However, there has not yet been an effort of replicate these findings in other contexts. Highlighting the importance of replication, Makel and Plucker (2014) state: "*Replications will help uncover the precision with which we know size of the effects, not to mention the extent to which they generalize across contexts. As a field, we need to weed out false and narrow findings and buttress findings that generalize across contexts*." (p. 312). This study contributes to this by allowing conclusions to be drawn about the validity of the results of Fischer et al. (2021). If the results of this study correspond to their results, this can be seen as extra evidence that the found effect of COVID-19 on work performance exists and occurs in multiple contexts. Like the Fischer et al. (2021) paper, this research is an addition to literature on the long-term effects of a COVID-19 infection.

The main findings of this study are that players are less likely to play in a game after a COVID-19 infection. The lower chance of playing seems to last for more than five months. When players do play after an infection, they play less minutes on average. But this effect does not last, and the minutes played return to pre-infection levels short after the infection. In game, player performance is not significantly different than before their infection. The expected reason for not finding any significant effect of a COVID infection on game performance is that players who would have performed worse after an infection, did not get the chance to play and could not put in the performance. Therefore, the expected drop in performance cannot be observed in the analysis. These findings suggest that the costs of an individual getting infected by COVID-19 is higher than previously thought and policymakers should account for this in their cost-benefit-analyses of COVID measures.

The rest of this paper first discusses the existing literature. Then the dataset and experimental setting are explained. This is followed by the introduction of the regression models used to analyse the data. After that, the research results are presented. Finally, the findings are summarized, and the results are discussed.

Literature Review

This section discusses the existing literature on COVID-19 effects and the effect of previous pandemics.

Effects of COVID-19 on health

COVID-19 was first detected at the end of 2019 (World Health Organization, 2020). As it has been around for 2.5 years, there are few papers written about the effects of COVID-19, and even less about the long-term effects of the virus. Most papers about the long-term effects of COVID-19 on health are focused on `long COVID`. They describe ‘long COVID‘ as a term used for people who have symptoms after recovering from a COVID-19 infection and elaborate those ongoing symptoms can have economic and social impact as it can put extra pressure on the health care (Raveendran et al., 2021). Just as the paper of Fischer et al. (2021), this paper examines the effect of COVID-19 on every infected person, while research on long COVID only looks at people who show symptoms that last.

Shanbehzadeh et al. (2021) analysed 34 studies among hospitalized and non-hospitalized patients. In their literature review, they found that fatigue is most often cited as a long-term COVID health complication. They also mention the decline in physical capacity and daily activities as health problems up to three months after a COVID infection. This is in line with the findings of Tabacof et al. (2022). Their survey taken by 156 patients with long COVID shows that fatigue and brain fog are the most mentioned symptoms. The physical activity of these patients is lower than before their COVID-

19 infection. The persistent symptoms appear to last for at least two months and more often for more than twelve months.

Beck and Flow (2022) examined the effect of COVID-19 on cognitive failure at work. By matching infected and non-infected individuals on demographic variables and analysing their survey data, they found that workers who had COVID-19 had significantly more cognitive failures at work compared to non-infected individuals. Their study reports that a COVID infection had a significant effect on task performance through cognitive failures. This research goes further by using a causal identification strategy (staggered difference-in-difference) and by looking at “hard” measures of performance rather than self-reported measures.

Effects of COVID-19 on work performance

Allen (2022) pointed out the importance of looking at long-term effects in estimating the costs and benefits of COVID-19 measures. He mentions that only looking at a loss in Gross Domestic Product (GDP) causes an underestimation of the costs. Lockdowns have shown to increase domestic violence, loss in educational progression and loss of non-COVID-19 medical services. It could also be that a decrease in work performance is one of the costs that has not been considered. Most calculations do not consider how long COVID-19 affects work performance and this paper will add necessary evidence of this effect.

Looking at work performance during the COVID-19 pandemic, Bloom et al. (2020) estimated a drop in total factor productivity of up to 5% during the pandemic, due to COVID-19. Compared to a productivity growth rate of less than 1% in the last decade, it is clear that the pandemic had a substantial impact on productivity. Despite this, the paper report forecasts that the impact will not be lasting over the medium term (from 2023). Their findings are based on a monthly survey panel of UK firms.

Vaudreuil et al. (2021) and Fischer et al. (2021) examined the effect of a COVID-19 infection on individual productivity. Vaudreuil et al. (2021) looked at the influence of the virus on performance by looking at sample of twenty NBA athletes. Using a paired t-test, they found that NBA players who came back from a COVID-19 infection scored less goals and played less minutes compared to the season before the shutdown. These findings were significant for 5% significance level and suggest that COVID-19 infections do influence player performance.

Fischer et al. (2021) investigated the impact of a COVID-19 infection on the performance of footballers in the Bundesliga and Serie A. Through a staggered difference-in-difference design and event studies they found that players with an infection performed 6% worse compared to before they got infected, and the performance was 5% worse after six months.

This paper tries to find out whether the results of Fischer et al. (2021) can be found in the English competition. The English premier league (EPL), also one of the top five domestic European football leagues (Pawlowski et al., 2010), has not been examined yet. The English premier league is the most viewed league in the world (Killick & Griffiths, 2020). Because of this, it is anticipated that this is the league, in the top five domestic football leagues, with the most detailed data regarding the performance of players and whether a player had a COVID-19 infection.

The same results that Fischer et al. (2021) found in the Bundesliga and Serie A are expected to be found in this study. First, this paper predicts that players will have a lower probability of playing in a match after a COVID-19 infection compared to before. The expectation is that if players who had an infection play, they do play less minutes compared to before their COVID-19 infection. It is also hypothesized that players with an infection have a worse game performance when playing than they had before the infection. If these effects are found, it is expected that they will diminish over time, as the effect of COVID-19 on performance is likely to become smaller as time passes.

Using football data to test the hypotheses is useful in this case. Professional football is one of the sports that resumed relatively fast after a suspension in March 2020. After resuming, the Premier League implemented regular testing protocols. As far as is known, this is one of the few industries where almost every COVID-19 positive worker is known because of frequent testing and the possibility to retrieve their identity through online sources. In addition to this, the data is also available over a large period, especially compared to the time that COVID-19 has been around.

Effects of other pandemics

There are pandemics that occurred before the COVID-19 pandemic. One of them was the Great Influenza Pandemic, which lasted from 1918 to 1920. It is estimated that during that period, one in three people in the world's population was infected with the so-called 'Spanish flu'. This virus was especially dangerous for young adults without pre-existing medical conditions, making the economic impact of the pandemic greater than when the elderly or young children are most at risk. The estimation is that the pandemic reduced real per capita GDP by 6 to 8 percent for a typical country. This decline is comparable with that of the Great Recession in the United States (2007-2009). During this pandemic, 2.1 percent of the population died from flu-related causes. This corresponds to 40 million deaths among the world population at the time (Barro et al., 2020).

After the Great Influenza Pandemic and before the COVID-19 pandemic there were three other pandemics. The Asian flu of 1957, the Hong Kong flu in 1968 and the Swine flu in 2009. The 1957 and 1968 pandemics both caused an estimated one million deaths, where the 2009 pandemic caused less than 0.3 million deaths (Jordan et al., 2019).

Jinjarak et al. (2022) estimate that the 1968 Hong Kong flu caused a drop in productivity of 1.9% and a decrease in output growth rate of 2.4%. In comparison, the Swine flu has had less economic impact. Estimates during the 2009 pandemic were that the Swine flu would cause a decline in GDP of between 0.5 and 1.5% (The Economist, 2009). But Page et al. (2012) reported that the impact of the pandemic on the GDP was small and indirect. Kim et al. (2013) and Fukac and Lees (2009) found that estimates on the economic impact of the Swine flu were more likely to be around 0.5%, which is low for a pandemic. The Asian flu of 1957 also does not seem to have had a major economic impact. According to Henderson et al. (2009): "*a Congressional Budget Office estimate found that a pandemic the scale of which occurred in 1957 would reduce real GDP by approximately 1%*" (p. 270).

Data

This section outlines the context in which this study was conducted, a description of the data used and a discussion of the representativeness of the sample.

Research setting

To examine the effect of a COVID-19 infection on physical performance, a dataset of *FBref* with detailed game performance statistics of English Premier League players in season 2020/2021 is used. This platform has data of all Premier League players who played in that season, the matches they played and how they performed in those games. From the game statistics, this paper focusses on the minutes played, passes, touches and interceptions. Based on the matches played by a certain player in the season, there could be derived what matches a player did not play. This game and performance data was then linked to manually scraped data from *Transfermarkt GmbH & Co*, statements from football clubs, players and football associations, and news organisations to identify when a certain player was diagnosed with a COVID-19 infection.

The performance measures used in this paper are passes, touches and interceptions. Passes refer to the number of completed passes. For touches, this is the number of times a player touches the ball.

Here, receiving the ball, dribbling and then passing count as one touch. Interceptions stand for the number of times a player intercepts the ball.

Passes are related to a player's positioning on the field and their physical condition. A player's physical and cognitive ability are the building blocks of his performance on the field. Additionally, COVID-19 is expected to affect both cognitive and physical health of players. This makes the number of passes a suitable measure to base our analysis on. Touches and interceptions are also measures involving positioning and physical measures, which make them appropiate to control the robustness of our findings.

The season 2020/2021 is chosen because ever since the start of the COVID-19 pandemic, this is the only season where COVID-19 was around for the whole season. The virus has been around since the end of 2019, which was during the 2019/2020 Premier league season. The 2021/2022 season is yet to be finished at the moment of writing.

Using the 2020/2021 season also means that most football player have not been vaccinated against the virus. The estimated effect could be influenced by COVID-19 vaccines because they decrease the severity of the symptoms people get after an infection (World Health Organization, 2022). In the United Kingdom, adults aged between 25 and 29 mostly received their vaccination from June 2021, which was after the ending of the analysed Premier league season (Roberts, 2021). Since footballers did not get priority for a COVID-19 vaccination, it is expected that the coefficient estimated is the effect of an COVID-19 infection on work performance for non-vaccinated individuals.

Sample description

The dataset consists of player statistics of the 2020/2021 EPL season and their game statistics. Data of *Transfermarkt GmbH & Co*, and statements from football clubs, players and football associations are used to investigate COVID-19 infection among players since the start of the pandemic until the end of the 2020/2021 season, like Fischer et al. (2021) did in their paper.

The English Premier League season 2020/21 had 20 participating teams and the data consists of the 524 Players who have played in the English premier league 2020/21 season. It was played behind closed doors for the most matches and six games were rescheduled because of COVID-19 outbreaks within clubs among players and staff members (Premier League, 2020). Two players who made a transfer from one Premier League team to another team in the league during the season were dropped from the dataset.

The data consist of 19836 match-player observations of 522 players. Of these observations, 10,348 are from players who made minutes in the match. The descriptive statistics can be seen in Table 1.

Table 1: Descriptive statistics

	N	Mean	Std. Dev.	Min	Max
Infected Player	19836	0.155	0.362	0	1
Post-Infection	19836	0.114	0.317	0	1
Age	19836	25.492	4.328	16	38
Goalkeeper	19836	0.079	0.269	0	1
Defender	19836	0.377	0.485	0	1
Midfielder	19836	0.293	0.455	0	1
Forward	19836	0.251	0.434	0	1
English	19836	0.349	0.477	0	1
Round	19836	19.5	10.966	1	38
Played (Yes/No)	19836	0.522	0.500	0	1
Minutes Played	10348	72.315	28.456	1	90
Passes	10348	29.588	21.833	0	144
Passes per Minute	10348	0.411	0.281	0	5
Touches	10348	45.191	26.407	0	169
Touches per Minute	10348	0.649	0.356	0	7
Interceptions	10348	0.803	1.164	0	9
Interceptions per Minute	10348	0.012	0.033	0	1

Notes: This table shows the descriptive statistics of the players. The sample consists of 522 players from the 2020/2021 Premier League season. The competition had 38 rounds.

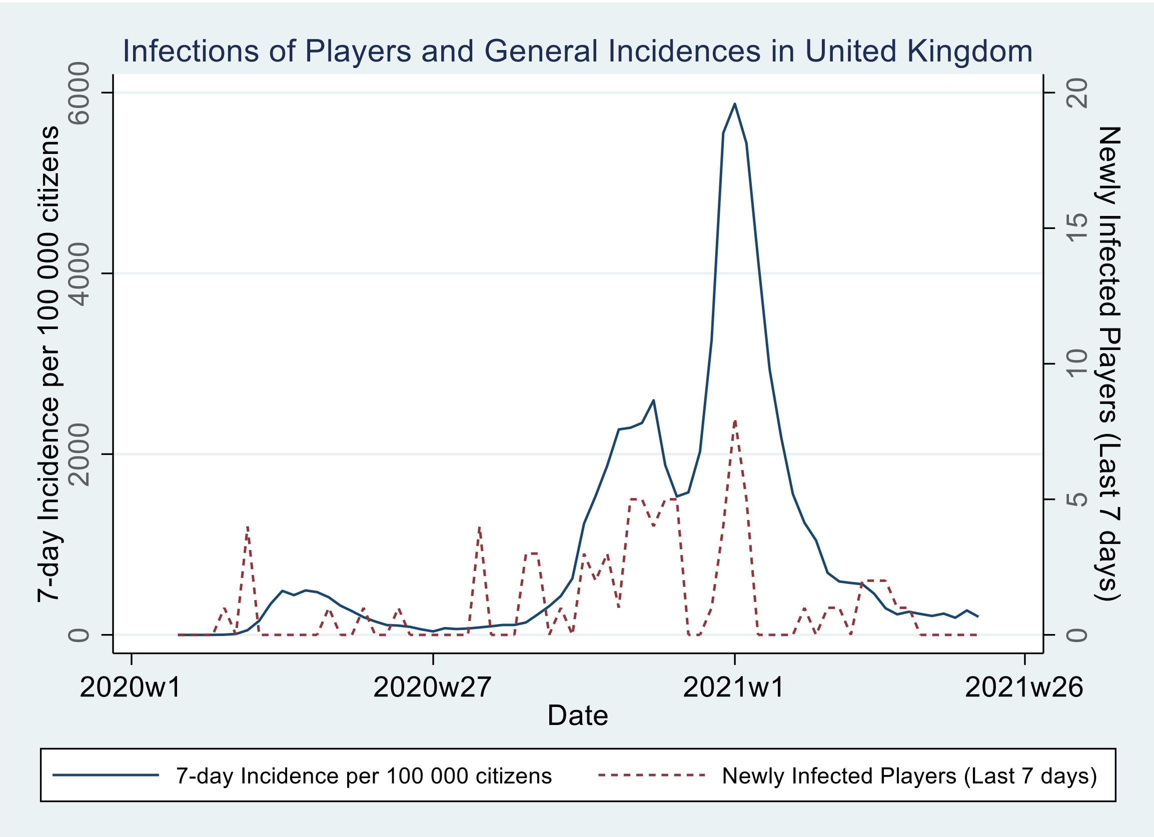
The players were divided into four positions. This could be goalkeeper, defender, midfielder or forward. Some players could play on more than one of these positions on the field, hence some adjustments were made to give every player one position. If a player had multiple positions, the first position mentioned in the *FBREF* database was chosen. For example, if a player's position was originally Midfielder/Forward then this is seen as a Midfielder in our analysis.

Representativeness of sample

Of the 522 players, 81 players were identified to have a COVID-19 infection before the end of the season 2020/2021. This means that about 15.5% of the players had to deal with a COVID-19 infection. This corresponds to the percentage in the Fischer et al. (2021) paper, where 18% of the players was infected. It looks like this percentage is higher than the average percentage of infections in this age group, which was around 7% up until May 2021 (Ritchie et al., 2021). Like the Fischer et al. (2021) paper mentioned this could be due to the traveling and testing frequency of football players, which is higher than the average young adult.

When the COVID-19 infections in our sample are compared with the overall infection trend in the United Kingdom, they look similar. In Figure 1, there is a clear peak in confirmed COVID-19 cases in the months December 2020 and January 2021. There is a similar trend in our dataset, where most of the players seem to be infected within this period. This suggests that EPL players are representable sample to some degree. However, despite the similar trends, it should also be taken into account that football players are younger than the average citizen, and it is likely that their physical condition is better than many other people, not to mention the medical treatment they enjoy. It is therefore important to apply findings from this paper to other settings with caution.

Figure 1: Infected players and general COVID-19 Incidences



Notes: This plot shows the comparison of the 7-day incidences in UK per 100 000 citizens and newly infected players. The data represents infections from 31 January 2020 up to 31 May 2021. The highest peaks in the number of infections seems to occur almost simultaneously for both around the last weeks of 2020. Source UK incidences: (Ritchie et al., 2021).

Methodology

This section outlines the models used for the analysis, the assumptions associated with them and a description of the non-infected and infected group.

Baseline specification

Among football players, the treatment (COVID-19) has not been applied to all observations at the same time. In this case the treatment is not fully an individual choice. In addition, we have a panel dataset with extensive information about the performance of football players over the season. We can compare infected players with non-infected players before and after infection, with a staggered difference-indifference estimation. This estimation also controls for variation over time and across individuals.

Following Fischer et al. (2021), the staggered difference-in-difference regression estimation is as follows:

$$Performance_{PM} = \beta Post\text{-}Infection_{PM} + X'_{PM}\gamma + Z'\zeta + \varepsilon_{PM}. \quad (1)$$

In Equation (1) the dependent variable *Performance*$_{PM}$ stands for a performance measure of player p in match m. This dependent variable is regressed on multiple control variables contained in the variable vector *X,* and fixed effects contained in the variable vector *Z*. The variables included are matchday fixed effects, player fixed effects, team-season and opponent-season fixed effects. *Post-Infection*$_{PM}$ is a treatment dummy with value one for all observations of a player after his COVID-19 Infection. Thus, β is the coefficient of interest. This model is used to estimate the relationship between COVID-19 infection of football players in the Premier league and their performance. As in Fischer et al. (2021), heteroskedasticity-robust standard errors clustered on the player level will be used to control for correlation in the residual of players' observations. The idiosyncratic error term Is ε_{PM}.

This staggered difference-in-difference method comes with some assumptions. First, the parallel trend assumption, which assumes that the difference between treatment group and the control group stay the same over time in absence of the treatment. It is important for this to hold because otherwise the unobserved counterfactual would be estimated wrongly, and the estimated coefficient of the difference-in-difference would be biased. This assumption is tested by an examination of pre-treatment performance trends, which suggest that the parallel trends assumption hold if the pre-treatment trend is flat.

Another assumption is that there is no self-selection of players into treatment. It is very unlikely that this assumption is violated. Players are informed about the dangers of COVID-19 and kept to certain COVID-19 protocols. There seems to be no reason for a football player to deliberately infect himself and it is also not possible to consciously prevent an infection as a football player because having any contact with others as a football player is unavoidable.

This method also assumes that there are no spillover effects. Fischer et al. (2021) pointed out that there are probably spillover effects since the performance of a player is expected to have an effect on the rest of the players on the field. If a player has lower performance after a COVID-19 infection and plays in a game, his lower performance could influence his teammates. For example, if a player's passing is worse, then it is expected that the players in the team will also be negatively affected by this and might also give less passes or perform differently in another way (e.g., higher distance covered due to loss of ball possession). This implies that players of the non-infected group still get influenced by the treatment and the no spillover effect assumption is violated. In this paper it is assumed that the estimated treatment effect is still on the low side because the regression does not take into account that other players probably also suffer from a COVID-19 infection of a teammate.

Dynamic effect specification

An additional assumption of the static difference-in-difference specification (Equation 1) is a constant treatment effect over time. This is likely not the case in this setting, as it is probable that the effect of a COVID-19 infection on player performance will decrease over time. For this reason, this thesis will also employ event studies estimator in order to examine a dynamic treatment effect.

The method for this is also derived from the analysis of Fischer et al. (2021) and the following equation is used to investigate the dynamic effects of COVID-19:

$$\text{Performance}_{PM} = \sum_{\tau=\underline{k},\tau\neq 0}^{\bar{k}} \beta\tau \;\; \text{Post-Infection}_{PM,\tau} + X'_{PM}\gamma + Z' \zeta + \varepsilon_{PM}. \quad (2)$$

Equation (2) gives multiple coefficients of interest βτ. The observations are divided in groups of 30 days around the infection date (t=0). Again, Likelihood to Play, Minutes Played and Pass Performance are used as main dependent variables. This gives us a better picture of how the effect develops over time. Additionally touches per minute and interceptions per minute are used as dependent variable to compare it with the pass performance.

This regression is also used to test the parallel trends assumption by comparing the trends in outcome variables of the infected and non-infected group before t=0. If there is a flat pre-trend in the event study graph, it means that the trends in the pre-treatment outcome are parallel, and the parallel trends assumption is considered to hold.

Outcomes examined

Before looking at the effect of game performance one must look at if people who got infected even had the chance to play. If a player does not play after an infection, this could take away part of the effect this study examines in game performance. Thus, the analysis starts with looking at the effect of a COVID-19 infection on chances of playing. After that it looks at the infection's effects on minutes played if one actually plays. Because maybe people with COVID-19 play less minutes and this could take away some of the effect found on their performance. After that, the effect of COVID-19 on in game performance is looked at.

For game performance we examine the number of passes, the variable that is also used as proxy for productivity in the Fischer et al. (2021) paper. Because the number of passes is also related to the minutes a player is on the field, the variable passes per minute is used as dependent variable. This allows us to control for the minutes a player played and at the same time measure the performance of a player.

After estimating the difference-in-difference equations. It is checked if the coefficient β is a statistically significant. Afterwards there will be additional regressions made with interceptions per minute and touches per minute as dependent variable, to check if the coefficient β is statistically significant and similar to the difference-in-difference with passes per minute as dependent variable

It is expected that a COVID-19 infection lowers the game performance, this is what could be seen in the Fischer et al. (2021) paper. This would mean that β is negative and statistically significant. If the estimated β is indeed negative and statistically significant, then there is a negative relationship found between a COVID-19 infection and a football player's performance. This would suggest that a COVID-19 infection causes a decrease in work performance.

Balancing tests

Before analysing the data, the infected and non-infected group are compared. This is done to check for initial differences between both groups. The game performance of both groups in the first five rounds are compared. The result of these comparisons can be seen in Table 2. The age and the positions are not significantly different in the control and treatment group at a 5% significance level. The English variable is indicating that in the dataset there are relatively few English players infected.

This suggest that a COVID-19 infections is not fully randomly distributed among nationalities. This could be due to English players traveling less or having less (different) contacts. The Table also shows a significant difference in games played, passes per min and interceptions per min. Suggesting that there was already a difference within likelihood to play, passes and interceptions per min. However, the regression specifications (Equations 1 & 2) used in this paper attempt to control for these initial differences by controlling for individual effects in the regressions.

Table 2: Balance test

	Non-Infected	Infected (Pre-Infection)	p-value
Match involvement/Performance			
Played in Game	0.499	0.685	0.000***
If played…			
Minutes Played	71.714	75.126	0.116
Passes per Min	0.442	0.390	0.036**
Touches per Min	0.687	0.629	0.067*
Interceptions per Min	0.005	0.008	0.004***
Presses per Min	0.173	0.158	0.283
Tackles per Min	0.022	0.017	0.263
Blocks per Min	0.020	0.021	0.896
Carries per Min	0.429	0.386	0.057*
Shots per Min	0.015	0.014	0.769
Others			
Age	25.338	26.334	0.057*
Goalkeeper	0.080	0.074	0.871
Defender	0.367	0.432	0.270
Midfielder	0.306	0.222	0.128
Forward	0.247	0.272	0.642
English	0.369	0.235	0.019**

Notes: This table shows the results of the balance test. Column 1 shows the mean of the variables within the non-infected group. Column 2 indicates the mean outcomes for the variables within the infected group. Column 3 shows the p-value for the difference in means. Game performances are based on the first five rounds of the season. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

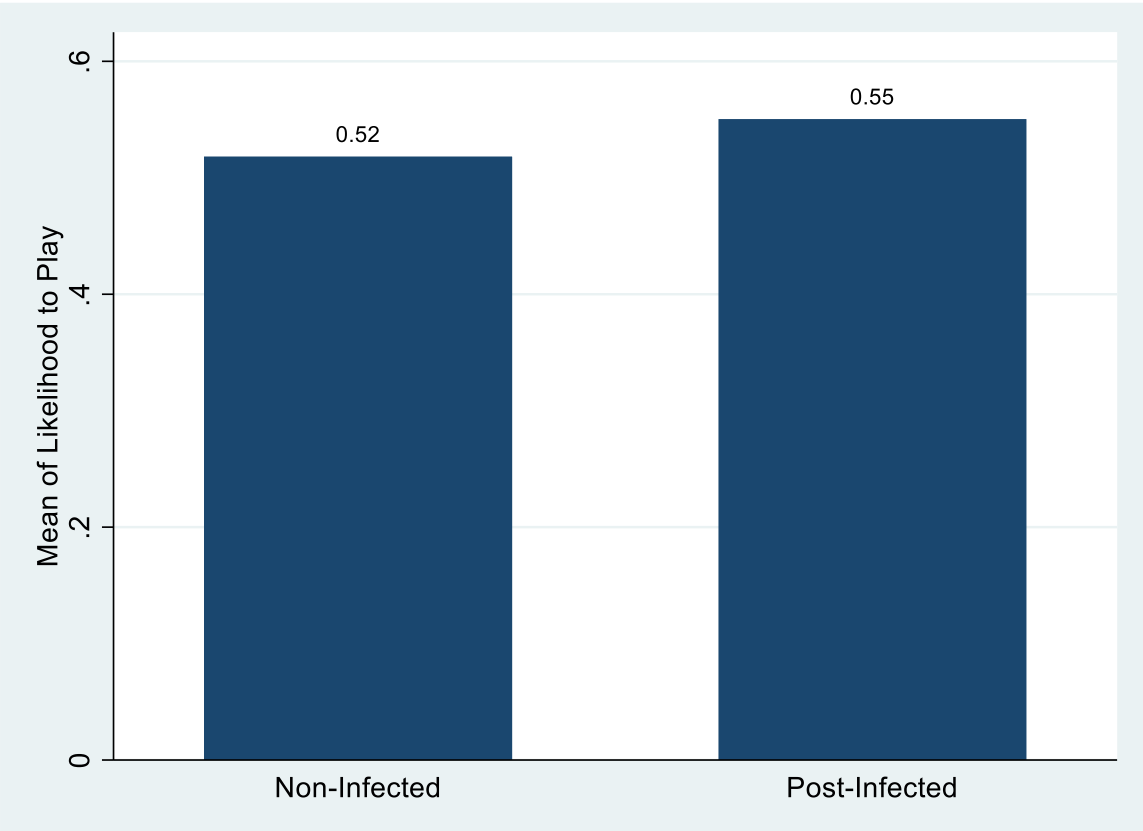
Results

This section outlines the differences between the non-infected and post-treatment group and the results of the staggered difference-in-differences and event studies.

Preliminary results

Before looking at the results of the regressions, we first look at the graphical representation of the differences between the pre- and post-treatment groups. Figure 2 shows that the non-infected players played on average slightly less than the players after the infection. But, as we saw in the balance test, the infected players played significantly more before the treatment. The figure shows that the difference between probability has become smaller, suggesting that the COVID-19 infection caused a drop in the likelihood to play of infected players compared to before their treatment.

Figure 2: Likelihood to play Post-infected and Non-infected

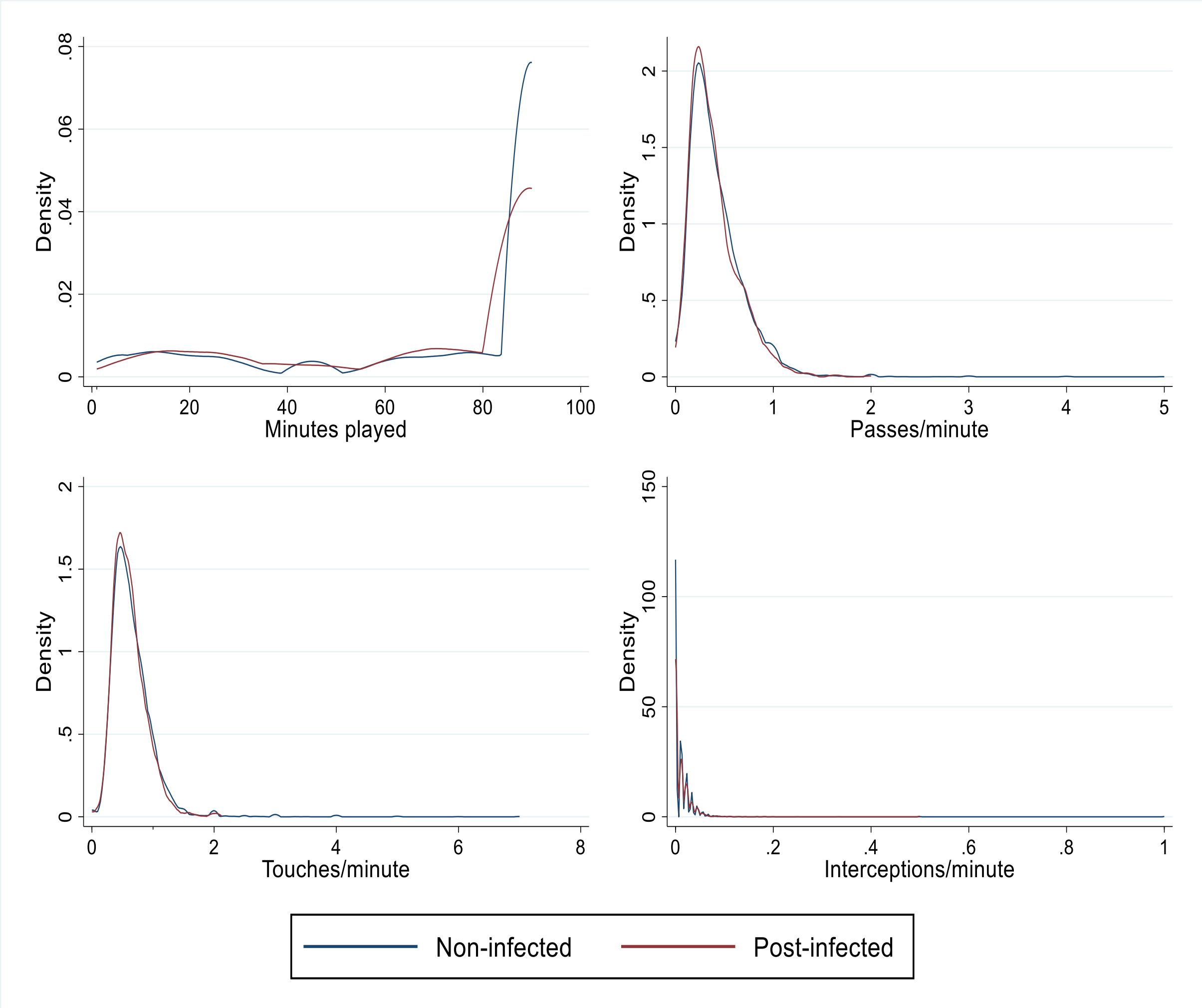


Notes: This figure shows a bar plot of the average number of matches played in the non-infected and Infected players after their infection.

Figure 3 shows the comparison of the minutes played and performance measures between non-infected and post-infected groups. The graph shows that the minutes played are distributed approximately the same until the last ten minutes. There we see that the non-infected players seem to have played more games until the 90th minute. As we saw no significant difference in minutes played in the balance test, this suggest that players were substituted more after a COVID infection.

The passes, interceptions and touches per minute show a similar distribution for non-infected and post-infection group. We also see that for the three performance measures, the uninfected group has some outliers, causing the distribution to continue a little longer. However, the number of outliers in the performance measures is neglectable. The graphs of performance measures are similar in the sense that in all cases the distribution of the non-infected group and the post-infection group are almost identical, suggesting that the measures are valid as a robustness check.

Figure 3: Distribution of outcome variables for Non-infected and Infected players



Notes: This figure shows a kernel density estimation of the minutes played and the passes, touches, and interceptions per minute in the non-infected and Infected players after their infection. The kernel density estimation is a method to estimate a probability density function, which can be used to analyse the probability distribution (Węglarczyk, 2018).

Static results

After seeing a graphical representation of the data, the results of the regression are now discussed to provide causal interpretation of the findings.

For the analysis, the likelihood to play and minutes played are examined first and after that the game performance. This is because a COVID-19 infection could affect the playing time of a football player. This can lead to an underestimation of the effect of an infection on the player's performance, as a player has no performance statistics for time he is not playing. Estimating the playing time gives an indication of how much a player playing less could influence the measured performance. The regression results using Equation 1 are presented in Table 3.

Table 3: Baseline regression results

	(1) Likelihood to play	(2) Minutes played	(3) Passes per Minute	(4) Touches per Minute	(5) Interceptions per Min
Post-Infection	-0.151^{***}	-5.131^{**}	0.009	0.009	0.000
	(0.03)	(2.33)	(0.01)	(0.02)	(0.00)
Observations	19836	10309	10309	10309	10309
R^2	0.39	0.39	0.48	0.39	0.14

Notes: This table shows the regression results of the staggered difference-in-difference designs. The control variables are player fixed effects, team fixed effects, opponent fixed effects and matchday fixed effects. Standard errors are clustered at player level. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In the first regression, the effect of a COVID-19 infection on the likelihood that a player plays is estimated. In Column 1 players with an infection were on average 15 percentage point less likely to play a game compared to players who did not get an infection.

In Column 2 it shows that when players did play, they played on average 5 minutes less than players who did not have a COVID-19 infection. This equates to their playing time dropping by about 7 percent. This is in line with the findings of Fischer et al. (2021), who also noted that a decrease in playing time implies that more players were used as substitutes, either because they had to leave the field earlier or because they were brought in later. This could be due to players being less fit and like Fischer et al. (2021) suggested it may be that players were substituted before they could put in a substandard performance.

For the performance measures the passes per minute were analysed first. Column 3 of Table 3 shows that there is no significant effect of a COVID-19 infection on the players per minute performance. This suggests that players who play after a COVID-19 infection do not perform significantly worse than before their infection.

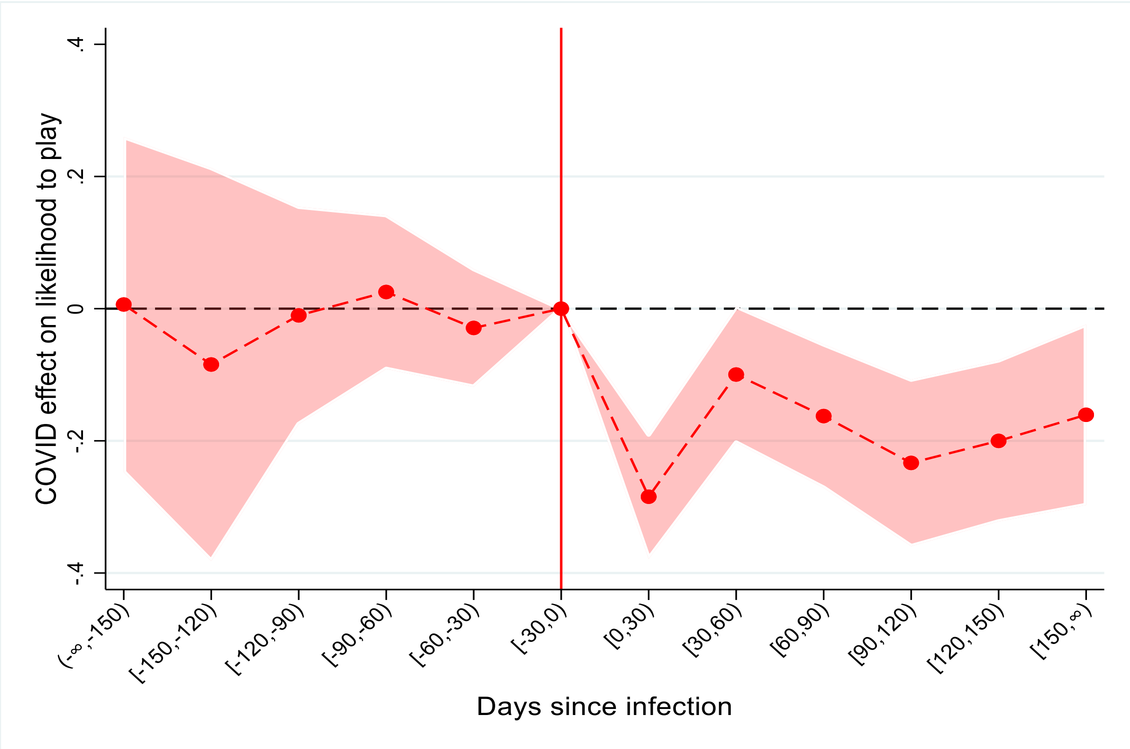
After looking at passes per minutes, touches and interceptions per minute are looked at, to check the robustness of the last regression. Column 4 and 5 of Table 3 show that these regressions also did not give a significant effect of a COVID-19 infection on a player’s performance. The results are similar with passes per minute and thus suggest that the game performance findings are robust and reliable.

Dynamic effects

The Staggered difference-in-differences showed that players with a COVID-19 infection indeed have less chance to play and if they play, they also make fewer minutes on the field. As suspected, this can lead to underestimating the effect of a COVID-19 infection on a player's performance. This is because one of the conditions of measuring a player's performance is that the player was on the field and because of a COVID-19 infection fewer players meet this condition. With the event studies following Equation 2, we look at how the effect develops over time. The event study graphs contain plots with a bin size of 30 days. Equivalent plots with a 75 day bin size can be found in Figure A1, A2 and A3 in the appendix. The corresponding regression results of the 75 day bin size and 30 bin size plots can be found in Appendix table A1 and A2 respectively.

The event study graph in Figure 4 shows dynamic effect on likelihood to play in 30 days bins. Before the treatment none of the effects are significantly different. After the infection, there is significant drop in likelihood to play in the first 30 days, this was to be expected as players who had a COVID-19 infection had to go in quarantine. This drop does not return to previous levels and the likelihood to play does significantly differ from the pre-infection likelihood to play.

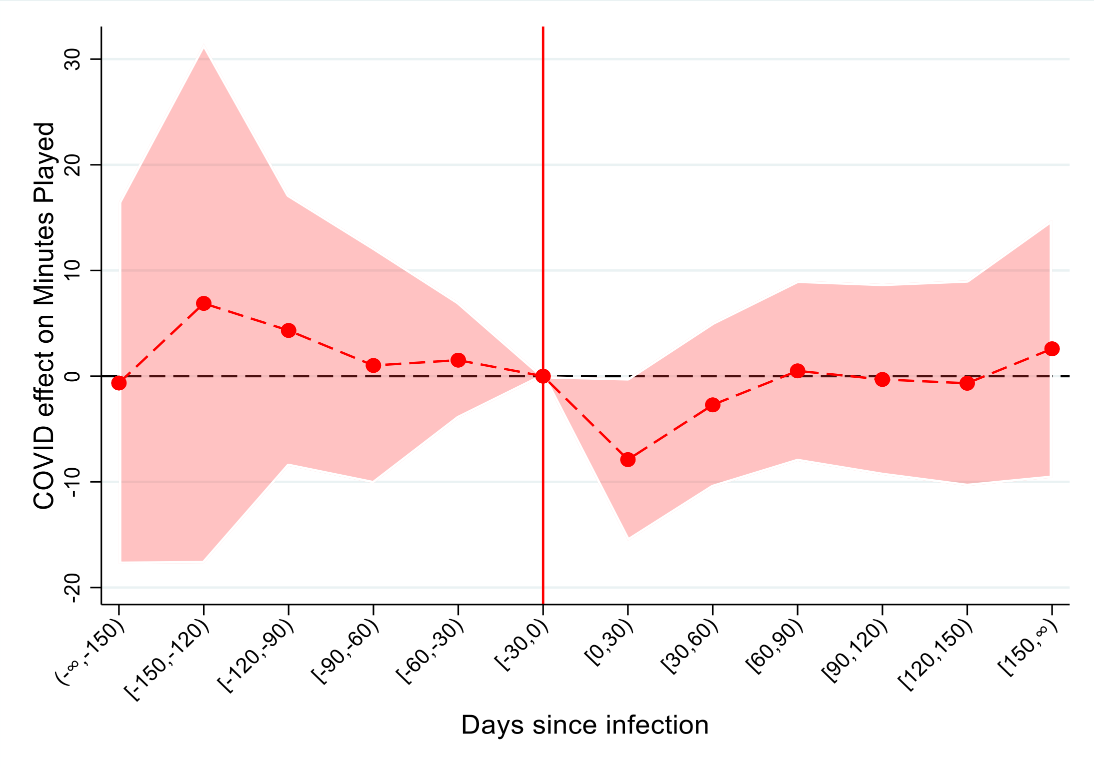
Figure 4: Dynamic effect on likelihood to play



Notes: This figure shows the results of the OLS estimated coefficient $\beta\tau$ of the Equation (2). The reference period is 30 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the dummy variable that indicates whether a player played or not.

The event study graph in Figure 5 shows dynamic effect in 30 days bins. Before the treatment none of the effects are significantly different. After the infection, the graph shows significant drop in minutes played for players who actually played. Contrary to findings of Fischer et al. (2021), the effect disappears after just 30 days, whereas in their case it only returned to a level that is not significantly different from the pre-infection playing time after 150 days. This indicates that the drop in minutes played only lasts for a short time.

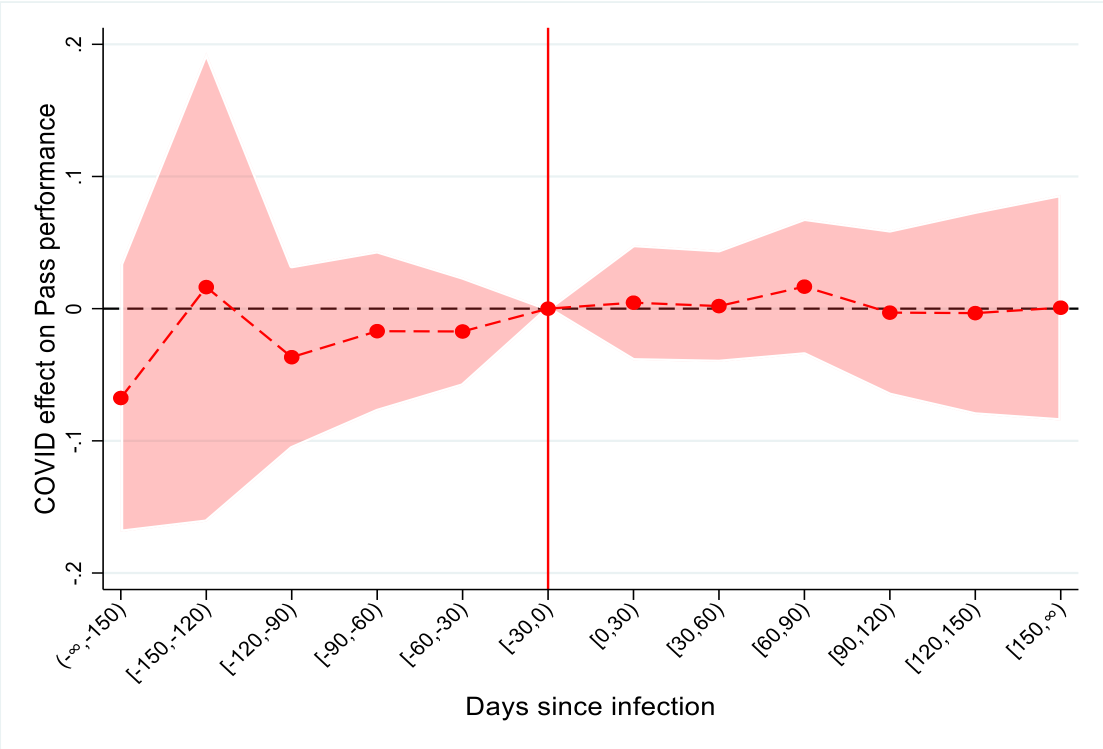
Figure 5: Dynamic effect on minutes played



Notes: This figure shows the results of the OLS estimated coefficient $\beta\tau$ of the Equation (2). The reference period is 30 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the minutes a player played when he played.

The event study in Figure 6 also shows no significant change in passes per minute after COVID-19 infections. The event studies of interception and pass performance, which can be seen in the appendix Figure A4 and A5, show a trend similar to the one of pass performance. The reason that no significant differences are measured in performance may be that players who would perform less, do not get the chance to achieve that performance at all. They are substituted before this can happen or not played at all. Since the graphs show that minutes played return to the original level quickly and at the same time there is no significant difference in performances found, it is likely that players who are able to perform at their former level will soon be used again and play as many minutes as before. However, there is also a group that is still less likely to play at all after a COVID-19 infection. This is probably the group of players that would perform less if they played and therefore do not get the chance to play more often. This cannot be measured in this last regression because they did not actually play, which is a condition for measuring their performance, but for this reason the effect measured is presumably an underestimation of the real effect.

Figure 6: Dynamic effect on within-match work performance



Notes: This figure shows the results of the OLS estimated coefficient $\beta\tau$ of the Equation (2). The reference period is 30 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the Passes per minute.

Difference-in-difference assumptions

All the event study showed a flat trend before the treatment. This indicates that the parallel trend assumption of the difference-in-difference has not been violated. The results do show a variation in treatment effect over time after the treatment, this indicates that the assumption that the effect size is constant over time is violated.

These results also suggest that the assumption of no spillover effects is realistic, as no significant difference was found in the performance of players that could possibly affect team performance.

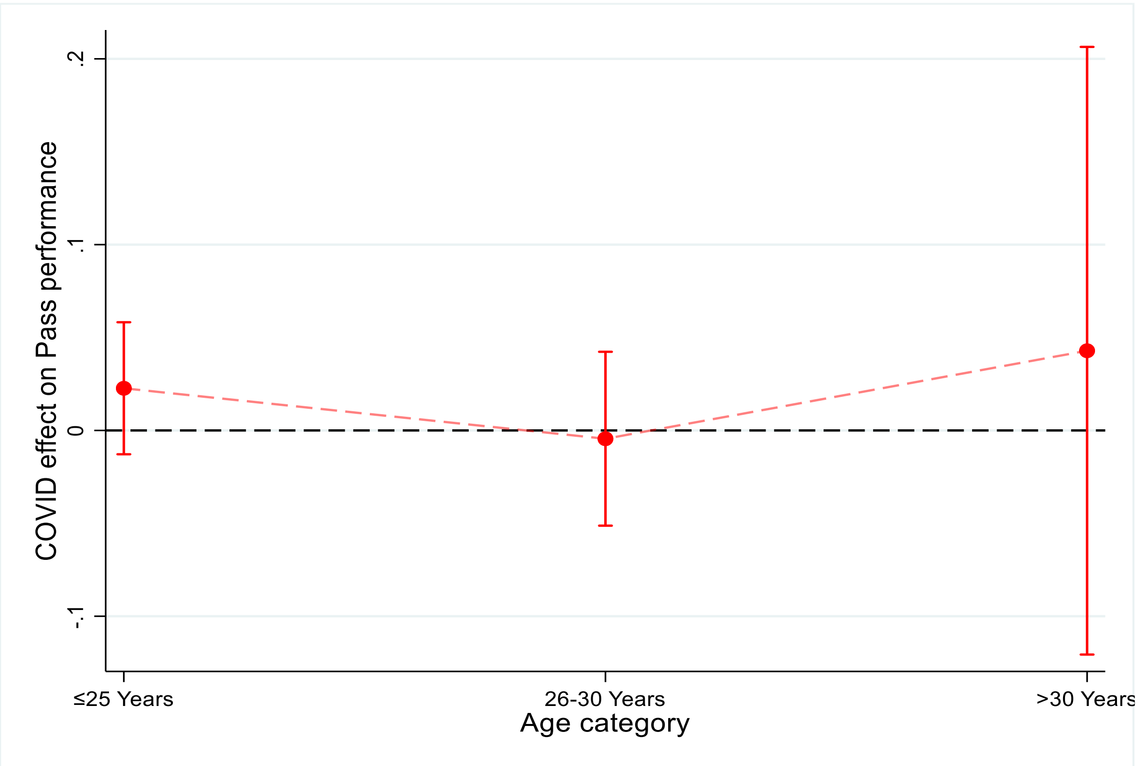
Effect heterogeneity

It is possible that there is heterogeneity in the effect of a COVID-19 infection. The heterogeneity in age and position is tested in this paper.

Starke et al. (2020) examined the isolated effect of age on COVID-19 severity. Through a literature review, they found that the likelihood of disease severity increases by 2.7% with each year a person ages. Thus, it is possible that age also plays a role in how much a player's performance is affected by an infection. Fischer et al. (2021) found that players older than 30 years had a relatively strong decline in performance compared to other age groups.

Figure 7 shows that there is no heterogeneity between age groups in our sample. This suggests that the effects of a COVID-19 infection on player performance do not differ between any of the age groups.

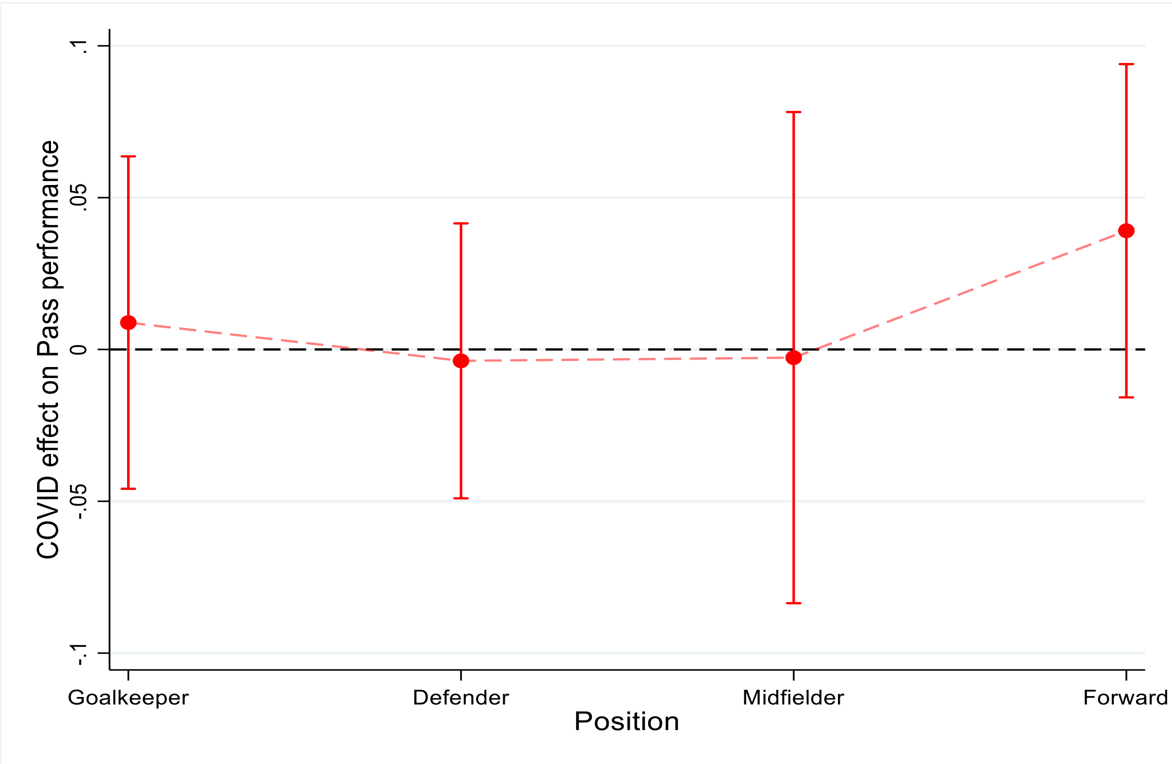
Figure 7: Effect Heterogeneity: Age effects



Notes: This figure shows the results the interaction effects between the post-infection dummy and age categories included in Equation (1). Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured bands indicate the 95% confidence intervals. The dependent variable is the Passes per minute.

Heterogeneity of the effect of COVID-19 between positions is also examined. Depending on his position, a player's performance may be affected differently by an infection. Figure 8 shows that no significantly different effect was found for any position. This indicates that there is no difference between the positions in how a COVID infection affects player performance. Plots on heterogeneity analyses on likelihood to play can be found in appendix Figure A6 and A7, they also show no significant stronger effects among age or positions.

Figure 8: Effect Heterogeneity: Position effects



Notes: This figure shows the results the interaction effects between the post-infection dummy and positions included in Equation (1). Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured bands indicate the 95% confidence intervals. The dependent variable is the Passes per minute.

Discussion

This paper studied the effect of a COVID-19 infection on work performance of football players. Data of English premier league players were analysed to quantify this effect. Firstly, it appeared that infected players are significantly less likely to play after a COVID-19 infection compared to players who did not have an infection. This is in line with the first hypothesis that players would play less after a COVID-19 infection. This drop in likelihood to play is persistent and does not return to pre-infection level within the observed timeframe.

Secondly, players play significantly less minutes after a COVID-19 infection compared to players who did not have an infection. The reason for this might be that players who return from a COVID-19 infection are not fit and are taken out of the field before their performance would deteriorate. The findings are in line with the expectation that players would play less minutes after a COVID-19 infection. The drop in minutes played returns to pre infection level after 30 days. This means that players leave the field earlier or are brought in later after a COVID-19 infection, but it takes a relatively short time before they play the same minutes as before the infection.

Thirdly, players performance after a COVID-19 infection does not significantly differ from players who did not have a COVID-19 infection. Over the measured period there is no difference in the game performance compared to before the treatment. This is not in line with the hypothesis that players perform less after a COVID-19 infection. But because of the first two findings, the actual coefficient is expected to be negative. Possibly, players are prevented from performing worse because they play less after a COVID-19 infection. It might be that football coaches already expect that a player will perform less based on training sessions and therefore choose not to play someone after a COVID-19 infection in that case.

The results of this paper have some similarities with the study by Fischer et al. (2021) but there are also some differences. Both papers observed that football players play less after a COVID-19 infection, but the measured effect was greater in this research. They found a 5.7 percentage point lower chance of playing where this paper found 15 percentage points lower. This is a substantial difference and perhaps it has to do with the difference in the selection width between the English Premier League on the one hand and the Bundesliga and Serie A on the other. Premier league teams may have more players in their squad who are qualitatively comparable to the usual first eleven players and can therefore be brought in and compensate more easily when another player underperforms.

The English Premier League is known to be the richest league in the world (Barros et al., 2006). It might be that their clubs can afford to not field an infected player. While in other leagues, clubs do not have the budget for replacement and force infected players to play. If this is the case this could also imply that richer countries or firms might not be affected as much by COVID, since they can afford to replace a worker until the infected worker is recovered enough. This indicates that the cost and benefits of lockdowns and other COVID measure are context dependent.

The analysis also showed a short drop in minutes played. The static coefficient was 5 which is similar to the 6 minutes Fischer et al. (2021) estimated. However, in the dynamic effect plot the effect disappears after 30 days, were in their paper the effect became insignificant after 150 days.

The main difference in the findings of this paper is that there was no significant difference in pass performance found, while in their (2021) paper there was a clear decline in performance. Table 4 gives an overview of the most important differences in the results found between this paper and the Fischer et al. (2021) paper.

Table 4: Comparison with results of Fischer et al. (2021)

	This paper		Fischer et al. (2021)	
	Significant effect of COVID-19 Infection	Does effect persist multiple periods?	Significant effect of COVID-19 Infection	Does effect persist multiple periods?
Likelyhood to Play	Yes	Yes	Yes	Yes
Minutes Played	Yes	No	Yes	Yes
Passes per Minute	No	No	Yes	Yes
Touches per Minute	No	No	Yes	Yes
Interceptions per Minute	No	No	Yes	Yes

In addition, we also found no heterogeneity in the effect of COVID-19 between age or player position. Fischer et al. (2021) did find heterogeneity in these dimensions. These findings do not appear to be reproducible in our sample. This suggests that the impact of COVID-19 infection on performance is equal across the used sample.

The results of this paper also suggest that COVID causes a decline in work performance. Meaning that if many people get infected, this has a significant economic impact. This makes it more important for society to prevent COVID infections, as the infections reduce work performance, and the decline lasts longer. A drop in work performance can cause a drop in production, which can harm businesses and economies for extended periods. In most professions it is not as easy as in football to replace one employee with another. If it is possible to replace a worker, there is a limit to employee replacement. If many companies have this problem, there can be much demand for replacement, which can cause problems for countries and/or firms that are not able to afford the replacement. Other solutions to compensate for loss of production could be to replace workers with machines.

This thesis found that the findings of Fischer et al. (2021) are not applicable to every setting. They found significant performance drop due to COVID-19 infection. But this paper shows that this is not necessarily the case after an infection. We have seen that a COVID infection can also lead to a player having less chance to play, so it does not have to be the case that a player is still fielded and performs less. Based on the observations, it cannot be said for sure that COVID causes a decrease in player performance. Thus, based in the analysis one cannot say that the findings of Fischer et al. (2021) are not valid in the EPL setting. But this paper does find a different pattern of how COVID affects a player.

One of the limitations of this research is that only the performance of players on the field can be observed, and it is not known how people perform off the field, for example in training. Because of this, it cannot be seen how players would have performed in the minutes and matches they did not play in. This decreases the internal validity of the research, as the actual effect of a COVID-19 infection on work performance cannot fully be measured, and the estimated coefficient might be biased.

Another limitation is the specific subsample of these research analyses. This study looked at professional male football players from the English Premier League. They are men who are younger than the average working person and who are also fitter than many people. In addition, football is not comparable to many other professions. This makes it difficult to generalize our findings. Additional research will be needed to check whether the effect found also applies to other groups.

In addition to these limitations, the group examined is also a group wherein many people are not vaccinated. As much more people get vaccinated it becomes interesting to examine how and if the effect changes for fully vaccinated individuals.

Conclusion

This paper examined the effect of a COVID-19 infection of work performance of a football player in the English Premier League season 2020/2021. The results show that players are less likely to play after an infection. When they played, they played for less time, but that trend was only present for a short time. In terms of performance, no significant difference was found between players after a COVID-19 infection compared to before the infection. The question is whether this is because there is no effect of COVID-19 on the performance of a player or whether it is because players who would actually perform less have not played and therefore could not achieve that performance. It seems that COVID-19 makes it less likely for a player to get fielded. This could be an indication that players are less likely to perform on the level that is sufficient to play a game after a COVID-19 infection. It is therefore suspected that a COVID-19 infection has a negative influence on work performance. But this could not be observed in this paper. Possibly because players had less chance to play and perform in a match after an infection.

The findings of this research indicate that costs of getting a COVID-19 infection are even greater than previously thought. It should be assessed if measures against COVID-19 were useful taking into account the long-term costs of COVID. With these new costs, the consequences of future policy must also be estimated.

As said earlier, one important limitation of the analysis is that the performance of players who did not play could not be observed. This leads to the suspicion that the effect found is lower than the real effect, because there is a chance that individuals who suffered a lot from COVID-19 were not observed. In addition to the inability to observe the game performance of COVID-19 infected in the games they did not play, another limitation in this paper is the use of a specific the sample which is not comparable to many other citizens. This decreases the external validity of the research.

Suggestions for further research would be to test the same effect for women. If it turns out that women are influenced differently, this could have consequences for the policy. For example, if the effect is higher for women, they might get priority for new COVID-19 vaccination, and they would have an extra incentive to get vaccinated.
It may also be possible to look at training results of players. This is because a limiting factor in this study was that performance could only be observed when a player was actually fielded.
As Fischer et al. (2021) suggested, it is also possible to look at how the effect is now that a large part of the population has been vaccinated. This may have a dampening effect on the impact of COVID-19

on performance. Likewise, variants of COVID-19, other professions and other age groups can be looked at.

This paper showed that players had a smaller chance of playing after a COVID-19 infection. However, in most occupations outside the context of football, an employee will continue to work after a quarantine period. If the decrease in the chance of playing is actually due to reduced player fitness, then this would be proof that COVID-19 affects the performance of a football player. For employers, it will in that case be a reason to take more action to prevent employees from becoming infected with COVID-19, as the costs of an infection turn out to be higher than previously thought. They can then, for example, encourage working from home, regularly test for COVID-19 or maintain mutual distance between colleagues. For the same reason, Individuals would have an extra incentive to get vaccinated.

The findings suggest that wealthier companies and countries will be less affected by the effects of COVID, as they can more easily compensate for a loss in work performance. As a result, it may be even more rewarding for poorer countries and firm to take COVID measures. The incentive to prevent COVID-19 infections will be higher for them because of the decrease in work performance that results from an infection.

Regarding football, it might be rewarding for clubs and players' unions to take more measures to prevent COVID-19 infections, as the costs of a player getting infected by COVID-19 seems higher. The virus having less effect on wealthy clubs is an additional reason to ensure a uniform COVID policy in the league, so that differences between clubs in the number of COVID-19 infections, which lead to a drop in performance, do not increase. The English Premier League would also benefit from measures against COVID because the performance of players is one of the building stones of an attractive and competitive competition.

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Appendix

Table A1: Regression results of Dynamic effect with bigger bin size

	(1) Likelihood to play	(2) Minutes played	(3) Passes per Minute	(4) Touches per Minute	(5) Interceptions per Minute
[-225, 150)	0.15	-2.08	-0.04	-0.01	-0.00
	(0.11)	(7.15)	(0.04)	(0.05)	(0.01)
[-150, -75)	0.08	0.84	-0.02	0.01	0.00
	(0.06)	(4.75)	(0.03)	(0.03)	(0.00)
[-75, 0)	0	0	0	0	0
[0, 75)	-0.22***	-5.08	0.00	0.00	0.00
	(0.05)	(3.52)	(0.02)	(0.02)	(0.00)
[75, 150)	-0.35***	-1.17	-0.01	-0.02	0.00
	(0.07)	(4.36)	(0.03)	(0.03)	(0.00)
[150, 225)	-0.35***	1.38	-0.02	-0.04	0.00
	(0.09)	(6.29)	(0.04)	(0.05)	(0.01)
[225, ∞)	-0.43***	-0.24	-0.04	-0.07	-0.00
	(0.12)	(9.18)	(0.04)	(0.06)	(0.01)
Constant	0.80***	73.6***	0.40***	0.64***	0.01***
	(0.05)	(3.36)	(0.02)	(0.02)	(0.00)
Observations	3063	1745	1745	1745	1745
R^2	0.35	0.31	0.56	0.48	0.15

Notes: This table show estimated coefficients βτ of regression results of Equation (2). The bin size is 75 days. The control variables are player fixed effects, team fixed effects, opponent fixed effects and matchday fixed effects. Standard errors are heteroskedasticity-robust and clustered on the player level. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Regression results of Dynamic effect with small bin size

	(1) Likelihood to play	(2) Minutes played	(3) Passes per Minute	(4) Touches per Minute	(5) Interceptions per Minute
(-∞, -150)	0.01	-0.65	-0.07	-0.04	-0.00
	(0.13)	(8.59)	(0.05)	(0.06)	(0.01)
[-150, -120)	-0.09	6.89	0.02	0.00	-0.01
	(0.15)	(12.34)	(0.09)	(0.10)	(0.01)
[-120, -90)	-0.01	4.33	-0.04	-0.01	0.00
	(0.08)	(6.44)	(0.03)	(0.04)	(0.00)
[-90, -60)	0.03	1.01	-0.02	0.02	0.00
	(0.06)	(5.60)	(0.03)	(0.04)	(0.00)
[-60, -30)	-0.03	1.52	-0.02	-0.01	0.00
	(0.04)	(2.75)	(0.02)	(0.03)	(0.00)
[-30, 0)	0	0	0	0	0
[0, 30)	-0.28***	-7.89**	0.00	0.01	0.00
	(0.05)	(3.86)	(0.02)	(0.03)	(0.00)
[30, 60)	-0.10*	-2.71	0.00	0.01	0.01
	(0.05)	(3.90)	(0.02)	(0.02)	(0.00)
[60, 90)	-0.16***	0.50	0.02	0.00	-0.00
	(0.05)	(4.28)	(0.03)	(0.03)	(0.00)
[90, 120)	-0.23***	-0.31	-0.00	-0.00	0.00
	(0.06)	(4.54)	(0.03)	(0.03)	(0.00)

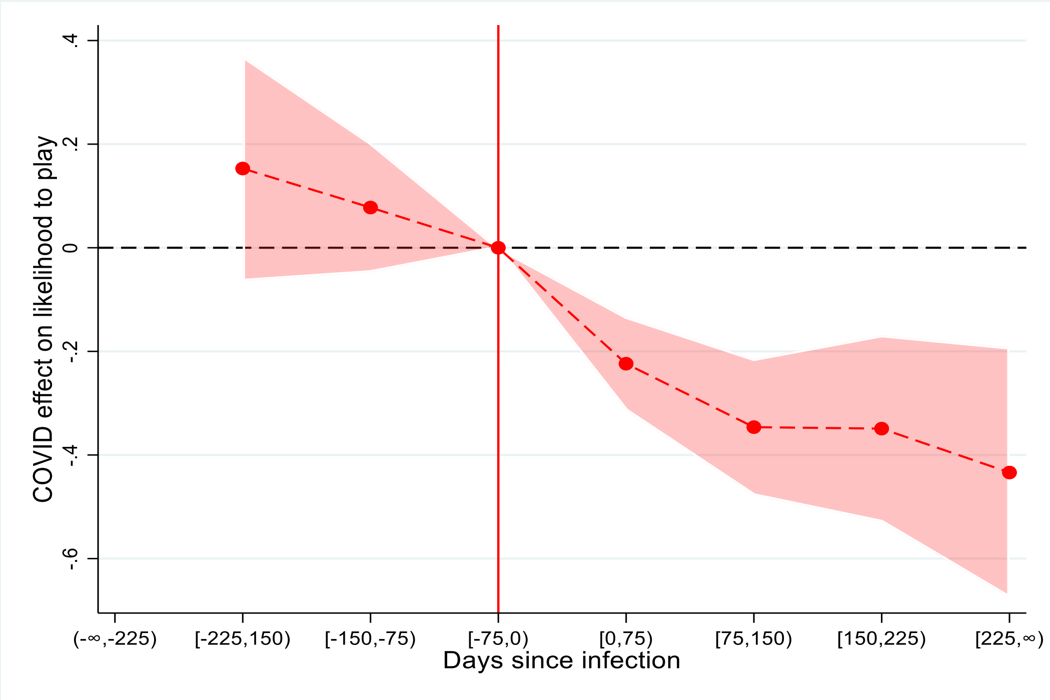
Table A2 (continued).

[120, 150)	-0.20***	-0.67	-0.00	0.01	0.00
	(0.06)	(4.88)	(0.04)	(0.04)	(0.01)
[150, ∞)	-0.16**	2.59	0.00	-0.00	0.00
	(0.07)	(6.13)	(0.04)	(0.05)	(0.01)
Constant	0.71***	72.3***	0.40***	0.62***	0.01***
	(0.04)	(3.16)	(0.02)	(0.02)	(0.00)
Observations	3078	1756	1756	1756	1756
R^2	0.35	0.31	0.56	0.48	0.16

Notes: This table show estimated coefficients βτ of regression results of Equation (2). The bin size is 30 days The control variables are player fixed effects, team fixed effects, opponent fixed effects and matchday fixed effects. Standard errors are heteroskedasticity-robust and clustered on the player level. Standard errors in parentheses.

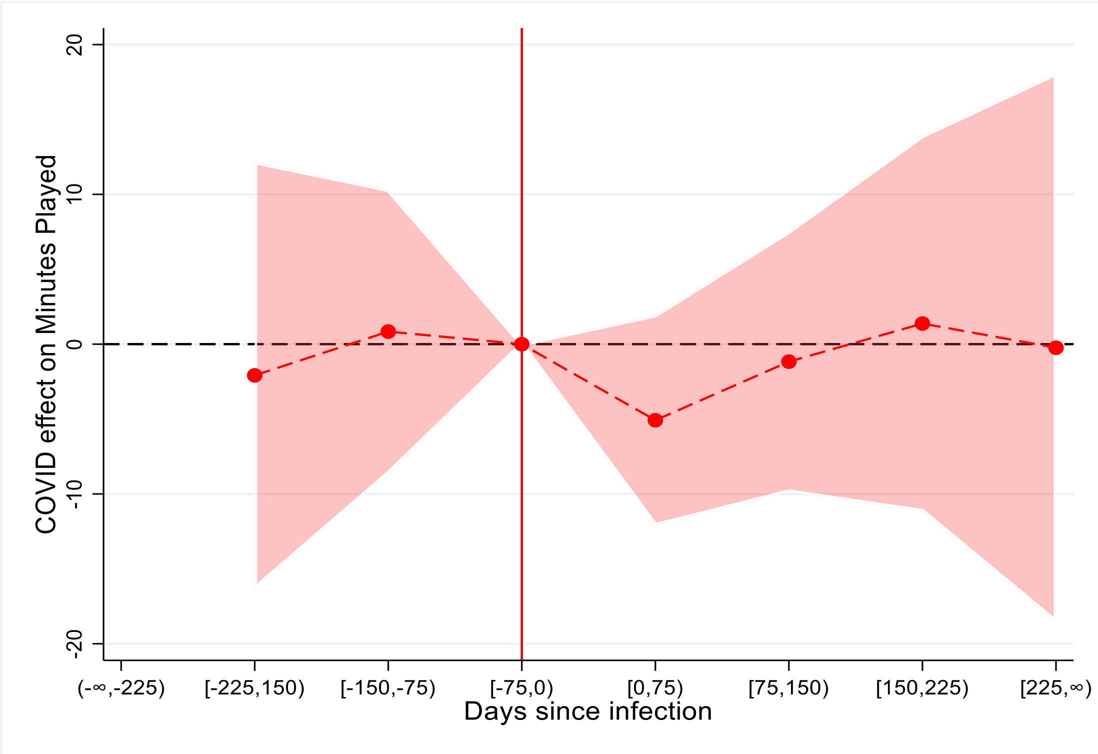
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Dynamic effect on Likelihood to play: Bigger bin size



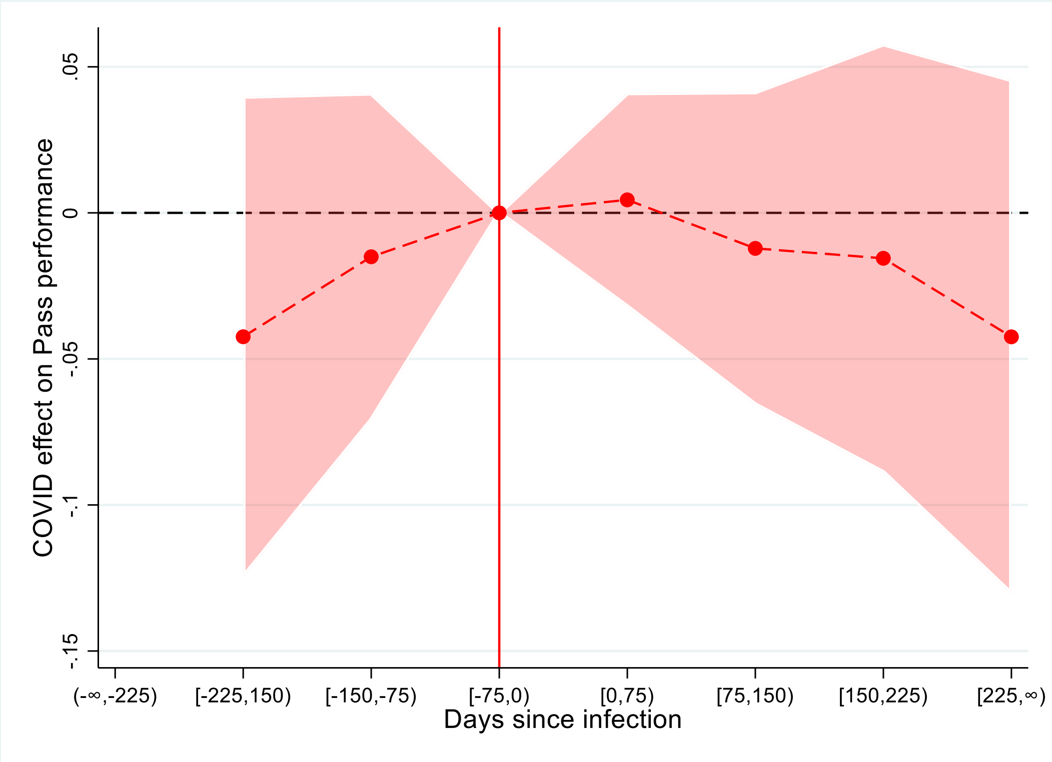
Notes: This figure shows the results of the OLS estimated coefficient βτ of the Equation (2). The reference period is 75 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the dummy variable that indicates whether a player played or not.

Figure A2: Dynamic effect on minutes played: Bigger bin size



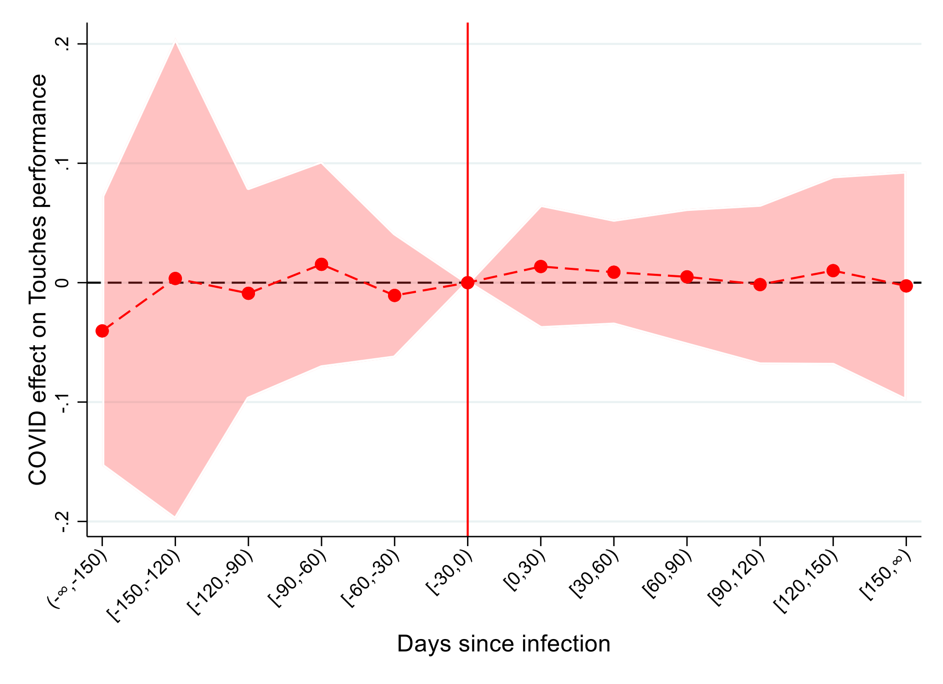
Notes: This figure shows the results of the OLS estimated coefficient βτ of the Equation (2). The reference period is 75 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the minutes played.

Figure A3: Dynamic effect on within-match work performance: Bigger bin size



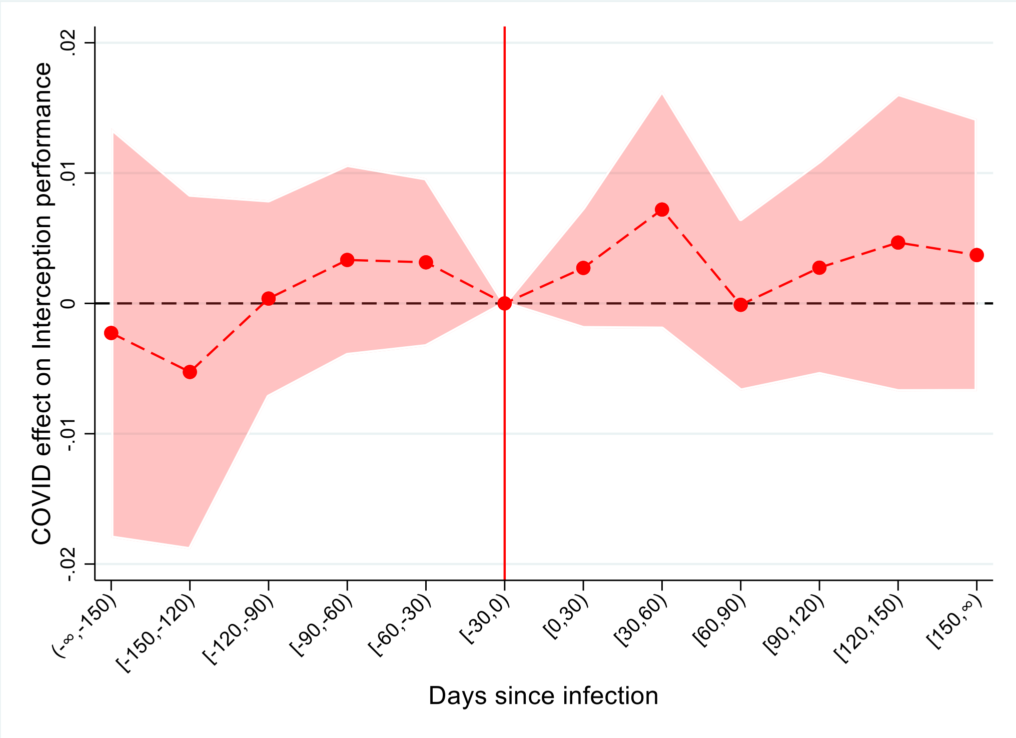
Notes: This figure shows the results of the OLS estimated coefficient βτ of the Equation (2). The reference period is 75 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the Passes per minute.

Figure A4: Dynamic effect on within-match work performance: Touches per minute



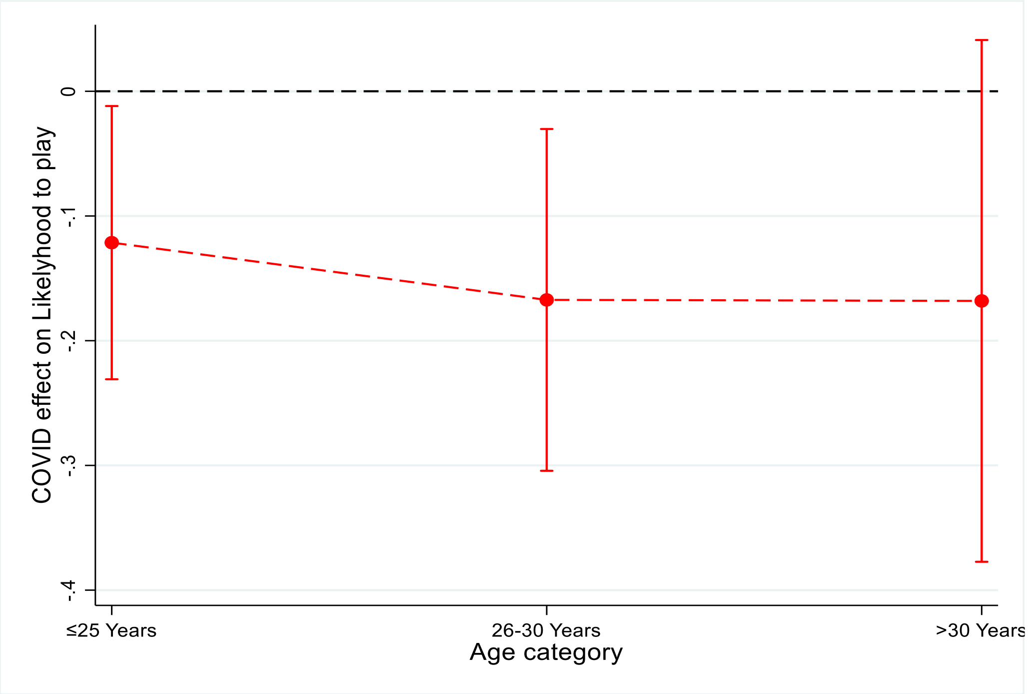
Notes: This figure shows the results of the OLS estimated coefficient $\beta\tau$ of the Equation (2). The reference period is 30 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the Touches per minute.

Figure A5: Dynamic effect on within-match work performance: Interceptions per minute



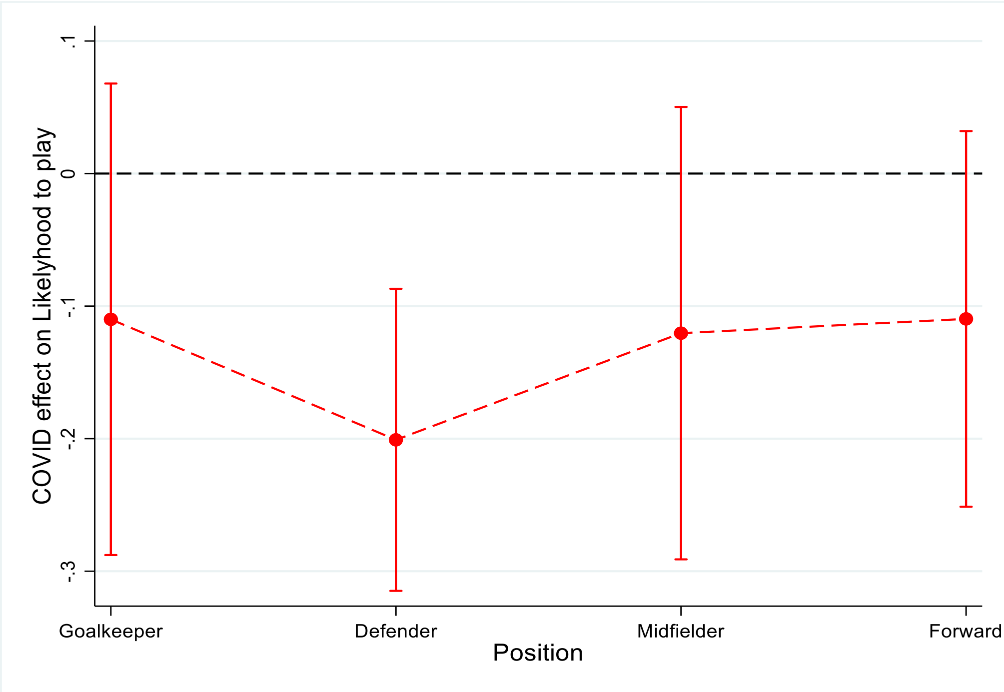
Notes: This figure shows the results of the OLS estimated coefficient βτ of the Equation (2). The reference period is 30 days to 1 day before the treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured area indicates the 95% confidence intervals. The dependent variable is the Interceptions per minute.

Figure A6: Heterogeneity for effect on likelihood to play: Age



Notes: This figure shows the results the interaction effects between the post-infection dummy and age categories included in Equation (1). Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured bands indicate the 95% confidence intervals. The dependent variable is the Likelihood to play.

Figure A7: Heterogeneity for effect on likelihood to play: Position



Notes: This Figure shows the results the interaction effects between the post-infection dummy and positions included in Equation (1). Standard errors are heteroskedasticity-robust and clustered on the player level. The red coloured bands indicate the 95% confidence intervals. The dependent variable is the Likelihood to play.