

The Long Shadow of an Infection: COVID-19 and Performance at Work

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Abstract

The COVID-19 pandemic has caused economic shock waves across the globe. Much research addresses direct health implications of an infection, but to date little is known about how this shapes lasting economic effects. This paper estimates the workplace productivity effects of COVID-19 by studying performance of soccer players after an infection. We construct a dataset that encompasses all traceable infections in the elite leagues of Germany and Italy. Relying on a staggered difference-in-differences design, we identify negative short- and longer-run performance effects. Relative to their pre-infection outcomes, infected players' performance temporarily drops by more than 6%. Over half a year later, it is still around 5% lower. The negative effects appear to have notable spillovers on team performance. We argue that our results could have important implications for labor markets and public health in general. Countries and firms with more infections might face economic disadvantages that exceed the temporary pandemic shock due to potentially long-lasting reductions in productivity.

Keywords: Labor Performance, Economic Costs of COVID-19, Public Health

JEL Classification: I18, J24, J44

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1 Introduction

The COVID-19 pandemic continues to be a historical challenge for the global community as this disease has been infecting millions and affecting billions of people. As a consequence, many governments reacted with a wide range of non-pharmaceutical interventions (NPI). Numerous studies have shown that these policies have been associated with high direct and indirect costs (see, e.g., [Fuchs-Schuendeln et al. 2020](#), [Lin and Meissner 2020](#), [Miles et al. 2021](#), [Ravindran and Shah 2020](#), [Rowthorn and Maciejowski 2020](#)). Among others, such policies led to increased domestic violence or long-term earnings losses for children due to school closures. These effects caused lively debates about the timing and extent of re-openings and lifting restrictions (see e.g., [Gostin and Wiley 2020](#), [Jamaludin et al. 2020](#), [Savulescu and Cameron 2020](#)).

While the mortality risk seems to be much lower for most people in the labor force ([Yanez et al., 2020](#)), a hitherto unknown factor is the impact of an infection on individual labor output after recovering from the actual sickness. The present paper sheds light on this question by investigating quasi-weekly productivity of high-performance workers up to fifteen months post-infection. We apply a difference-in-differences framework on a natural experiment among professional soccer players. Making use of a uniquely accurate testing scheme and employing high-frequency performance data, we find causal evidence for a significant and persistent deterioration in worker productivity due to COVID-19. Our work adds to the economic analysis of events related to the COVID-19 pandemic. [Brodeur et al. \(2020\)](#) as well as [Padhan and Prabheesh \(2021\)](#) provide comprehensive overviews on the economics of this disease, covering a wide range of topics.

We analyze an occupation with comparatively low confounding of individual productivity as capital and technology are hardly driving forces of output in soccer. Productivity can rather be considered as a function of various health aspects; mainly physical measures, for example acceleration, condition, and endurance, but also the cognitive capability to position oneself optimally on the pitch. The number of passes is related to all of these measures, which is why we base our analysis on this parameter. We consider COVID-19 as a shock to the underlying health aspects, that consequently causes a deterioration in performance. Subsequently, we use the term ‘work performance’ to make clear we do not measure productivity directly but a variable that is well-suited but still a proxy.

Our approach is in line with earlier work in this field. [Lichter et al. \(2017\)](#) analyze the impact of air pollution on productivity of soccer players. They also rely on passes as productivity measure. A core result is that a deterioration in air quality by one percent decreases a player’s performance on the field by up to 0.02%. Work by [Carmichael et al. \(2001\)](#) and [Oberstone \(2009\)](#) try to disentangle the drivers of success in soccer. They also find passes to be a core factor.

Obviously, our work also corresponds to medical research addressing the health effects of COVID-19 infections which shape performance changes. As we estimate long-term economic effects of an infection, we focus on research dealing with persistent health impairments which many researchers aggregate under the ‘long COVID’ label. There is growing evidence for such a deterioration in well-being far beyond the infection itself.¹ According to [Venkatesan \(2021, p. 129\)](#), “[t]he list of persisting and new symptoms reported by patients is extensive, including chronic cough, shortness of breath, chest tightness, cognitive dysfunction, and extreme fatigue.” This label, however, only captures people with persistent symptoms. We are interested in overall productivity effects among infected individuals. Hence, our analysis has a broader scope, providing an economic analysis of post-infection performance for all types of previously infected individuals.

With respect to productivity, there exists economic research addressing the impact of the pandemic. [Bloom et al. \(2020\)](#) exploit a large monthly firm panel in the UK, e.g. on sales, employment and R&D investments. They base their analysis on questions of how the pandemic and the NPIs have affected the surveyed firms. From that, they measure a decline in total factor productivity of 3-5% in the UK throughout 2020. The effects of work-from-home (WFH) schemes are ambiguous. [Bloom et al. \(2014\)](#) find in a field experiment conducted well before the pandemic a positive effect of WFH on productivity. [Etheridge et al. \(2020\)](#) analyze self-reports from workers during early phases of the pandemic and find on average no negative effects. Contrary to this, [Künn et al. \(2020\)](#) find a significant deterioration for the cognitively demanding task of chess matches. They study the likelihood to make a major mistake when playing from home compared to in

¹[Mahase \(2020\)](#) and [Carfi et al. \(2020\)](#) provide early findings on ‘long COVID’. [Sudre et al. \(2021\)](#) identify a higher age, a higher Body Mass Index and being female as coarse predictors. [Blomberg et al. \(2021\)](#) find that half of young people between 16-30 years have persistent symptoms even six months after the infection. [Buonsenso et al. \(2021\)](#) find at least one ‘long COVID’ symptom being persistent among children as many as two months. Nevertheless, ‘long COVID’ is still subject to methodological problems ([Yelin et al., 2020](#)). For example, [Maxwell \(2021\)](#) points out that many studies rely on self-reporting from patients, which is often questioned. We circumvent this issue by solely relying on observational data.

situ tournaments. For learning from home, [Altindag et al. \(2021\)](#) find that online learners have significantly worse outcomes compared to fellow students in class rooms. These studies have in common that they investigate NPI shocks implemented due to the pandemic but do not analyze treatment due to a virus infection itself. In contrast, we are the first to provide an economic analysis of the virus’ impact on individual productivity. To the best of our knowledge, the only exception is medical work by [Vaudreuil et al. \(2021\)](#), who descriptively assess the performance of twenty professional basketball players in the US basketball league, NBA, before and after becoming infected.

In our empirical set-up, we are able to differentiate precisely between infected and non-infected individuals as the soccer leagues implemented rigid regimes of frequent and systematic testing for all players. This is a distinguishing feature of our analysis as it does not suffer from the problem of many unidentified infected individuals that distort identification as some infected players are part of the control group. Furthermore, we can exploit highly granular real-time performance data, that are likely to be unique among occupations. Henceforth, our empirical analysis asks two questions: Does a COVID-19 infection affect the probability that a player participates in a match and the amount of time he plays? This extensive margin captures general absence effects related to the infection but also takes up the non-consideration of post-infected players by the medical or coaching staff. Second, does the performance of previously infected players decrease once they play again? Here, our particular interest is the within-match performance among players on the field – the intensive margin effect. Methodologically, we conduct a range of difference-in-differences estimations to answer these questions. We do this applying a dynamic event study setting for both the extensive and intensive margins.

Utilizing sports data has been found to be helpful in many economic contexts ([Bar-Eli et al., 2020](#)) such as testing theoretical hypotheses from game theory (see e.g., [Kassis et al., 2021](#)) or deriving conclusions for public and labor economics (see e.g., [Kahn and Sherer, 1988](#); [Kleven et al., 2013](#); [Lichter et al., 2017](#); [Parsons et al., 2011](#)). By studying professional men’s soccer, we consider an industry that continued its business quite quickly. After a comparatively short suspension in spring 2020, the major European soccer associations implemented testing procedures that enabled the top leagues to proceed. The benefit of this opaque testing procedure is twofold: Relative to the overall length of the pandemic, it offers an exceptional opportunity to analyze long-lasting productivity effects.

Second, we hardly suffer from measurement errors caused by unknown positives.

We do not find a persistent drop in the likelihood to play following a recovery from infection. Apart from a short-run effect that can be attributed to the quarantining phase, players do not miss a considerable number of games due to the infection. However, the probability of being substituted on and off increases in response to an infection, which leads to a shorter time on the field (on average). At the intensive margin, we are able to identify a significant deterioration in infected players' productivity as defined by the literature (e.g. passes) by about five percent after an infection. This effect becomes visible right after a player's return on the pitch but remains persistent for far more than six months. This is different to, for example, influenza-related infections, whose productivity effects diminish over days (Keech et al., 1998). We also identify a falling performance of infected players over the course of single matches, indicating reduced physical fitness.

We further find negative reduced-form effects of COVID-19 infections on overall team performance. Regressing team productivity on team-level infection exposure reveals a negative effect that is likely larger than the sum of individual effects.

All of these findings raise sizable policy concerns. When calculating cost-benefit-analyses of lockdown measures, medium- and long-term decreases in work performance have not been accounted for yet. Also, indirect channels on team production are often neglected. Our study suggests that these effects should be accounted for to get a more realistic estimate about the benefits and costs of lockdowns and other restrictions.

Of course, professional male soccer players constitute a highly specific subsample of the society.² On the one hand, they are younger and fitter than the average individual and benefit from excellent medical support. On the other hand, they face more physical strain and cognitive pressure in public than the average worker. Overall, the parallels should bear scrutiny as many 'real world' jobs are physically very demanding, for example manufacturing, construction, or care work.

The remainder of this paper proceeds as follows. In Section 2, we provide background information on the setting of this natural experiment and explain the data at hand. In Section 3, we outline our empirical analysis, before Section 4 presents and discusses our results on the individual and the team level. Section 5 concludes with a summary, discusses limitations, and provides an outlook for future research.

²We only cover men's soccer as male players are much better tracked than their female peers which allows for a much more detailed analysis.

2 Institutional Setting and Data

2.1 COVID-19 Figures and Employment in Germany and Italy

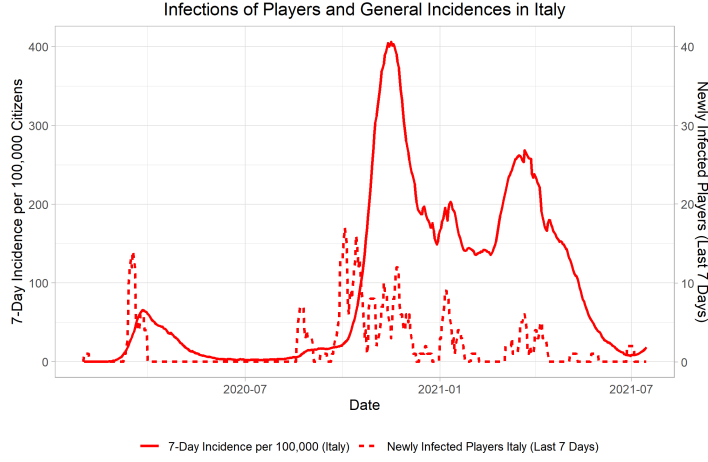
The ‘Robert-Koch-Institut’ (RKI), Germany’s governmental agency for infectious diseases, up to July 4, 2021, registered about 3.7 million cases and more than 90,000 deaths related to a COVID-19 infection (compared to an overall population of 83 million).³ As we are interested in work performance effects, we focus on people being in the labor force (or being there soon). Hence, for the age group from 10 - 59 years, the RKI reports about 2.7 million cases, which accounts for 71.6% of the overall number of cases. Among those, 12,500 people died. In total, this means that in Germany at least 2.67 million labor force members have a previous COVID-19 infection, which might potentially affect their work performance. A similar, but worse, pattern can be found for Italy. The governmental health agency ‘Istituto Superiore di Sanità’ reports (up to July 28, 2021) 4.3 million cases and some 127,000 casualties (compared to an overall population of 60 million).⁴ Within our defined labor force age range, 2.93 million people were infected and are now recovered. The discussed countries are just two examples and many countries face similar issues. Thus, the problem of potentially persistent negative effects of an infection on work performance might be large given the large numbers of infected and recovered individuals. To illustrate the case numbers further, Figure 1 provides information on 7 day incidences over time – i.e., the number of newly infected persons per 100,000 inhabitants.

Considering the job profile of a professional soccer player, one might question whether this correlates with the average population. While it is undoubtedly true that the physical requirements are demanding, even in a highly developed country as Germany millions of jobs are located in sectors that heavily rely on physical input. Despite the fact that work performance in the manufacturing sector might be mainly driven by technological advances, a single sector such as construction still employs seven-digit numbers of employees – 1.8 million jobs in Germany, 1.3 million in Italy. The health and social work sector encompasses 4.9 million or 15 percent of all German jobs.⁵ It is perhaps illustrative

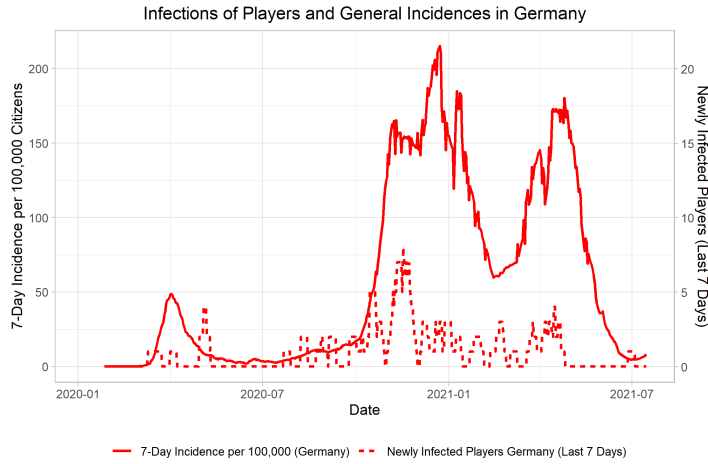
³Source for data on case numbers: https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Daten/Altersverteilung.html, last update 22.07.2021. Source for data on casualties: https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Projekte_RKI/COVID-19_Todesfaelle.html, last update: 22.07.2021.

⁴Source for data on cases and casualties: Epidemia COVID-19: Aggiornamento nazionale 28 luglio 2021 (National update): https://www.epicentro.iss.it/coronavirus/bollettino/Bollettino-sorveglianza-integrata-COVID-19_28-luglio-2021.pdf, published 30.07.2021

⁵Table A1 in the appendix provides overviews of the German and the Italian economy by sectors.



(a) Italy



(b) Germany

The plots show the seven-day incidence for both countries over time (left y-axis). The seven-day incidence counts all cases over the last seven days and scales them on 100,000. Also, cases among players are given (right y-axis). Source country incidences: (Ritchie et al., 2021, data downloaded: 16.07.2021).

Figure 1: General Incidences and Player Infections

to compare the profile of a professional soccer player with, for example, a construction worker or a care assistant. Both might not have the same concentrated workload as a soccer player over 90 minutes. However, it appears not unreasonable to argue that both jobs require high physical effort, so that health effects might result in similar performance effects. Furthermore, the average worker might be much less trained than a professional sports person. Hence, we are confident that our analysis also bears some external validity.

2.2 Data

We construct a novel dataset consisting of data on player and match statistics, as well as data on COVID-19 infections of players in Germany's Bundesliga and Italy's Serie A. Both leagues are their country's highest division in men's soccer and among the most

successful five leagues worldwide.⁶ These two leagues have characteristics that make them particularly appropriate to study. The Bundesliga was the first major soccer league that resumed its season in 2020 after the suspension of almost all leagues in spring.⁷ Italy has been a country hit severely by the virus in Spring 2020, but continued its season in June, too.⁸ Figure 1a demonstrates this pattern. Hence, both leagues provide long time periods for infected players, allowing us to estimate persistent and long-run effects.

We have granular data on the match and at the minute level, allowing for overall but also match phase-specific analyses. We amend this data with information on the injuries and sicknesses that forced players to miss matches.⁹ We collect data on all COVID-19 infections in both leagues since the outbreak of the pandemic. While every infection has to be communicated to the local authorities by the club carrying out the testing, clubs may prefer to keep an infection anonymous, only announcing the number of cases. We identified the large majority of all infected players via a meticulous review of newspapers, reliable websites, and statements from the clubs, players and soccer associations.

There have been 81 true-positive tests among players in Germany and 176 in Italy until mid of July 2021. We can clearly identify 76 players in Germany and 157 in Italy.¹⁰ Hence, we build our analysis upon the 233 identified players from a sample of 257 positive cases in total. This results in a coverage of above 90%. The higher case rates in Italy are likely to be driven by more registered cases in the overall population, and because Italy's Serie A includes more teams (20 compared to 18 in Germany). To our knowledge, the high coverage of identified cases comfortably should exceed the knowledge on infections in most of the industries and allows us to consider our results to be representative for the dataset at hand. We also conduct our analysis for a subsample of the data, in which we drop the observations of teams with anonymous cases. Doing that, we obtain a dataset of perfectly identified players. Our results are highly similar in this case.

257 infections among 1,406 players imply that 18% of all players got infected until mid of July 2021. This exceeds the general incidence of cases in the age group of young adults in both countries. This is likely a consequence of persistent testing and extensive

⁶In the European Football Association's five-year ranking, the Serie A is ranked #3 and the Bundesliga is ranked #4, see <https://www.uefa.com/memberassociations/uefarankings/country/#/yr/2021>.

⁷E.g. <https://www.theguardian.com/football/2020/may/06/bundesliga-set-for-go-ahead-to-resume-season-in-second-half-of-may>, published 07.05.20.

⁸E.g. <https://football-italia.net/official-quarantine-rule-softened/>, published 18.06.20.

⁹Injury data obtained from transfermarkt.de, the largest database on soccer players globally.

¹⁰A full list of all positively tested and known players is available on request. Relying solely on publicly available data, we consider this project as being in line with data protection regulation.

traveling. Additionally, both leagues implemented rigid rules for club and player behavior. In the Bundesliga, compulsory testing once or twice a week and before a match has been in place.¹¹ The Serie A required a PCR test before a match.¹² Hence, we are confident to have a true picture of the overall infections.

Figure 1 plots not only the incidences of the overall population in Germany and Italy but also the number of infections of the respective soccer league. One can see for both Italy (Fig. 1a) and Germany (Fig. 1b) that the number of infected players roughly follows the general infection pattern. Figure 1 also highlights incidences close to zero in the summer break between the two seasons. This probably would have been the only period in which clubs could have kept an infection secret without media recognizing the absence of a player. As the overall incidences were very low during this time, we suspect the number of non-identified but infected players to be, if anything, very low.

For player and match statistics, we apply data from *Opta Sports*. The company is one of the leading firms for statistics in sports and has an official partnership with the Bundesliga and the Serie A.¹³ The company tracks every player and all of his actions during a match using software that analyses video records. We are able to gather information on which players participated in each match of the 2019/2020 and the 2020/2021 seasons, and how these players performed in a match. Hence, we are confident to have the best data available to track work performance of players.

In total, our dataset consists of 72,807 observations from 1,406 players ranging over both seasons and leagues. These data encompass all players having played on at least one match day of a season. 40,607 of these observations track players who have actually played in a certain match, i.e., we can construct within-match work performance for them. The remainder covers players who were not nominated or substituted on at a particular match. Their observations will be included in the analysis at the extensive margin, i.e. whether a player plays. Table A2 in the appendix provides descriptive statistics.

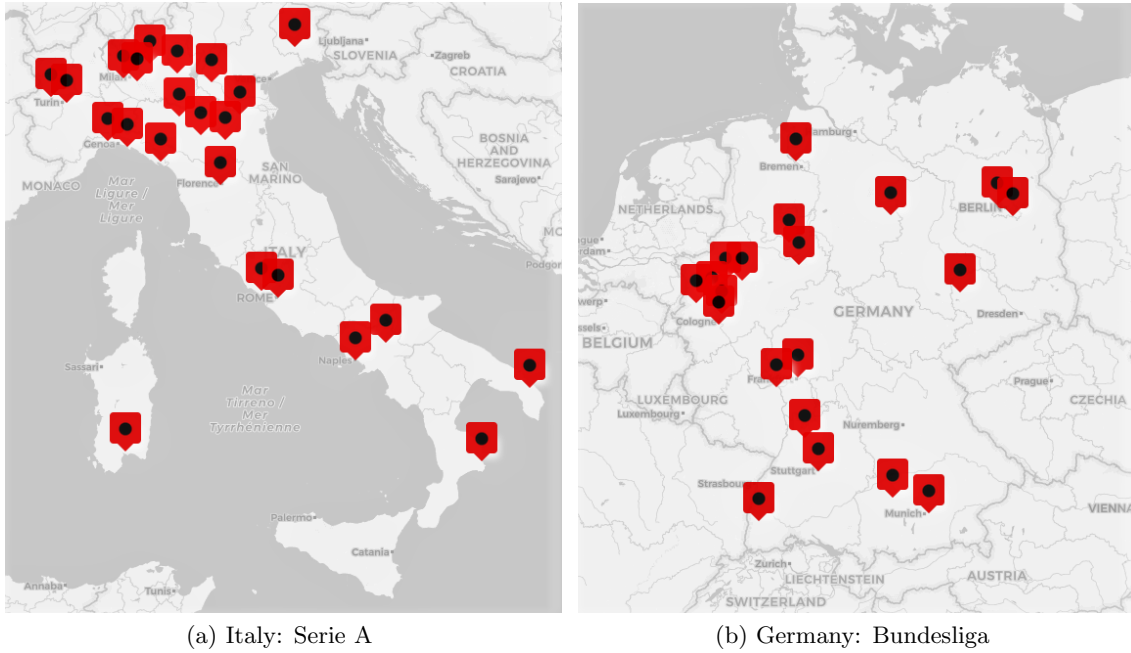
With an increasing likelihood of soccer players being or getting vaccinated in the season 2021/22, our analysis of the previous two seasons brings two advantages: At first,

¹¹https://www.dfb.de/fileadmin/_dfbdam/226090-Task_Force_Sportmedizin_Sonderspielbetrieb_Version_3.0.pdf – one or two PCR tests per week depends on the severity of the infection process. One PCR test per week was only allowed in case the region or district of a club had a 7 day incidence < 5 per 100,000 people, which was hardly ever the case during the seasons. PCR testing is the most accurate form of testing for a virus with almost 100% sensitivity (Guglielmi, 2020).

¹²<https://www.figc.it/media/123076/circolare-quarantena-calcio-def-2.pdf>

¹³<https://www.statsperform.com/team-performance/leagues-federations/>. There also exists some literature that validates the quality of the data from Opta, see Liu et al. (2013).

we are able to track the unbiased effect of infections without the mitigated effects of an infection due to vaccinations, as the Serie A and the Bundesliga started vaccinations only after the end of the 2020/2021 season.¹⁴ Second, vaccinations are likely to increase the degree of self-selection into treatment if some players prefer to remain non-vaccinated. Moreover, our still relatively short treatment period of 15 months (since the beginning of the pandemic) enables us to disregard sample selection issues, for example that severely hit players may drop out of the top leagues. Contract rigidity in elite soccer ensures that most players remained with their clubs for the whole period.¹⁵



The maps give the clubs' location (left: Italy, right: Germany). The maps capture clubs being part of the respective league in one or both seasons. Underlying maps by www.openstreetmap.org.

Figure 2: Location of the Leagues' Clubs in the Dataset

The comparison between infected – treatment group – and non-infected players – control group – is relevant in our setting. We match both groups and their characteristics with each other in Table 1. While infections in general should mostly be random across players, we find some disparities in performance measures. Players from Italian clubs are slightly over-represented in the sample of infected players. This might be due to the overall incidences, which have been much higher in Italy compared to Germany (as shown in Figure 1). Case numbers were particularly high in Northern Italy, where most of the

¹⁴See for the Serie A (19.07.21): <https://football-italia.net/figc-wants-serie-a-and-serie-b-players-to-get-vaccinated/> and for the Bundesliga (in German, 18.05.21): <https://www.kicker.de/dfl-empfiehl-impfung-der-profis-fan-rueckkehr-realistisch-806070/artikel>.

¹⁵Older work by Frick (2007) reports an average contract length of 3 years in the Bundesliga.

clubs in the Serie A are located (see Figure 2a). Furthermore, infected players seem to have played more often and longer before the treatment. They also performed better in terms of passes and touches per minute. There are no economically relevant differences in age or other demographics, which might be important for the severeness of the symptoms. With regard to positions, it seems that midfielders are over-represented. We try to address the differences between the treatment and control groups by controlling for player- and position-specific effects later on.

Statistic	Units	Non-Infected (1)	Infected (Pre-Infection) (2)	Δ (p-value) (3)
Match Involvement/Performance				
Played at all <i>if played...</i>	yes/no	0.539	0.659	0.000***
Minutes Played	min	66.340	71.509	0.000***
Played Full-time	yes/no	0.484	0.564	0.001***
Passes/min	#/min	0.511	0.546	0.023**
Ball Recoveries/min	#/min	0.057	0.057	0.778
Touches/min	#/min	0.681	0.713	0.042**
Possession/min	#/min	0.491	0.526	0.017**
Dribbles/min	#/min	0.019	0.019	0.402
Aerials/min	#/min	0.038	0.033	0.021**
Shots/min	#/min	0.015	0.017	0.103
Demographics				
Age	years	26.550	26.886	0.351
Height	cm	183.350	184.268	0.049**
Weight	kg	77.273	77.754	0.339
Body Mass Index (BMI)	kg/m ²	22.966	22.879	0.376
Others				
Italian League	yes/no	0.541	0.636	0.013**
Goalkeeper	yes/no	0.043	0.052	0.567
Defender	yes/no	0.223	0.251	0.281
Midfielder	yes/no	0.150	0.225	0.001***
Forward	yes/no	0.077	0.087	0.519
Substitute	yes/no	0.506	0.384	0.000***

Columns (1) and (2) show the means of the respective variable for all observations of non-infected players and infected players (pre-infection). Column (3) reports the p-value of a two-sided t-test. Significant differences are indicated by stars as follows: *p<0.1; **p<0.05; ***p<0.01. The significance of differences between infected and non-infected players is obtained from simple regressions of each outcome on an intercept and a dummy for infected players pre-infection. Standard errors of these regressions are clustered on the player level. Variables which give performance per minute omit observations with zero minutes on the field which make up 232 out of 36,903 observations (approximately 0.6%).

Table 1: Descriptive Statistics for Non-Infected and Infected Players

3 Empirical Strategy

Infections can be modelled as a staggered treatment across players. To disentangle the effect of the infection from other shocks that may limit work performance, we compare infected players' performance before and after their positive test result with the evolution of outcomes of non-infected players. Hence, we apply a difference-in-differences estimation that controls for variation over time and across individuals.¹⁶ For this setting to be valid, several assumptions need to hold. Within our static difference-in-differences setting, we need parallel trends of treatment and control group in absence of the infection. We have no reason to question this, because there is no conceivable cause for diverging evolvement of work performance without COVID-19. Within the dynamic event study setting outlined later on, this corresponds to the requirement that treatment cannot predict outcomes prior to treatment. As our event study plots will show flat pre-trends, we see the parallel trends assumption satisfied. Furthermore, we assume that there is no self-selection of players into the treatment. For this assumption to be invalid, players would need to actively infect themselves or should clearly be able to prevent an own infection. Even if some player would deny the risks of an infection, he would face compulsory quarantine. In the meantime, he would miss matches and maybe lose his position in the team. Additionally, every team has good medical advice, such that all players should have up-to-date knowledge about the dangers of COVID-19. Also, we consider infections as not anticipated in the short-run.

For reliable estimations in the static difference-in-differences setting, we need no variation in the effect size of the treatment over time. This will not be true if for example a new medication would have been developed that changed the impact of an infection. In general, there is no reason to believe that the work performance effects of an infection are constant over time, so we will analyze dynamic patterns in event studies. Eventually, a difference-in-differences estimator requires that the treatment only causes partial equilibrium effects. As we find team spillover effects, there might be some confounding, which collides with the partial equilibrium condition. This does not invalidate but strengthens our empirical findings. In theory, it is a priori unclear whether a deterioration in a player's performance

¹⁶For this methodology a rapidly developing literature has emerged, which mainly addresses the distortions arising from staggered treatments in plain two-way fixed effects settings (among others, see e.g., [Sun and Abraham \(2021\)](#), [Callaway and Sant'Anna \(2021\)](#), or [De Chaisemartin and d'Haultfoeuille \(2020\)](#)). A main critique is that treatment effects at a certain relative point of time to the treatment might change with heterogeneity in real time. We consider our setting as appropriate as the corrections build upon absolute time periods while our approach is based on time relative to the treatment. Related to the critique we later show that there is no significant change of the treatment effect between early and recent infections.

either causes overall lower performance of the team or leads to an (over-)compensation of this deterioration. Indeed, we find strong evidence for the former. An increasing number of recovered players on the pitch decreases their team’s performance disproportionately. This implies a negative effect on the control group. By that, our estimates underestimate the true effect in absolute terms. We elaborate on this in the latter part of Section 4.

As we consider the identifying assumptions as fulfilled and the spillovers as innocuous, our model allows us to extract the treatment effect. We implement the regression setup

$$\text{Performance}_{pm} = \beta \text{Post-Infection}_{pm} + X'_{pm}\gamma + Z'\zeta + \epsilon_{pm} . \quad (1)$$

Performance_{pm} on the LHS refers to a set of performance or involvement measures of player p in match m . In our setting, this is, for example, a dummy capturing whether a player played at all, or the exact number of passes. Passes suitably proxy the involvement of players in a match. For example, players are more likely to play more passes when being well-positioned. Former papers on work performance in sports have also exploited the number of passes as measure of interest (for example [Lichter et al., 2017](#)), so we take this approach here as well. Results on other measures (e.g., touches and possession) – which also account for slightly different behavior – are provided later on as a robustness check. Hence, cross-validation with different measures should give a thorough picture of player performance.¹⁷

$\text{Post-Infection}_{pm}$ is the treatment dummy that turns one for all observations of a player after he has been tested positive. Hence, β is our coefficient of interest. To account for variation in the cross-section and over time, we control for a large set of covariates X_{pm} and fixed effects (FE) Z . ϵ_{pm} is the idiosyncratic error term. In particular, we include player fixed effects, team-season and opponent-season fixed effects as well as matchday fixed effects and an FE capturing variation before and after the break in spring 2020. Doing this, we control for a general underlying performance effect during the COVID-19 pandemic for all players, as [Santana et al. \(2021\)](#) find a worse running performance after the restart in 2020 but an improved passing accuracy. Also, the exclusion of fans might have impacted player behavior during this period ([Bryson et al., 2021](#)). All of these FEs

¹⁷Running performance would be another natural measure to study as COVID-19 is a respiratory infection. However, [Lichter et al. \(2017\)](#) find running and pass performance to be highly correlated. We obtain player-match level running data for the Bundesliga and measure a correlation of 0.64. Later on, we use a variable similar to running performance that shows a significant drop after an infection as well.

shall capture performance differences unrelated to an infection.¹⁸ We also consider minutes played and its squared term to control for the cumulation of passes over time. We use heteroskedasticity-robust standard errors clustered on the player (i.e. the treatment) level to account for correlated residuals across a player’s observations. To test your identifying assumption of parallel trends absent a treatment and to understand the dynamic nature of effects, we also apply an event study setting as a dynamic model:

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

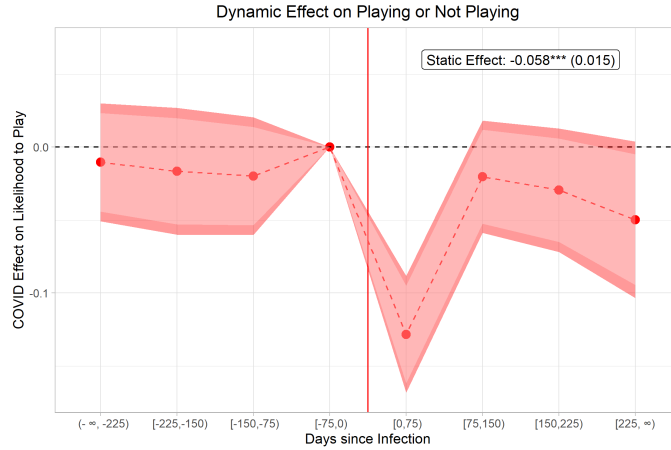
This leads to several β_{τ} coefficients of interest. Subscript τ is the running index of leads and lags. We bin these one-day binary variables to group dummies of 75 days. Endpoints are binned and hence include all observations which lie beyond the second-last bins on either side ([Schmidheiny and Siegloch, 2020](#)). Our results are robust to different specifications of the effect window size. We mainly plot bins up to 225 days before and after infections and bin all observations beyond these thresholds in the outer bins to have sufficiently much observations in each bin. As infections are hardly anticipated and voluntary precautions are only possible with limitations in the world of professional soccer, we do not struggle with a number of identification challenges which have been addressed in the context of COVID-19 studies, as for example voluntary precautions, anticipation, and variation in policy timing (see e.g. [Goodman-Bacon and Marcus, 2020](#)).

4 Results

Our analysis takes a two-step process. First, we investigate whether a COVID-19 infection has a short- or long-term impact on the participation of players. Subsequently, we look at within-match performance after an infection. The intensive margin could underestimate persistent effects of a COVID-19 infection as players hit the most might not play at all. Hence, analyzing both effects is indispensable and might give intuition on performance-related mechanisms. While the main measure of interest is within-match work performance, the effect on the extensive margin helps to understand the severeness of the post-infection work performance drops.

¹⁸We experimented with several reasonable FE combinations. All results go in the same direction.

Extensive Margin: First, we analyze the effect of a COVID-19 infection on the probability to play and the number of minutes played. Figure 3 reports the corresponding estimates. From the static effect panel, in the upper right of the plot, we infer that players have a 5.7 percentage points lower probability to play. However, effects appear to be mechanical, mainly driven by the first weeks after an infection, when quarantine breaks do not allow a player to participate in a match. The observed drop in playing frequency becomes insignificant quickly, but does not fully return to its former level. These results indicate that players marginally experience persistent effects on their likelihood to play. A flat pre-trend validates our finding.

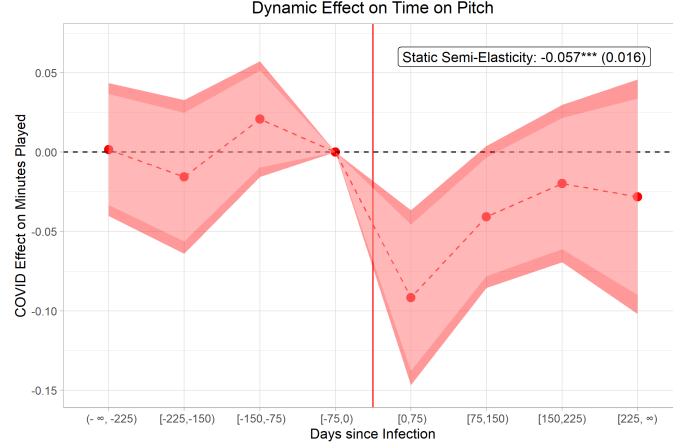


This figure plots the OLS (LPM) estimated coefficients β_T of the event study regression following Equation (2). The reference time period is one to seventy-five days before treatment. An equivalent plot with a 30 day bin size (for a better description of short-run effects) can be found in Figure A2 in the appendix. Standard errors are heteroskedasticity-robust and clustered on the player level. 90% and 95% confidence intervals are given by the red-shaded areas. The dependent variable is a dummy indicating whether a player played or not.

Figure 3: Dynamic Effect on Likelihood to Play

Figure 4 shows the corresponding effect on minutes played by players who play. Immediately after the infection and his return on the pitch, a player spends on average 6 minutes less on the field than before – this corresponds to a decrease by almost ten percent. This indicates that several players might have been only used as substitutes leaving the pitch earlier or entering it later. This might point to a general fitness problem of the players and make it more likely that work performance effects at the intensive margin might be underestimated as the player might be substituted off before the severest effects hit in. Players might be substituted off before showing poor performances during later stages of a match. The effect is visible right after an infection but quite long-lasting. Only after

approximately 150 days or five months minutes played return to a level which does not significantly differ from pre-infection match times.

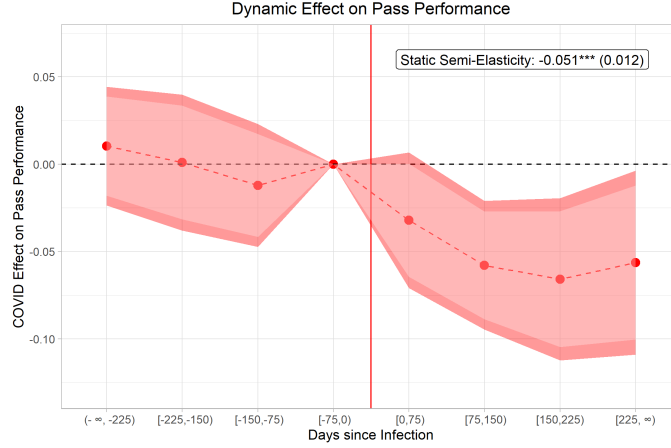


This figure plots the OLS estimated coefficients β_τ of the event study regression following Equation (2). The reference time period is one to seventy-five days before treatment. An equivalent plot with a 30 day bin size (for a better description of short-run effects) can be found in Figure A2 in the appendix. Standard errors are heteroskedasticity-robust and clustered on the player level. The 90% and 95% confidence intervals are given by the two red-shaded areas. The dependent variable is $\ln(\text{minutes played})$ conditional on having played.

Figure 4: Dynamic Effect on Minutes Played

Our findings on the extensive margin are confirmed by an increasing likelihood to be substituted on and off the pitch after an infection. Hence, players on average play for a shorter time which may signal insufficient fitness to participate for 90 minutes. The respective event studies can be found in Figure A1 in the appendix. In general, our results on the effects at the extensive margin indicate a return to initial levels of infected players over time. Either players return to the former work performance levels or badly performing players re-enter the subsample of players on the field. This would shift the treatment effect from the extensive to the intensive margin, so that worse work performance effects should be observed over time in within-match data.

Intensive Margin: We next take a nuanced look at a player’s performance conditional on being on the field. As outlined previously, the main building block of our performance analysis is the number of passes as shown in Figure 5. Besides that, we provide results on two related performance measures, possession and touches in Figure A3. Figure 5 above presents the corresponding event study providing the dynamic estimates of a COVID-19 infection on within-match performance. This plot, as well as the additional measures in the appendix, show rather flat pre-trends. We find a highly significant static difference-



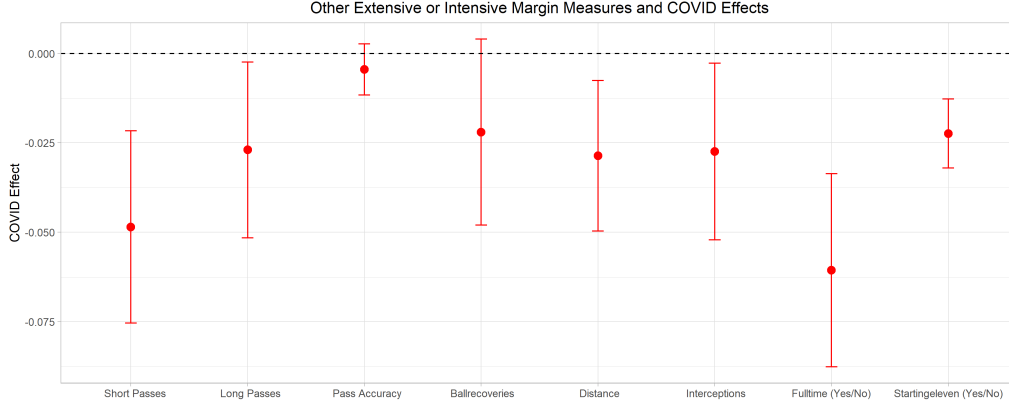
These figures plot the OLS coefficients β_τ of the event study regression following Equation (2). The reference time period is one to seventy-five days before treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The 90% and 95% confidence intervals are given by the two red-shaded areas. The dependent variable is $\ln(\text{passes})$. Additional work performance measures can be found in Figures A4 and A5 in the appendix.

Figure 5: Dynamic Effect on Within-Match work performance

in-differences effect of -5.1 percent. Hence, we can precisely identify a deterioration in work performance following a cured COVID-19 infection. This effect is not transient but actually remains notably negative in course of time. We consider this as causal evidence for COVID-19 infections causing long-lasting performance drops for infected individuals.

Interestingly, we also observe work performance to partly fall over time, while the effect stabilizes after some months post-infection. This gives rise to two remarks: First, players do not return to their former level within the period of observation. Second, the reduction over time also captures the return of infected players on the field as there is more involvement at the extensive margin after several months. It may be possible that players, who still suffer from decreased work performance, eventually return on the field and negatively affect the treatment effect over time. Our results may be interpreted as a lower bound of the real effect due to the chance that more severely affected players are not observed, because they do not play.

Robustness Checks: We find similar results for several other performance measures at both the extensive and intensive margin. Figure 6 reports significant performance drops for measures like running distance or the number of interceptions. Moreover, clear effects on the likelihood to play full-time or to be part of the starting eleven are evident.



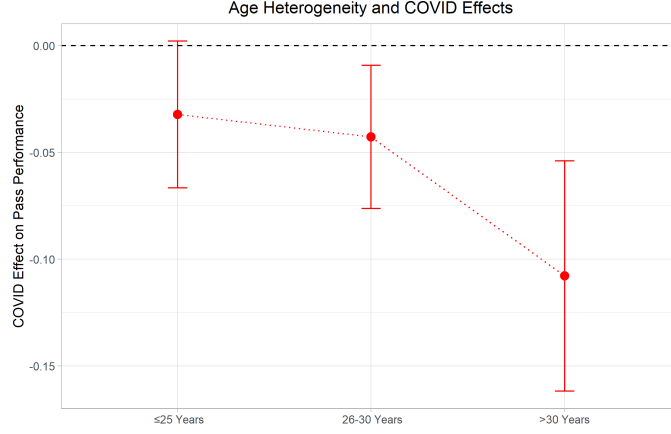
The plot shows the OLS estimates of the post-infection dummy included in the baseline regression (1) for different performance measures. Dep. variable: given on the x-axis of the plot (always in logarithmic form except for the dichotomous variables ‘full-time’ and ‘starting eleven’. SEs: Heteroskedasticity-robust and clustered on player level. 95% confidence bands are given.

Figure 6: Robustness Check: Other Performance Measures

Our dependent variable is the logarithm of passes such that observations with zero passes etc. are dropped. This relates to players which participated just for few minutes of the match and hence makes up around half a percent of the observations. To demonstrate that our results do not depend on the functional form, we provide in the appendix results for a specification in levels (Figure A4) and for using the inverse hyperbolic sine transformation for the dependent variable (Figure A5). Our results do not change. Also note that our results are not driven by one specific league. Figure A6 presents extensive and intensive margin effects for both leagues separately.

Effect Heterogeneity: We do not only find a significant and persistent deterioration in work performance but also heterogeneity in several dimensions. While an infection’s effect on the underlying health status should be quite homogeneous in the homogeneous group of players, the consequences of changes in health might impact player performance differently. First, throughout the COVID-19 pandemic, age has been one of the main determinants of how likely an infected person is to develop symptoms or to even die (e.g., Gallo Marin et al. 2021). It seems natural to investigate whether older players also suffer more from an infection. While such players of course cannot be compared to the elderly population, their recovery may take longer and symptoms may be more persistent. Figure 7 provides some intuition that especially players of an age above 30 face the strongest performance drops of above ten percent. In comparison, younger players up to 25 years are

only affected marginally. This finding might hint at some additional underlying channel through which performance is afflicted as the bare health effect of the disease should be similar across this small age range.



The plot displays OLS interaction effects between the post-infection dummy and age groups included in equation (1). Dependent variable: $\ln(\text{Passes})$. SEs: Heteroskedasticity-robust and clustered on player level. 95% confidence bands are given.

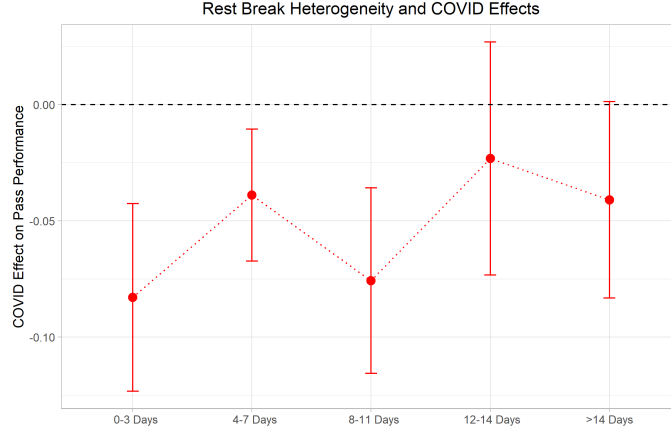
Figure 7: Effect Heterogeneity: Age Effects

Second, COVID-19 infections are often associated with additional fatigue. Hence, it is of interest whether players need more time to recover from a match post-infection. Put differently, it may be that post-infected players perform worse if the rest break between two matches they played in is insufficient. We compare the treatment effect for different lengths of rest breaks.¹⁹ In Figure 8 we show that the treatment effect especially arises for short breaks of up to eleven days. In case of such a short break between two matches played, the negative COVID-19 effect accounts for up to eight percent. Our results indicate that post-infected players can only perform as well as before the infection if there is enough regeneration time – beyond the typical six to eight days (as matches mostly take place weekly on Friday to Sunday) between matches.

We also analyze heterogeneity with regard to positions, team and player strength, and infection timing. Results are intuitive as we find stronger effects for more enduring positions or weaker players.²⁰ Also, there is no clear difference between effects from early or

¹⁹While the length of a break may be a function of the infection itself, this would induce players with longer breaks to perform worse. As we do not observe such confounding behavior, we are confident that the break heterogeneity effects are directly related to longer recovery breaks.

²⁰The heterogeneity analyses on positions also shows that the treatment effect is not purely driven by substituted players but also by starters.



The plot displays OLS interaction effects between the post-infection dummy and different recovery breaks included in equation (1). The length of a break is calculated on the player level, i.e., the number of days between two matches the player has played in. Dependent variable: $\ln(\text{Passes})$. SEs: Heteroskedasticity-robust and clustered on the player level. 95% confidence bands are given. The first observation of every player is dropped as no recovery break to previous matches can be calculated.

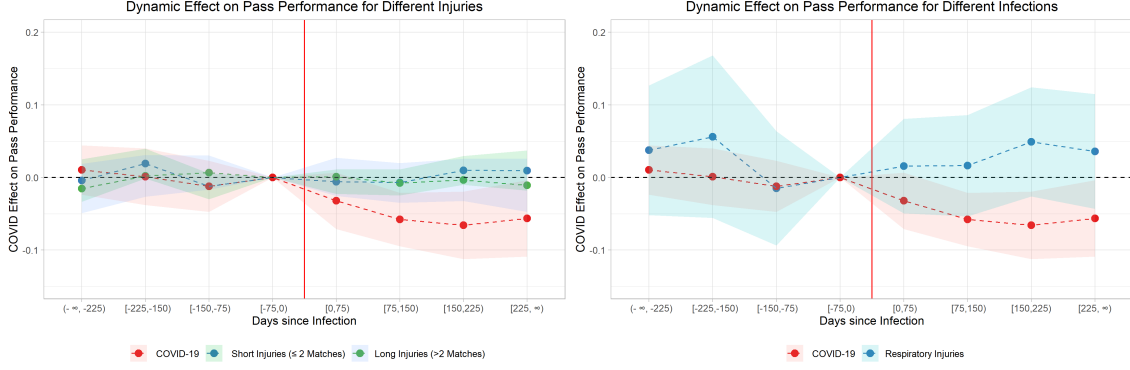
Figure 8: Effect Heterogeneity: Recovery Break Effects

late COVID infections, so no treatment effect heterogeneity in real time. All plots can be found in Figure A7 in the appendix. There we also provide equivalent heterogeneity analyses for the extensive margin (Fig. A8). The results are very similar.

Comparison to Other Injuries: It may be that players and teams treat COVID-19 just as any other injury – a player rests for a while and returns into team practice afterwards. If COVID-19 infections have performance effects beyond typical injuries and illnesses, this would emphasize the relevance and uniqueness of this particular viral infection. We investigate this by analyzing the work performance effects of all other injuries which happened during our sample period. They range from muscle and ligament injuries to simple colds. In Figure 9, we distinguish the effects of a COVID-19 infection from both short and long injury breaks. We split the data at the median injury duration (2 matchdays) to investigate heterogeneity in injury length. Unlike for COVID-19, we find no significant work performance effects for other injuries – neither after short nor long ones.

Moreover, we are able to exploit information on the exact type of injury in our sample. We specifically identify absences which are related to similar diseases and infections as COVID-19, such as colds, influenza and respiratory ailments.²¹ This gives us some 100 occasions where players being absent due to such reasons. The right plot of Figure 9

²¹Note that COVID-19 infections are sometimes free of any symptoms, while the other respiratory infects are likely to be symptomatic as there is no testing.



The plots give the time-specific COVID-19 or injury effects on the number of passes on the player and match level estimated by OLS. SEs: Heteroskedasticity-robust and clustered on the player level. 95% confidence bands are given. As begin of an injury, the first match a player missed injured is taken. The regression set-up follows equation (2). Under ‘respiratory injuries’, we subsume colds, influenza infections, pneumonia, bronchitis (data from www.transfermarkt.de. 95% confidence bands are reported.

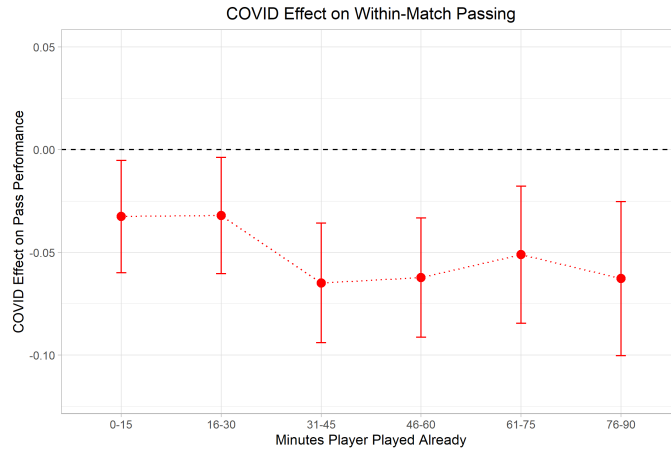
Figure 9: Time-Specific COVID-19 and other Injuries’ Effects on Performance

provides the comparison between the COVID-19 repercussions and the respective effect of other respiratory infections in course of time. Again, it is evident that COVID-19 infection seems to have more severe work performance effects than sicknesses affecting similar parts of the organism. This corresponds to earlier research of [Keech et al. \(1998\)](#), who find a work performance deterioration for influenza-like sicknesses after returning to the workplace only over 3.5 days on average.

Within-Match Mechanism: We can identify substantial and persistent effects of a COVID-19 infection on player performance. Our granular data allow us to study not only outcomes by matchday but also work performance within a match. As COVID-19 is a respiratory infection and soccer requires endurance in physical activity, it may be likely that players perform worse in the later stages of a match. We investigate this in Figure 10, in which we plot time-specific COVID-19 effects by decomposing the match of a player into a maximum of six parts of 15 minutes length each.

The results show decreased physical work performance from the first minute on the pitch onwards in cases when a player has recovered from an infection. Furthermore, performance declines over the course of a match. While the effect seems to be stable at around -3% in the first thirty minutes, post-infected players face a deterioration of some additional three percentage points in later phases. Such a downward trend would be in line with COVID-19 affecting player’s endurance. Note that Figure 10 shows relative time.

Hence, especially the first two bins capturing match time up to thirty minutes also encompass players that have been substituted *on* the pitch in the second half of a game. Even though they play a lower amount of time and know this in advance, i.e., they do not need to manage their physical energy to last the full 90 minutes, their performance is lower compared to their non-infected peers. It again underlines that we are likely to estimate a lower threshold of the treatment effect in absolute terms, and that a COVID-19 infection causes a non-negligible deterioration in performance. Also, players who perform worse during later parts of a match might be substituted off more early, so that their negative contribution at the end of matches might not be observable. Hence, the extensive margin effects might even hide a steeper downward trend throughout the match.



The plots show the time-specific COVID-19 effects on $\ln(\text{passes})$. The x-axis shows the number of minutes a player has already been on the field. The y-axis documents the effect on the outcome variable. Standard errors are heteroskedasticity-robust and clustered on the player level. 95% confidence bands are given. The regression setup is very similar to (1) estimated via OLS except for additional interactions of the COVID-19 term with the fifteen minute time slots, which also results in up to six observations per player and match (for each time category if on the field) instead of one aggregate observation.

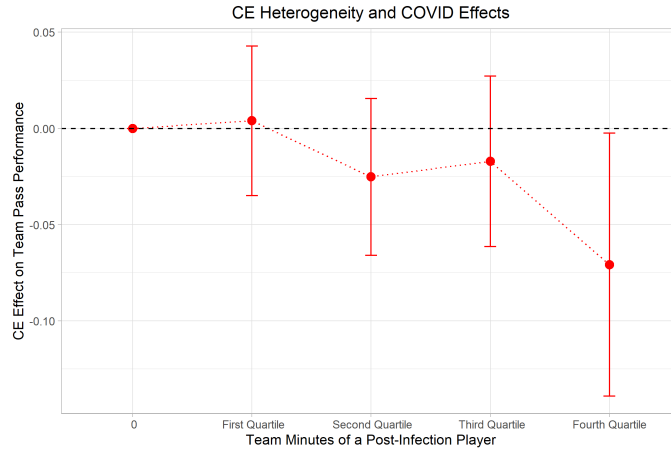
Figure 10: Time-Specific COVID-19 Effects on Within-Match Performance

Spillovers on Team Performance: Essential in team collaborations is the aggregate outcome of all individuals and aggregate performance may differ from the sum of its individual components. A crucial question is whether deteriorated work performance of post-infected players creates spillover effects on other players on the field. Hence, is a player's performance also affected by others' health shocks? We observe treated players to play fewer passes. Hence, teammates might be less involved in the match as well. Alternatively, they could compensate for the decreased performance of infected fellow

players by taking more responsibility and being more involved in the game. We address this issue by analyzing a team’s performance depending on its exposure to COVID-19 infections. More specifically, we proxy a team’s exposure to COVID-19 by the number of players recovered from an infection as a share of the overall team size (at any point in time before a match) on the match level. We construct the variable ‘COVID-19 Exposure’ as:

$$CE_{tm} = \frac{\sum_{p \in t} \text{Post-Infection}_{pm}}{\# \text{Players}_{tm}} \quad (3)$$

The numerator is the number of infected players of team t on matchday m . The denominator is the overall number of players of team t at match m , i.e. the squad size. Figure A9 in the appendix displays the distribution of the positive values of this variable. In almost half of the team-match observations, recovered players have been involved.



The plot shows the effect of CE on team performance measured in $\ln(\text{passes})$ estimated by OLS. We compare teams with $CE = 0$ to an exposure in four quartiles, which have the intervals $(0, 0.077)$, $[0.077, 0.130)$, $[0.130, 0.241)$, and $[0.241, 0.500]$ empirically or else $[0.241, 1]$ theoretically. The means are $\overline{CE}_{(0,0.077]} = 0.050$, $\overline{CE}_{(0.077,0.130]} = 0.096$, $\overline{CE}_{(0.130,0.241]} = 0.191$, and $\overline{CE}_{(0.241,1]} = 0.352$. The regression includes controls for home/away matches, ghost matches, the opponent’s COVID exposure (transformed by the inverse hyperbolic sine transformation) and team-season FE, opponent-season FE and matchday FE.

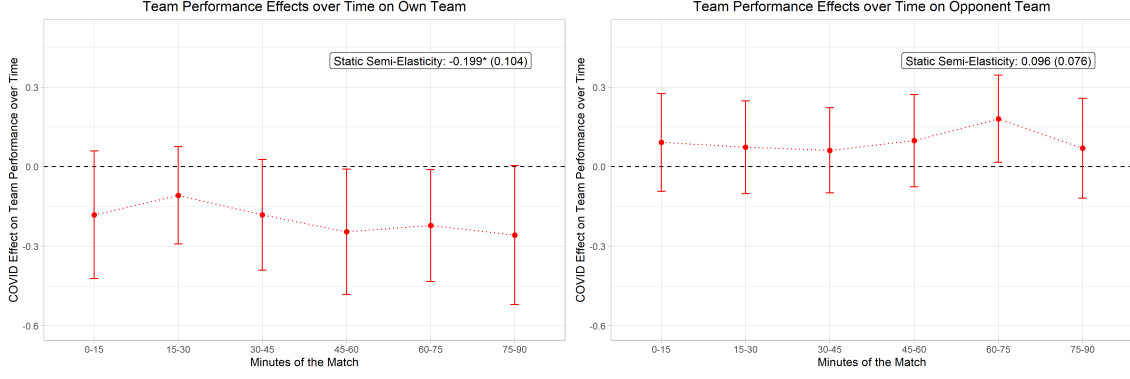
Figure 11: Effects of COVID-19 Exposure (CE) on Team Performance

Figure 11 displays the static reduced-form effect of CE on the logarithmic cumulative pass performance of a team. We separate CE in four equal quartiles for $CE > 0$. The decline in performance is increasing but only significant for the last quartile – $CE \in [0.241, 1]$, which encompasses an exposure of on average 35.2% recovered players (out of an average team size of 26.58 players). Hence, one additional infection has not a constant marginal effect. This could be relevant for other industries relying on collaboration in

team tasks, too. Research on direct health effects of COVID-19 typically does not consider such indirect mechanisms. Observable deterioration in team performance in the largest quartile corresponds to finding that performance losses due to sickness absenteeism of employees exceeds their wages (Pauly et al., 2002; Zhang et al., 2017). Other than in that research, our treated individuals are not necessarily absent but often on the pitch. It might be the case that a team is able to compensate for small declines in their team members' contribution but not for larger ones. The deterioration in performance for a $CE \in [0.241, 1]$ amounts to 7.08%, while the mean exposure in this interval is only roughly one third. This is strong suggestive evidence for spillover effects well-beyond the individual effect.

Our variable definition allows us to capture the direct effect from weaker performance on the pitch as well as performance deterioration due to missing players, because they are hit severely by the infection. Hence, CE captures both extensive and intensive effects. As we argue that non-infected players perform worse due to their under-performing teammates, we have an affected control group, which confounds the estimates of a difference-in-differences setup. However, this only implies that our results on individual effects should be interpreted as lower bounds as there might be performance drops related to the treatment in the control group as well. Moreover, previous research did not find spillovers of work performance (Lichter et al., 2017). These effects might be unique to COVID-19. While teams pass less in the presence of a higher exposure to recovered team mates, there are no robust effects on the number of goals or points earned by the teams. We consider the findings still as reasonable since goals and points are driven by highly multidimensional factors and, by that, are not necessarily valid performance measures.

The dynamic results for individual players discussed in Figure 10 hold for the aggregate team performance as well. Figure 12 provides estimates of the time-specific effect of a higher exposure to COVID-19 infections within a team on the logarithmic pass performance. We again find that the effect of more post-infected players on the field especially arises in later stages of the game, even though the static semi-elasticity for the own team is only significant on the 10% level. The marginal effect of -0.199 describes a hypothetical change of $\Delta CE = 1$. As $CE \in [0, 1]$, this has to be rescaled. At the end of the 20/21 season, the average COVID exposure has been around 0.2. Our within-team match results imply that such an exposure reduces performance by around 4% compared to not having a single case. This is another hint for spillovers as already a low share of recovered players



The plots show the time-specific COVID-19 effects on $\ln(\text{Passes})$ on team and match level of CE on own and opponent team performance estimated by OLS. SEs: Heteroskedasticity-robust and clustered on the team level. 95% confidence bands are given. The regression set-up is equivalent to (1) except for additional interactions of the COVID-19 term with fifteen minute time slots, which results in up to six observations per player and match. In contrast to Fig. 10, the time slots capture overall match time and not the minutes a player has been on the field. The regression includes controls for home/away matches, ghost matches and team-season FE, opponent-season FE and matchday FE, and time category FEs.

Figure 12: Effects on Within-Match Team Performance (Own vs. Opponent Team)

corresponds to a deterioration similar to the individual decline of 5.1%. Overall, the RHS of Figure 12 provides no evidence for major spillover effects on the performance of the opponent team.

5 Conclusion

This paper analyses the causal effect of a COVID-19 infection on productivity of high performance workers, utilizing a large panel dataset of elite soccer players. We are the first to quantify COVID-19 related performance effects for a whole industry. Productivity, approximated by pass performance, drops substantially and persistently by about five percentage points.²² Soccer players – although among the fittest individuals – seem to face significant deterioration in their performance following an infection with COVID-19. We find causal evidence that the deterioration in work performance does not diminish swiftly but remains prevalent over months. Allowedly, this occurs at the margin. But as millions got infected around the globe, this is not a problem of a handful of people but is likely to accumulate to an effect size that could be felt by the economy in total. Additionally, we find some mutually reinforcing effects among groups. Hence, a COVID-19 infection indeed casts a long shadow on an individual’s work performance.

²²For comparison, [Lichter et al. \(2017\)](#) find short-run work performance to drop by about 1-1.5 percent if air pollution increases by one standard deviation. Hence, our effects size is not negligible.

This is a novel and thought-provoking result as our findings correspond directly to recent policy debates. A ‘zero COVID’ strategy that aims for a complete elimination of the virus in a country or region is suggested for example by [Aghion et al. \(2021\)](#), while [Bardt and Hüther \(2021\)](#) warn of too strict lockdown measures. [Bianchi et al. \(2020\)](#) and [Helliwell et al. \(2021\)](#) highlight the indirect long-run effects of lockdowns on unemployment and health outcomes. Particularly the latter group finds that rigid NPI strategies leading to zero transmission rates have had superior outcomes in more dimensions than just case rates and mortality. We relate our research to this debate with direct effects.

Although we are confident that our findings are fairly robust and to some extent generalizable, we are aware that our analysis has important limitations. We have already discussed that professional soccer players are a highly specific subsample of a society. Even though it is ambiguous whether effects for the ‘average’ individual might be even worse, it would be helpful if our analysis were more diverse. Future research should, therefore, address gender, a broader age range, and various job profiles. Also, we are not capable of distinguishing the different variants of the virus or the severity of symptoms, because we only have test results as a dichotomous variable. Additionally, our results are based on non-vaccinated people. Even though our event study methodology encompasses a fairly long time horizon, for obvious reasons we cannot account for effects over several years. It would be interesting to re-examine this setting in a few years. Future research should also address the potential impacts on cognitive capacity, as our analysis primarily discusses physical measures.

Eventually, our findings might also serve as one more argument in favor of the vaccinations among fit and young people. While many Western countries have reached until Summer 2021 comparatively high vaccination rates, some of the world’s poorest countries have to wait until 2023 for sufficient supply of vaccines ([Padma, 2021](#)). Alas, especially these countries often rely more on physical work and have much less social security or support at the workplace to compensate for potential productivity deterioration. Thus, COVID-19 is likely to remain an important impact on productivity in the future.

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Appendix

Table A1: Number of persons employed by NACE sector: Germany (2018) and Italy (2019)

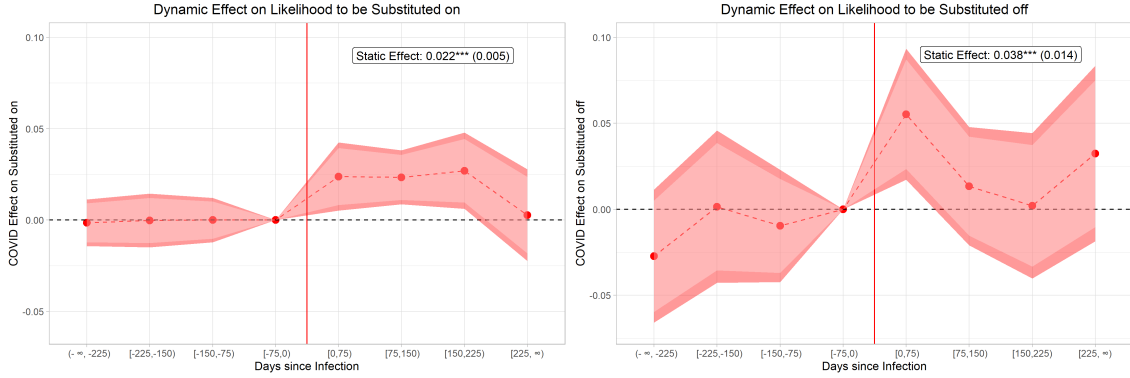
NACE	Economic Sector	# persons employed	
		Germany	Italy
B	Mining and quarrying	66,285	29,532
C	Manufacturing	7,031,103	3,762,760
D	Electricity, gas, steam & air conditioning supply	233,903	84,113
E	Water supply (Including sewerage, waste mgmt.)	253,737	209,284
F	Construction	1,848,673	1,320,574
G	Wholesale & retail trade, repair of motor vehicles	4,534,438	3,442,220
H	Transportation and storage	1,833,388	1,142,565
I	Accommodation and food service activities	1,062,005	1,591,691
J	Information and communication	1,106,601	586,399
K	Financial and insurance activities	970,926	546,029
L	Real estate activities	271,124	309,075
M	Professional, scientific and technical activities	2,271,367	1,294,993
N	Administrative and support service activities	2,319,615	1,392,143
O	Public administration, defense, social security	1,828,345	–
P	Education	1,315,715	117,679
Q	Human health and social work	4,912,305	938,960
R	Art, entertainment and recreation	293,017	189,864
S	Other service activities	841,705	480,196
Σ		32,152,547	17,438,077

Note: NACE: Statistical Classification of Economic Activities in the European Union. Data without agricultural sector. Italy does not report data for NACE code O in the ASIA enterprises database used here. Sources: German Federal Statistics Office/[Statistisches Bundesamt \(Destatis\) 2021](#), GENESIS database #13111-0003; Italian National Institute of Statistics/[Istituto Nazionale di Statistica \(Istat\) 2021](#)

Table A2: Descriptive Statistics on Players and Matches

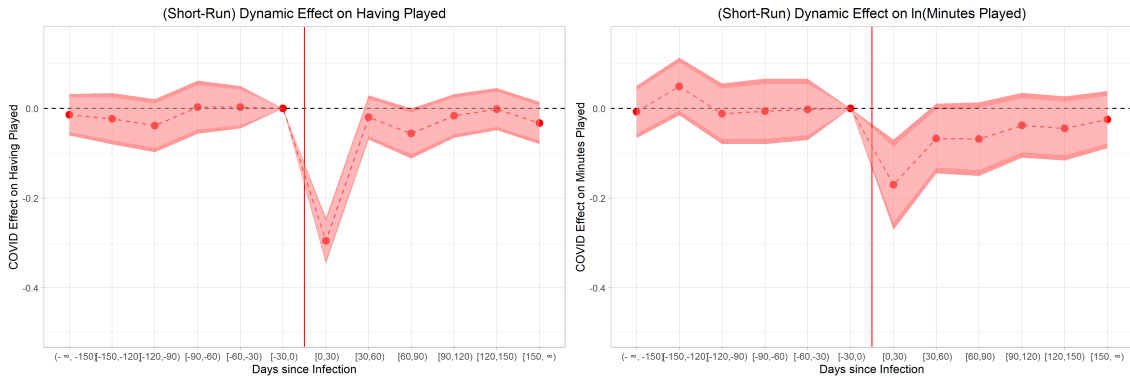
	N	Mean	St. Dev.	Min	Max
Treatment Indication					
Infected Player	72,938	0.195	0.396	0	1
Post-Infection	72,938	0.086	0.280	0	1
Player Characteristics					
Height (in cm)	72,938	183.502	6.139	163	202
Weight (in kg)	72,938	77.322	6.460	58	101
Age	72,938	26.596	4.683	15	43
COVID Game (Yes/No)	72,938	0.659	0.474	0	1
Matchday	72,938	18.592	10.515	1	38
Home (Yes/No)	72,938	0.500	0.500	0	1
Extensive Margin: Player Involvement					
Played (Yes/No)	72,938	0.557	0.497	0	1
Injured (Yes/No)	68,577	0.126	0.332	0	1
Suspended (Yes/No)	68,577	0.024	0.154	0	1
Substituted Off (Yes/No)	40,607	0.257	0.437	0	1
Substituted On (Yes/No)	40,607	0.257	0.437	0	1
Played Full-time (Yes/No)	40,607	0.488	0.500	0	1
Starting Eleven (Yes/No)	40,607	0.743	0.437	0	1
Minutes on Field	40,607	66.741	30.122	0	90
Intensive Margin: Player Performance					
1. General Measures					
Passes	40,607	33.884	22.946	0	167
Passes (Successful)	40,607	26.976	20.313	0	165
Short Passes	40,607	24.212	18.532	0	158
Short Passes (Successful)	40,607	19.624	16.629	0	157
Long Passes	40,607	9.672	6.867	0	50
Long Passes (Successful)	40,607	7.351	5.617	0	41
Distance Covered	40,607	1,175.5	642.9	0	3,878.6
Possession	40,607	32.541	22.152	0	167
Touches	40,607	43.916	26.027	0	177
Aerials	40,607	2.124	2.495	0	28
Aerials (Successful)	40,607	0.022	0.155	0	3
2. Defensive Measures					
Ball Recoveries	40,607	3.581	2.915	0	23
Defensive Aerials	40,607	1.063	1.543	0	17
3. Offensive Measures					
Shots	40,607	0.888	1.290	0	14
Shots (on Target)	40,607	0.311	0.654	0	7
Offensive Aerials	40,607	1.062	1.735	0	26

Figure A1: Dynamic Effect on On and Off Substitutions



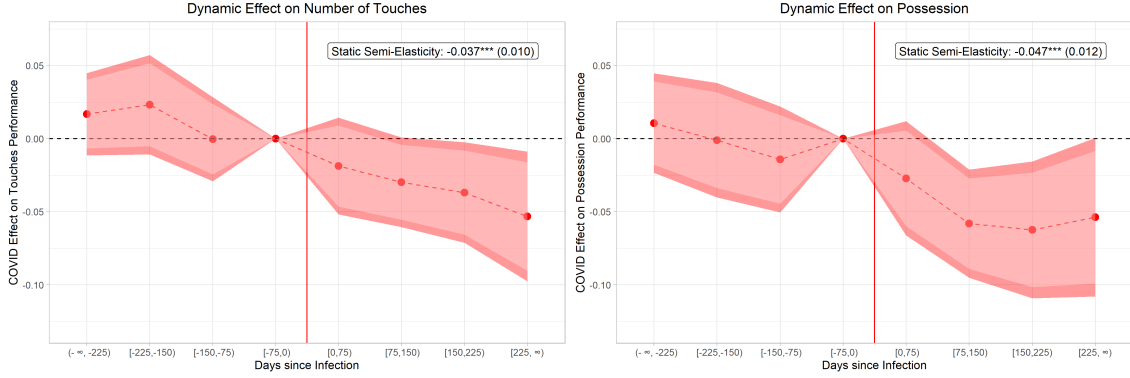
These figures plot the OLS (linear probability model) estimated coefficients β_τ of the event study regressions following Equation (2). The reference time period is one to seventy-five days before treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The 90% and 95% confidence intervals are given by the two red-shaded areas. The dependent variables is a binary variable indicating to be substituted on (LHS) or off the field (RHS).

Figure A2: Dynamic Effect on the Likelihood to Play and Minutes Played: Smaller Bin Size



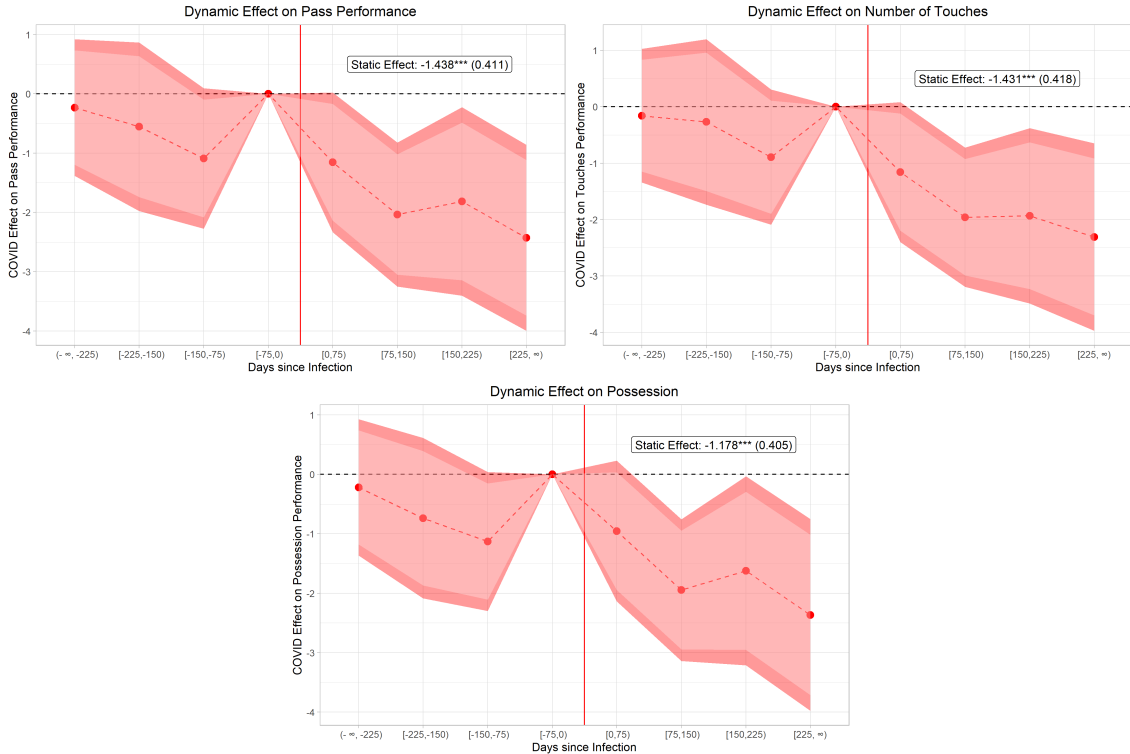
This figure plots the OLS estimated coefficients β_τ of the event study regression following Equation (2). The bin size is now 30 days, i.e. one month. The reference time period is one to 30 days before treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. 90% and 95% confidence intervals are given by the red-shaded areas. As the bin size is much smaller compared to the baseline setting in Figures 3 and 4, this affects the confidence bands. Due to much less observations within one bin, we severely lose statistical power, which leads to mostly insignificant results on a 5% significance level. Dependent variable LHS: A dummy indicating whether a player played or not. Dependent variable RHS: $\ln(\text{minutes played})$ conditional on having played.

Figure A3: Dynamic Effect on Within-Match Performance: Additional work performance measures



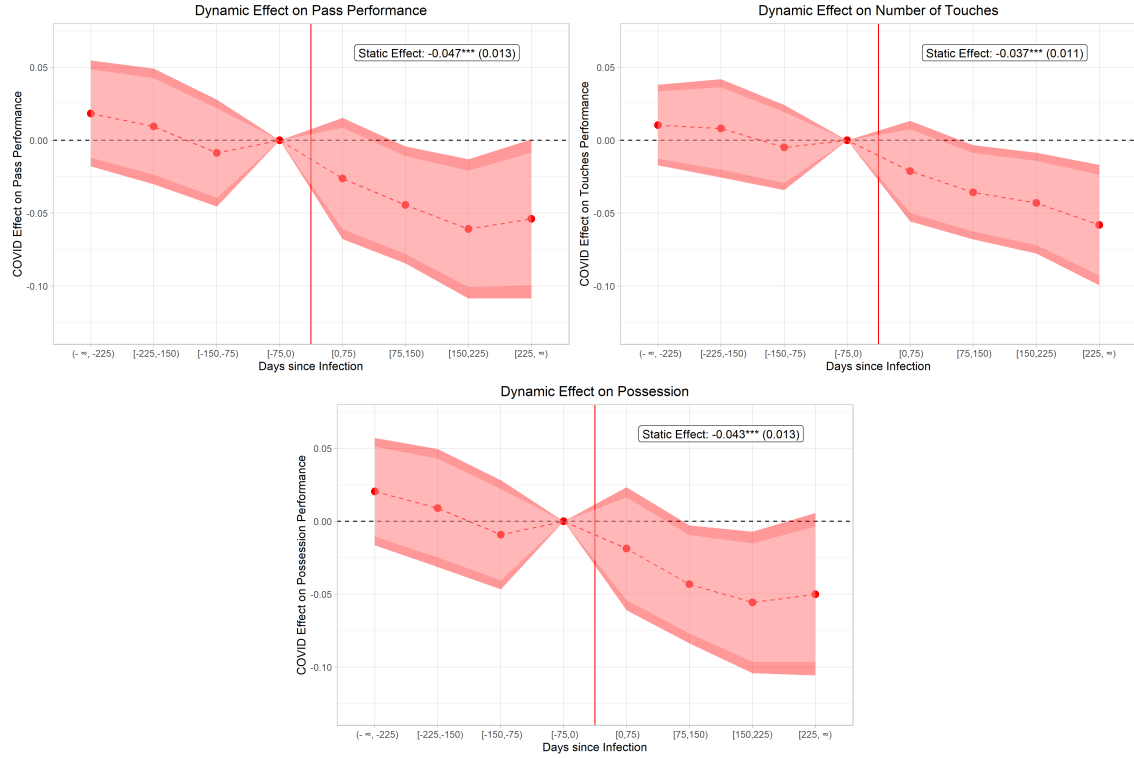
These figures plot the OLS coefficients β_τ of the event study regression following Equation (2). The reference time period is one to seventy-five days before treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The 90% and 95% confidence intervals are given by the two red-shaded areas. The dependent variables are $\ln(\text{touches})$ as $\ln(\text{possession})$ as additional work performance measures. The logarithmic specification excludes observations with zero passes, touches or possessions. Robustness checks in Figures A4 and A5 show that these results hold also for settings taking zero values into account.

Figure A4: Event Studies for Different Outcome Specifications: *Levels*



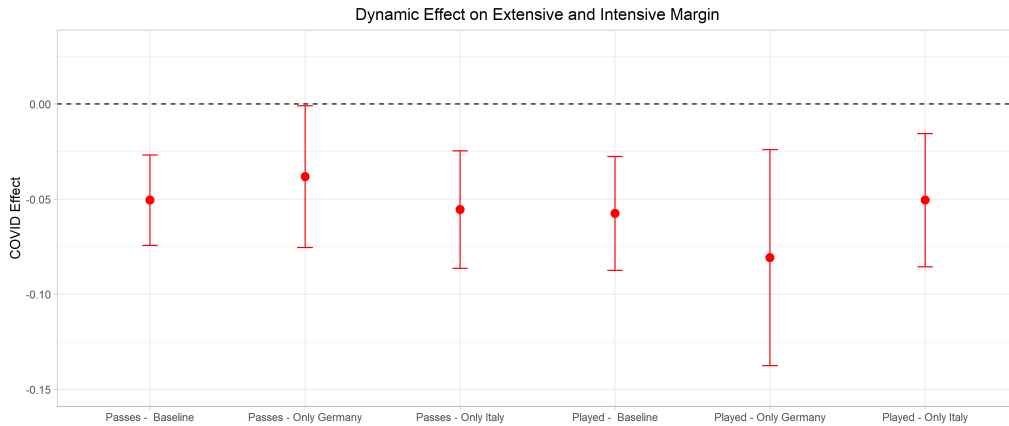
These figures plot the OLS estimated coefficients β_τ of the event study regression following Equation (2). The reference time period is one to seventy-five days before treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The 90% and 95% confidence intervals are given by the two red-shaded areas. The dependent variables are passes, touches and possession in their level specification.

Figure A5: Event Studies for Different Outcome Specifications: *Inverse Hyperbolic Sine Transformation*



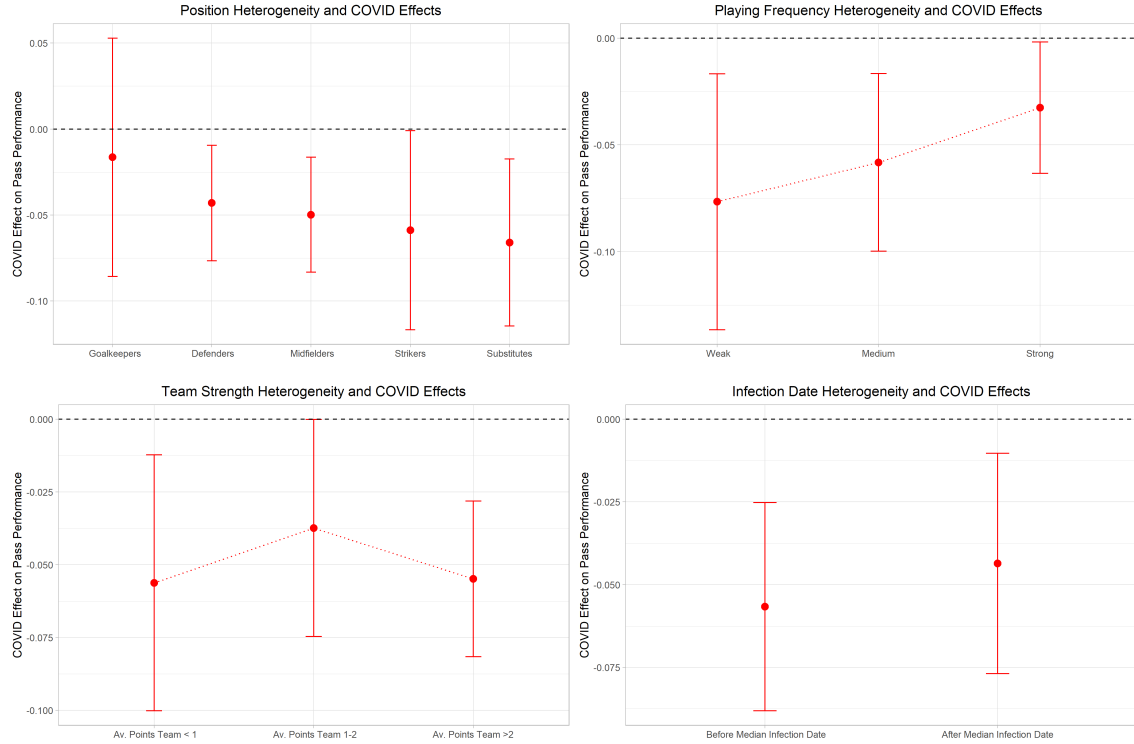
These figures plot the OLS estimated coefficients β_τ of the event study regression following Equation (2). The reference time period is one to seventy-five days before treatment. Standard errors are heteroskedasticity-robust and clustered on the player level. The 90% and 95% confidence intervals are given by the two red-shaded areas. The dependent variables are the variables passes, touches and possessions transformed via the inverse hyperbolic sine transformation to account for zero-values in the dependent variables. See for a critical assessment of this technique e.g. [Bellemare and Wichman \(2020\)](#).

Figure A6: League-Specific Effects



The plot shows the effects of the post-infection dummy included in the baseline equation (1) for the extensive and intensive margin estimated by OLS. The x-axis gives more precise information on the choice of the control group. Dep. variable: $\ln(\text{passes})$ and a dummy which turns 1 if a player has played. SEs: Heteroskedasticity-robust and clustered on the player level. 95% confidence intervals given.

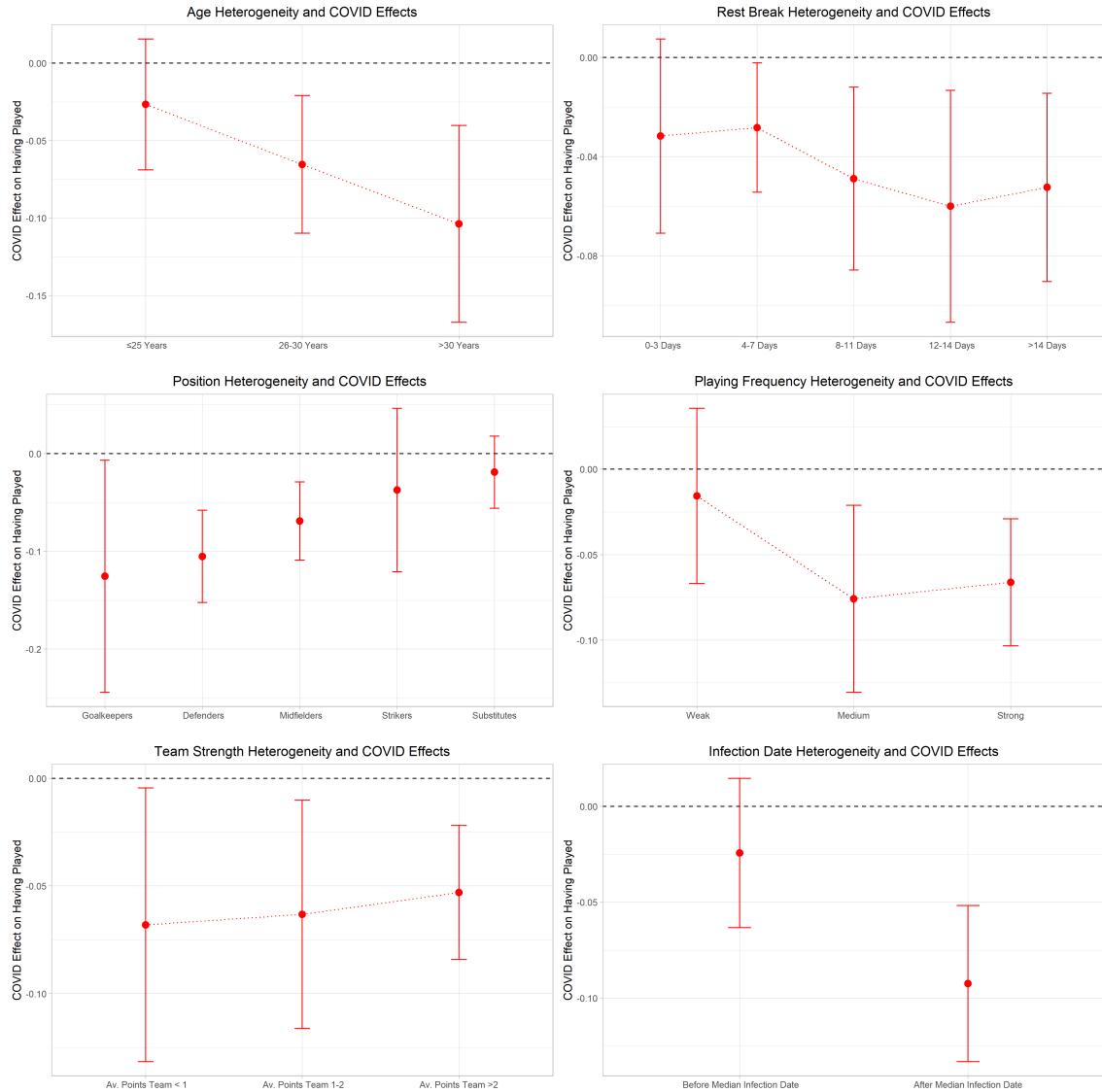
Figure A7: Additional Heterogeneity Analyses for Intensive Margin Effects: Position on the Pitch, Playing Frequency, Team Strength, and Infection Timing



These figures plot the OLS estimated heterogeneous semi-elasticity of a COVID-19 infection on pass performance. Standard errors are heteroskedasticity-robust and clustered on the player level. 95% confidence bands are displayed.

- *Position* addresses the effects on different types of positions a player might have on the pitch. ‘Substitutes’ captures all players that have not played from the beginning but have been substituted on during a match.
- *Playing Frequency* addresses differences in a player’s quality and significance for his team. To capture this, we calculate the share of available matches a player has played in before his infection took place and construct three groups for different terciles (from weak to strong) of this match-share distribution.
- *Team Strength* is the equivalent calculation on the team level. Better teams might have better medical support available while also allowing recovering players to not overtake full responsibility immediately. Contrary, above-average teams might perform on a level, which is harder to come back to again. We test this relationship by looking at heterogeneous treatment effects for teams which earned a different number of points up to a certain match in a season. Teams can earn zero (defeat), one (draw), or three points (victory) per match, so we group them into clusters of low-performing (average points < 1), medium (average points 1 – 2) and well-performing teams (average points > 2).
- *Infection Timing* tests whether early infected players show other work performance effects than players who got infected later during the pandemic. The plot at hand shows two groups of infected players which have been divided at the median infection date. One can see that the work performance effect is significant for both groups and not statistically different from each other.

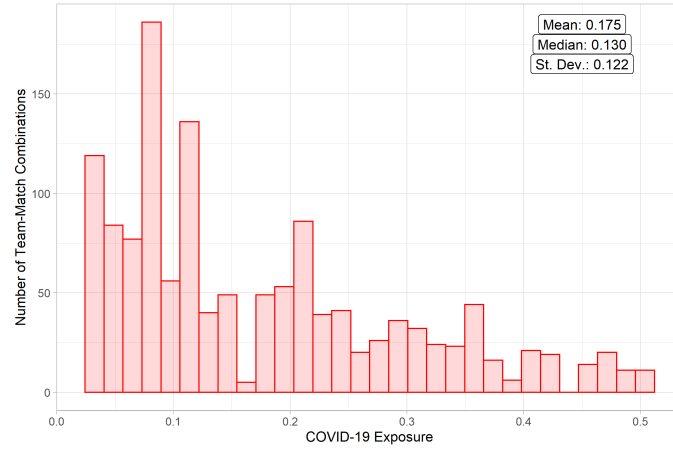
Figure A8: Heterogeneity Analysis for Extensive Margin Effects



These figures plot the OLS (partly linear probability model) estimated heterogeneous semi-elasticity of a COVID-19 infection on pass performance. Standard errors are heteroskedasticity-robust and clustered on the player level. 95% confidence bands are displayed.

Heterogeneity in Age and Rest Breaks correspond to the intensive margin effects shown in Figures 7 and 8. Position Heterogeneity, Playing Frequency, Team Strength and Infection Timing correspond to the intensive margin effects shown in Figure A7 above. The difference in Infection Timing is driven by technical reasons as for late infections there exists much less observations after the infection happened compared to early infections, such that missed matches have a higher weight causing a significant estimate.

Figure A9: Distribution of COVID-19 Exposure (CE) for $CE > 0$



This figure plots the absolute frequency of COVID-19 Exposure (CE) realizations for $CE > 0$ – as defined in eq. (3) – observed in the team data.