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Online Popularity Manipulation on Social Media: Short-term Benefits and Long-term Costs

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Abstract

Online popularity can be manipulated quite easily as there are firms selling fake social media metrics (followers, views, likes, etc.). They create an opportunity for individuals who can monetize their online popularity. This paper investigates the short- and long-term economic consequences of online popularity manipulation for professional athletes who acquire fake followers. Focusing on soccer, we created a unique dataset of 1,077 international players and took advantage of Twitter’s suspicious account removal in July 2018 to proxy fake followers. Empirical explorations show strong ties between Twitter account creation, transfer involving financial negotiation and fake followers. Results show that fake followers significantly impact players’ value – i.e. transfer fees – but only if the transfer occurs within six months of the Twitter account creation. In this case, fake followers are associated with an average 5% rise (\approx €450,000) in transfer fees. While boosting online popularity can help a few individuals over the very short-term, the public exposure of possible manipulation creates distrust and harms the overall market. Our results show that a large share of lost followers ($> 2\%$) has a significant and negative impact on transfer fees for transfers occurring soon after the removal of fake followers.

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1 Introduction

An investigation released in 2018 by *The New York Times* documents the existence of online firms that specialize in selling fake metrics (followers, views, likes, etc.) on social media.¹ This investigation named celebrities (politicians, artists, athletes, etc.) who had bought fake followers to enhance their online popularity artificially. Fake followers are a major concern for social media platforms as it casts doubt on the validity of their metrics (followers, likes, views, etc.). Increasing mistrust in online popularity measurements among users, advertisers, or investors can significantly harm the revenue and valuation of social media platforms (fewer advertising campaigns, decreasing audience size, etc.). Consequently, social media platforms try to circumvent the expansion of Fake Followers (FFs) by identifying such accounts and suppressing them, even if this leads to a significant decrease in the total number of users. Firms selling FFs create an opportunity for people interested in artificially enhancing their online popularity.² Popularity is indeed a major driver of superstars' value or earnings, in addition to performance and bargaining power (Rosen; 1981; Adler; 1985; Bebchuk and Fried; 2003). In sports, this relationship highlights the economic incentives associated with performance and popularity improvement for professional athletes.³ While enhancing performance in sport involves time and effort, increasing online popularity through the purchase of fake followers is much easier. Empirical studies in other contexts document online information manipulation practices – fake reviews or download – that aims at influencing the perceived quality of services or products (Mayzlin et al.; 2014; Li et al.; 2016; Luca and Zervas; 2016; He et al.; 2022). Moreover, it has been shown recently that the use of social media platforms and the resulting online popularity can generate economic returns for some individuals (Petrova et al.; 2021). The large amounts of revenue generated on the soccer player market through transfers – more than €6.2 billion in 2022⁴ for the main five European championships – provides a worthy context of manipulation.

This paper extends this literature by investigating whether the labor market is affected by online popularity manipulation on social media through the acquisition of fake followers. This analysis also addresses the impacts on an individual's value if manipulation is revealed publicly.

To conduct the analysis, we created a unique dataset of 1,077 international soccer players coming from 43 countries worldwide over the period 1997-2019. This includes more than 500,000 observations of players' careers (statistics, social media presence, transfers, etc.) collected from Transfermarkt.com. It notably contains the usual measure of soccer players' valuations, namely transfer fees. The transfer fee is the amount that a club pays to enroll a new player before the end of the player's current contract. Similar to the study by Luca and Zervas (2016), we rely on the detection of fake accounts made by the platform – Twitter – to proxy for the number of FFs associated with players' Twitter accounts. More precisely, we use the variation in the number of followers on players' Twitter accounts that occurred on the 12 July 2018 due to the large removal of suspicious accounts carried out by Twitter – referred to as the "*Great Purge*".⁵ According to Twitter, these suspicious

¹The investigation is available here: <https://nyti.ms/2Fm5rCC> (last retrieved: May 2024).

²Note that this practice violates Twitter's Terms of Service: <https://help.twitter.com/en/rules-and-policies/platform-manipulation> (last retrieved: May 2024).

³See for instance Lucifora and Simmons (2003) for soccer, Vincent and Eastman (2009) for hockey, Treme and Allen (2009) for American football or Ertug and Castellucci (2013) for basketball.

⁴See CIES report available at: <https://www.football-observatory.com/IMG/sites/mr/mr77/en/>, (last retrieved: May 2024).

⁵In July 2018 Twitter announced that suspicious accounts were soon to be removed from followers counts. This tweet was latter suppressed by Twitter or X. See Figure A.1 in Appendix A for a screenshot of this tweet. Articles in *The New York Times* (<https://www.nytimes.com/2018/07/12/technology/twitter-followers-nyt.html?action=click&module=RelatedCoverage&pgtype=Article®ion=Footer>) (last retrieved: May 2024) or on BBC News (<https://www.bbc.com/news/world-us-canada-44815550>) (last retrieved: May 2024) document that this removal of suspicious accounts led to a 6% drop in the total number of followers on Twitter on July 12 2018.

accounts were removed from account statistics in particular to ‘ensure that malicious actors aren’t able to artificially boost an account’s credibility permanently by inflating metrics like the number of followers’.⁶

Following the methodological approach used in the literature on cheating (Duggan and Levitt; 2002; Jacob and Levitt; 2003; DellaVigna and La Ferrara; 2010), we do not directly observe the acquisition of FFs but our analysis reveals consistent patterns for those players associated with FFs. First, they tend to move to another club shortly after creating their Twitter accounts, which illustrates the role of online popularity during transfer negotiations. Second, this pattern is particularly visible for transfers involving financial negotiations and players with high number of FFs. Third, after Instagram became the most popular social media platform for soccer fans around 2015, the numbers of newly created Twitter account associated with FFs was no longer significant. This suggests it is not worth purchasing FFs anymore on Twitter. Beyond these empirical evidence, our results show that the impact of FFs on players’ valuations (i.e. transfer fee) is not constant, and thus, does not capture an invariant behavior or player characteristics. FFs have a positive and significant impact on transfer fees only if the transfer occurs within six months of Twitter account creation. In this case, FFs are associated with an average 5% rise ($\approx \text{€}450,000$) in the transfer fee. This economic gain far exceeds the costs of buying FFs.⁷ This is consistent with the purchase of FFs to boost and monetize the online popularity of a newly created Twitter account during a transfer negotiation. A number of robustness checks validate this result and provide more details. They show that our results are not sensitive to players’ activity on Twitter or limited to high transfer fees. These robustness checks indicate also that the practice of buying FFs is successful only in a limited number of cases characterized by very large numbers of FFs.⁸ This short-term impact of online popularity manipulation is complemented by findings about the impact of a decrease in the number of followers on player values. Since the “*Great Purge*” occurred during a transfer period, it allows us to check for its impact on the transfer market. Our results show that large share of lost followers ($> 2\%$) had a significant and negative impact on transfer fees for transfers that occurred very soon after the “*Great Purge*”. More precisely, a 1 percentage point increase in the lost follower share is associated with 16% decrease in the transfer fee. However, this strong effect combines both the loss of followers and a market sanction for online popularity manipulation.

This article contributes to two literature streams. The first one highlights the positive effects of popularity on the market valuation of an individual, product or service (Adler; 1985; Bhaskaran et al.; 2013; Hofmann et al.; 2021). Although it is difficult to determine causality, the positive relationships between popularity, talent and earnings have been observed in many sport contexts and especially soccer. Consistent with this framework, many papers show that both performance (goals and assists) and popularity (citations in newspaper, queries in search engines, etc.) have positive effects on the market value of a soccer player (Lucifora and Simmons; 2003; Garcia del Barrio and Pujol; 2007; Lehmann and Shulze; 2008; Franck and Nüesch; 2012; Carrieri et al.; 2018).

Closer to our studies some research focus on the return on investment associated to social media adoption and popularity. These studies show a significant impact of online popularity on different outcomes: food sales (Bhaskaran et al.; 2013), donations during political campaigns (Petrova et al.;

⁶Details of Twitter’ policy against malicious behaviors using fake accounts are available at: https://blog.twitter.com/official/en_us/topics/company/2018/how-twitter-is-fighting-spam-and-malicious-automation.html (last retrieved: May 2024). This post was originally accessible by clicking on the hyperlink “here” in the document “Confidence in follower counts” attached to the tweet announcing the removal of suspicious account.

⁷In a study of the underground market of Twitter followers, Stringhini et al. (2012) report that in 2012 the cost of buying 1,000 fake followers ranged between \$20 to \$100. These costs are well below the potential benefits of the manipulation mentioned previously.

⁸Widespread use of online reputation manipulation would have been surprising since its effective implementation requires most labor market actors to be unaware of the practice.

2021), and firm stock prices (Lindenmayr and Foerderer; 2023). As raised by Hoffman and Fodor (2010), these papers sometimes distinguish short and long-term effect of popularity variations. This literature provides us with the main incentive scheme that underpin the manipulation of online popularity: higher online popularity may lead to a higher value or income for a soccer player.

We contribute to this literature by showing that performance and online popularity on social media affect individual value in the labor market. We document and measure the impact of social media adoption and the subsequent online popularity on individual value in the cases of Twitter and Instagram. This paper offers additional evidence regarding the influence of international soccer players' performance at the national and international levels on their value.

The second contribution of this paper is to a related strand of work investigating the question of online information manipulation. Analysis of illegal activities is not straightforward since those who engage in these activities make effort not to leave any trails (Duggan and Levitt; 2002; Jacob and Levitt; 2003). The lack of formal measure of illegal behaviors has resulted in scholars adopting approaches that provide indirect evidence of such behaviors based on consistent patterns related to cheaters and the mechanisms that underpin these activities (Duggan and Levitt; 2002; DellaVigna and La Ferrara; 2010; Mayzlin et al.; 2014). The literature has already highlighted "on the field" cheating practices among professional athletes motivated by economic gains (Duggan and Levitt; 2002; Wolfers; 2006; Jetter and Walker; 2017).⁹

Evidence of strategic manipulation of online information has been documented in empirical studies for different products and services: hotels (Mayzlin et al.; 2014), restaurants (Luca and Zervas; 2016), e-commerce (He et al.; 2022) or smartphone app (Li et al.; 2016). The variety of contexts in which such practices have been observed is not surprising. As Mayzlin et al. (2014) note, when a valuable characteristic of a product is imperfectly observable, those able to benefit from a higher level of this feature will be interested in influencing it through fake information. The authors use the differences in review distributions across two platforms to identify possible hotel review manipulations. They show that independent hotels located close to competitors have more fake positive reviews, suggesting that the hotels themselves are posting the fake reviews. Luca and Zervas (2016) investigate this issue in the context of online restaurant reviews using Yelp's filtering system to identify possible fake reviews. Their results suggest that independent restaurants are more likely to give themselves fake positive reviews and to post fake negative reviews about competitors offering similar food services. In the study of He et al. (2022), products with requests for fake reviews showed an increased number of reviews, ratings, and sales. However, these effects hold only in the short-term and begin to diminish after two weeks. Closer to our paper, some theoretical works (Anand et al.; 2022; Huang and Liu; 2022) provide game-theoretic models of fake follower acquisition by influencers on social media. Their models show that only influencers with intermediate follower counts benefit from buying FFs. They demonstrate that the manipulation can occur as long as the real popularity of an influencer is uncertain, that is at the start of her digital existence.¹⁰ These papers, and the study of Petrova et al. (2021) highlight the importance of the timing of the creation of the social media account. In their paper, Petrova et al. (2021) found that, after setting up their Twitter account, donations to politics increased by a range of 0.7% to 3.1%. In this article, we also use the timing of the creation of the social media account as an identification strategy.

Prior studies have focused on the strategic manipulation of information related to services and products sold on online platforms. The present paper extends this literature by focusing on the impact of online information manipulation on the labor market. We provide, moreover, measures

⁹Some scholars discuss the findings of Wolfers (2006), see for instance Bernhardt and Heston (2010).

¹⁰Zhou et al. (2023) use a lab experiment to demonstrate that the influence of an influencer increases when their number of followers is artificially inflated with fake accounts. However, disclosing the use of FFs does not have a negative impact on their future revenues.

for the economic impacts of manipulation. Our results show that labor market outcomes, in our case transfer fee, can be manipulated through the acquisition of FFs. We also document a negative impact on player values once the use of FFs is publicly revealed.

The paper is organized as follows. Section 2 introduces the data. Section 3 exposes the empirical evidence of FF acquisition by some international soccer players. Short and long-term impacts of manipulation are respectively presented in Sections 4 and 5. The final section concludes and discusses the implications of the study.

2 Data and empirical explorations

This section provides description of the data used for this study and proposes preliminary analysis of soccer players' careers and social media presence. We first describe the main sources of information used to create the dataset (*Transfermarkt.com*, *Twitter.com*, and *Instagram.com*). Then, we document the removal of suspicious accounts carried out by Twitter on 12 July 2018 in the second subsection. We exploit this event to measure the number of FFs associated with soccer players. In the third subsection, we test a possible alternative scenario explaining the existence of FFs. Rather than being acquired deliberately to manipulate online popularity, fake accounts may be result of the social spamming strategies of malicious actors.

2.1 Player Careers and Performance

We focus on international soccer players for two main reasons. Firstly, they are talented players who attract the attention of fans and the media. Online popularity can thus be a valuable asset for them (Garcia del Barrio and Pujol; 2007; Carrieri et al.; 2018). Secondly, they also attract attention of specialized websites, and then, various statistics about them (value, performance, clubs, etc.) are relatively more available. We include in this study players from 43 national teams: the 32 national teams which qualified for the 2018 World Cup (June 15-July 15, 2018) and 11 national teams that did not qualify.¹¹ The full sample includes 1,077 international players. The specialized soccer website *Transfermarkt.com* has been used to collect data on players' performances and careers. This website has been chosen because it is considered to be a reliable source of information about players (statistics, careers, achievements, etc.), and especially their values (Franck and Nüesch; 2012; Deutscher and Büschemann; 2016; Müller et al.; 2017). It provides information about players' characteristics (age, nationality, size, position, etc.), careers (clubs, achievements, agents, sponsors, etc.), performance (goals, assists, injuries, etc.), and value (transfer fee, loan fee, etc.). In some cases, *Transfermarkt.com* even contains links toward players' social media accounts (Facebook, Twitter and Instagram). Table B.1 in Appendix B provides some summary statistics for the players included in our sample. The data collected covers the period 1997-2020. They include around 520,000 player-match day observations (club and national team, competition and friendly games), 6,000 achievements (competition winner, award, etc.), 6,500 transfers, and 20,000 market value updates.

We are interested in particular in transfer information, as we measure player value based on the fees associated with their transfers. When a player switches from one club to another, it is generally

¹¹The 32 national teams that qualified for the 2018 World Cup were: Argentina, Australia, Belgium, Brazil, Colombia, Costa Rica, Croatia, Denmark, Egypt, England, France, Germany, Iceland, Iran, Japan, Morocco, Mexico, Nigeria, Panama, Peru, Poland, Portugal, Russia, Saudi Arabia, Senegal, Serbia, South-Korea, Spain, Sweden, Switzerland, Tunisia, and Uruguay. In addition, we selected national teams not qualified for the 2018 World Cup in each of the five main geographical soccer areas (Europe, Africa, North, and Central America, South America, and Asia-Pacific) distinguished by the International Federation of Football Association (FIFA): Algeria, Austria, Cameroon, Chile, China, Italy, Ivory Coast, Netherlands, New Zealand, Romania, and USA.

associated with financial negotiations (wages, transfer fees, contract duration, etc.) between the player and the buying club, and also the selling club if the player’s contract is not finished. Five different types of transfers are typically observed in soccer: transfer with fees, loan with fees, loan (without fees), free transfer and end of loan. More precisely, *transfers with fees* occur when a player leaves a club before the end of his contract. The buying club must pay a fee to compensate the early end of the contractual relationship between the player and the selling club. *Loans* and *loans with fees* are contracts that allow a player to play for another club for a short period of time and then return to his home club. In most cases, these contracts last for one season and can be associated or not with fees paid by the destination club. A *free transfer* occurs when a club recruits a player after his last contract has ended. In this case, the new club does not have to pay compensation to the player’s former club, but it is often associated with a signing bonus for the player. Finally, *end of loan* refers to players who return to their original clubs once the loan has expired. It is similar to a free transfer as neither club involved in the transfer has to pay a fee.

Table 1 presents statistics for the different transfer types. In this study, we consider only transfers related to players aged over 18 years. In some cases, the precise type of transfer is not detailed on *Transfermarkt.com*, and thus we categorize them as "undefined transfers". The statistics are provided for all observations ("Full sample") and for the sub-sample of players with Twitter account ("Twitter").

Table 1: Descriptive statistics on transfer types

	Full sample		Twitter	
	No. of transfers	%	No. of transfers	%
Transfer with fee	1,754	26.8	1,176	27.5
Loan with fee	248	3.8	172	4.0
Free transfer	924	14.1	521	12.2
Loan	1,029	15.7	707	16.5
End of loan	1,221	18.7	841	19.7
Undefined transfer	1,367	20.9	860	20.1
Total no. of transfers	6,543		4,277	

During players’ early careers (18-20 years old), the proportions of loans and transfers with fees tend to be similar (see Fig. A.2a in Appendix A). After the age of 20, transfers with fees become more prominent. Undefined transfers mostly concern young players. It is likely that most of these transfers refer to young players who move from the youth team to the reserve team, or to the professional team. In most cases, this is associated with the signing of a new contract. As they may not be so popular or talented at that time and/or play in minor championships, information about the new contracts is not publicly advertised.

The statistics related to fees presented in Table 2, highlight the economic importance of soccer. The cumulative total of transfer fees for these 1,077 players, even if some of them are far from the end of their careers, is approximately €14 billion. For most small- and medium-sized clubs, transfer fees are the main source of income. Many clubs ground their financial sustainability on *players’ trading*, that is, discovering and recruiting talented young players in order to sell them for much more money than they buy them.¹² Future sales are even included in the club’s budget. For example, in the French premier league, clubs are audited by an independent organization at the beginning of each season about how they plan to manage their budget, and especially how much

¹²See for instance this article in *The New-York Times*: <https://www.nytimes.com/2008/07/19/business/19soccer.html> (last retrieved: May 2024).

Table 2: Descriptive statistics on transfer fees

	Transfer fee (million €)		Loan fee (million €)	
	Full sample	Twitter	Full sample	Twitter
Mean	8.7	10.2	1.6	1.9
Standard dev.	15.3	17.2	3.0	3.4
Minimum	0.006	0.006	0.008	0.015
Maximum	222	222	35	35
Total no. of transfers	1,754	1,176	248	172

revenue they expect from selling players. Clubs that do not comply with the balanced budget rule may be heavily penalized, with transfer bans, restrictions on the number of players, or relegation to a lower league.¹³ Quansah et al. (2021) and Poli et al. (2022) detailed how much clubs depend on income generated by transfers in order to balance their books. Players’ agents play a crucial role in negotiations between clubs and soccer players. Their remuneration consists of a salary paid by the player and a share of the profits from the player’s transfer fee. The higher the value of the transaction, the better the agent is paid, through a direct percentage of the transfer fee in most cases.

2.2 Social Media and Online Popularity

Information on players’ online popularity (followers, friends, etc.) has been collected on Twitter and Instagram from the 14 June to 9 September 2018, twice a day (at 11 a.m. and 11 p.m.).¹⁴ This information was gathered both using social media API and direct scraping of players’ accounts. For each social media platform, we identified the player’s account using the following four-step protocol: (i) checking the availability of a link to the player’s social media account on Transfermarkt.com, (ii) searches the player’s account on Google using a query of the type: "*Firstname Name Twitter* or *Instagram*"¹⁵, (iii) check whether the player is among the followers of the social media accounts of his club or of the national team, and (iv) check whether the player appears among the followers of players of his club or national team. If the previous steps did not identify an account, we consider the player has not got an account on that particular social media platform. We can miss players’ social media accounts even if we follow the entire protocol. In this case, it is likely that this player is not at all popular online, as we found with this protocol players who only had a few hundred followers.

Using this protocol, we identified 666 Twitter accounts (61.8%) and 824 Instagram accounts (76.5%) in our sample of players. Most have verified profiles, meaning that the account owner’s identity has been checked by the social media platform, with respectively 83.6% and 83.4% for

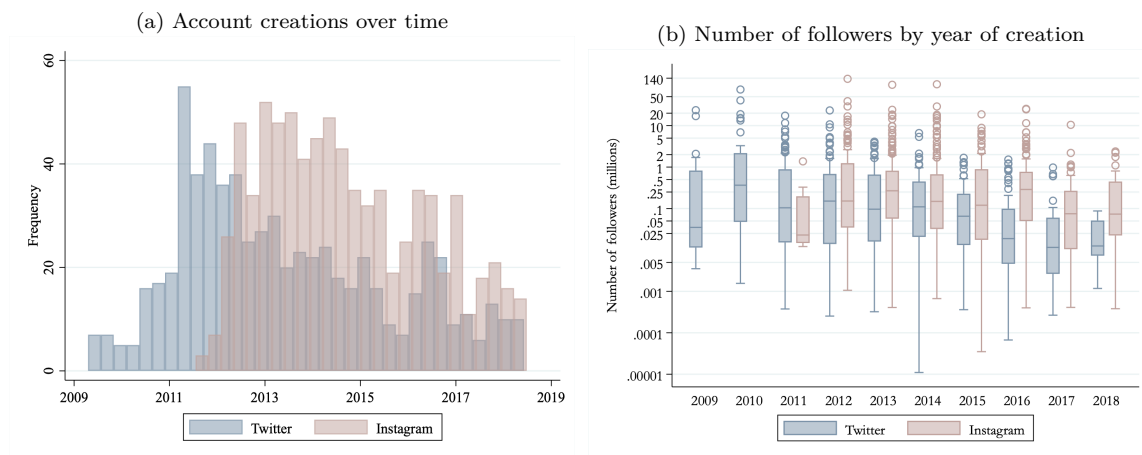
¹³See, for instance, the case of the French Bordeaux soccer team: <https://www.besoccer.com/new/bordeaux-and-angers-spared-relegation-from-ligue-1-by-french-authorities-1017828> (last retrieved: May 2024).

¹⁴Facebook was initially included, but after observing the small number of players with Facebook accounts, we decided to include only Twitter and Instagram in the study.

¹⁵We began by searching for the name and first name using the Western alphabet for all players. If we did not find the account and that player’s name is not originally written using the Western alphabet, we searched for his name and first name with its original alphabet. Transfermarkt website is particularly useful in this regard as it provides the player’s name and first name using their original alphabet (Arabic, Chinese, Cyrillic, Japanese, etc.).

Twitter and Instagram.¹⁶ It is noticeable that 561 players (52.1%) have an account on both social media. Figure 1 plots statistics for year of creation of Twitter and Instagram accounts and the number of followers in July 2018. We can observe that Twitter account creation occurred earlier, with the first ones in 2009 and a peak in 2011. Instagram accounts creation began in 2011 and peaked in 2013. Although Twitter seems to be the favorite social media platform used by soccer players at the beginning of the 2010s, Figure 1b shows that Instagram attract more followers a few years later.

Figure 1: Descriptive statistics about Twitter and Instagram



2.3 Twitter and Fake Followers

FFs are typically used to implement two malicious strategies: social media spamming and artificial increase in follower counts.¹⁷ Social media spamming refers to the practice of following a popular person using a fake account and posting promotional content on their wall that can potentially be seen by all of their followers. In the case of online popularity manipulation, a firm selling FFs will be contacted and a certain number of them will be purchased by the account owner or her relatives. Social media login information must be given to the firm, so as it can manage and control that the requested amount of FFs have really started to follow the targeted account.

These two practices, and the subsequent FFs generated, constitute thus major threats for social media platforms. Social spamming downgrades users' experience and information, and can lead them to reduce and even stop using the social media platform. Regarding FFs used to artificially enhance online popularity, this practice creates mistrust about social media metrics among advertisers and users. Users may feel deceived if they discover or come to understand that the statistics of the people they follow are false, and therefore reduce their use of social media. Loss of advertiser confidence is

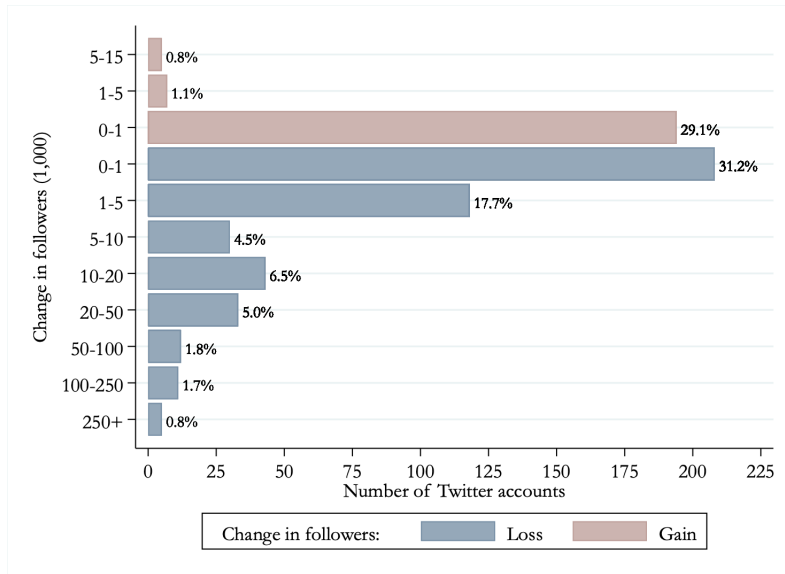
¹⁶Unverified profiles are included in the analysis if they satisfy the following conditions: player names and first names are used for the social media's screen name, the account is described as belonging to the corresponding soccer player, the player is clearly identifiable in "personal" photos in a soccer and/or personal context and the profile has at least 1,000 followers.

¹⁷For more details, see Twitter's policy against spamming and malicious behaviors (https://blog.twitter.com/official/en_us/topics/company/2018/how-twitter-is-fighting-spam-and-malicious-automation.html) (last retrieved: May 2024).

perhaps even more damaging for social media platforms, as advertising revenue is their main source of income. Advertisers may feel overcharged when paying for ad-campaigns due to the presence of FFs and therefore decide to reduce or even stop advertising on the platform.

To mitigate these threats, Twitter removes accounts suspected of being used for spamming or metrics manipulation. In particular, a large purge of fake accounts was carried out by Twitter on 12 July 2018.¹⁸ The twice-a-day collection of social media metrics allows accurate measurement of the number of suspicious accounts associated with the international soccer players in our sample. In Appendix A, Figure A.3 depicts typical trends observed for followers around 12 July 2018. It shows that fake follower removal did not impact all players but many players experienced a large reduction of the number of followers ($>1,000$ followers) on that day, while on other days the number of followers tended to increase for most players. Figure 2 provides summary statistics on the evolution of followers for our sample of players on July 12, 2018. It shows that the sample falls in three rough tiers. Those in the first tier gained a few followers (less than a thousand in most cases), those in the second tier lost only a few (less than a thousand) and those in the third tier experienced a huge loss of followers. The decrease can reach more than 10,000 of followers for 107 players (16.1% of players with Twitter). Figure 2 show that large FF losses are not widespread among players. However, some players are associated with large numbers of FFs, which raises the question of possible strategical use in these cases.

Figure 2: Twitter’s removal of FFs on the 12th of July, 2018



¹⁸A screenshot of the tweet that announced the removal of fake accounts is provided in Appendix A. This tweet included a link toward a post presenting Twitter’s policy about ‘Confidence in follower counts’ (see https://blog.twitter.com/official/en_us/topics/company/2018/Confidence-in-Follower-Counts.html, last retrieved: May 2024). The post contains a link toward more detailed descriptions about how Twitter fights spam and malicious behaviors (see https://blog.twitter.com/official/en_us/topics/company/2018/how-twitter-is-fighting-spam-and-malicious-automation.html, last retrieved: May 2024). In Appendix A, Figure A.3 provides statistics about the evolution of followers during all the month of July, 2018. The 12th of July, 2018 appears to be a very particular day, consistent with the announcement the day before of a large cleaning of fake accounts by Twitter. This deletion of Twitter users has been described by the media as a “Great Purge”.

2.4 Alternative Scenario

Suspicious accounts are used to achieve two main goals: social media spamming and online popularity inflation. Both cases lead to an artificial increase in the number of followers associated to an account, but their originations are clearly different. For the acquisition of FFs, the rise stems from a decision taken by the account owner or someone who manages it (the player’s agent, communication advisers, club’s communication department, etc.). In the case of social media spamming, the account owner suffers from the decision of a malicious actor. Social media spamming indeed consists of posting ad-related contents at cheap cost in order to benefit from the large audience of the targeted account.

In this paper, we investigate the possible manipulation of online popularity which means that social media spamming is beyond the scope of this study. However, since it relies on the same means – fake accounts – as popularity manipulation, we need to assess whether or not fake accounts associated to a player are the result of social spamming behavior. If suspicious accounts removed by Twitter mainly consist of fake accounts created for social media spamming, we might observe a strong correlation between the number of followers of a player and his number of FFs. These correlations are presented in Table 3. The number of followers has been corrected with the removal of FFs. Moreover, the sample has been divided into deciles based on the number of followers to have comparable groups of players.

Table 3: Correlation between followers and FFs by decile

Decile	Corr.	Fake followers		Followers	
		Min.	Max	Min.	Max.
1	.24	0	99	11	2,967
2	.10	0	188	3,026	7,656
3	.06	0	2,591	7,671	15,418
4	.35	0	1,300	15,922	34,482
5	.03	0	109,985	35,296	77,010
6	.37	0	4,992	77,685	154,127
7	.27	0	12,396	154,131	310,604
8	.22	0	20,027	311,016	767,382
9	.29	0	35,878	778,131	1,646,341
10	.97	114	1,215,302	1,659,446	73,326,669

Table 3 shows that in the first nine deciles the correlation between fake and "real" followers is very low and irregular. Moreover, these deciles systematically include some players who are not associated at all with fake accounts. This evidence is not consistent with the wide use of these fake accounts for social media spamming purposes. The last decile, however, exhibits a large and positive correlation. A closer look to this decile shows that this very high level of correlation holds only for the last 5 percent of the sample (see Table B.3 in Appendix B). The most popular players exhibit a pattern that matches social media spamming. Therefore, we excluded this 5% most popular players from the succeeding analysis and focus only on players with fewer than 3.2 million followers on Twitter.

3 Transfers, Social Media and Fake Followers

Social media spamming accounts for the presence of FFs only for the most popular players on the platform. For the remaining players, there may be other explanations. Further empirical investiga-

tion provides three main types of evidence that FFs are used to artificially inflate player popularity in our case: i) the absence of accounts with significant numbers of FFs on Twitter after Instagram became the most popular social media platform for players, ii) the strong correlation between Twitter account creation and subsequent transfers which illustrates the use of social media to monetize popularity, and iii) the significant relationship between a high number of FFs and subsequent transfers involving financial negotiations after the creation of a Twitter account. These findings are discussed in detail below.

3.1 The Rise of Instagram

A striking feature of Figure 3a is that creation of accounts with significant number of FFs almost disappears after 2014. This result echoes the previous statistics we observed in Figure 1 (see subsection 2.2). This Figure shows that after 2014 the number of followers on Instagram tend to outperform those on Twitter. It would seem that after 2014 Instagram became the most popular social media platform for soccer players. FFs seem to have disappeared because it is no longer worth investing in them on Twitter as it is no longer the reference for player popularity. Figure A.4 in Appendix A focus on players who use both social media platforms and provide additional evidence of this phenomenon. Although these players mostly created their Twitter account first (Figure A.4a), most of them have more followers on Instagram in 2018 (Figure A.4b). This means that, at some point, the numbers of followers on Instagram have exceeded those on Twitter. Figure 3b depicts this trend by plotting monthly average number of followers per account on both social media.¹⁹ Again, we observe that on average, Twitter accounts have been created before Instagram ones and that followers on Instagram outperform those on Twitter around 2014. The rise of Instagram as the main social media platform for soccer players in 2014 is therefore consistent with the disappearance of FFs, and provides evidence of their use for the purpose of online popularity manipulation.

3.2 Social Media and Transfer

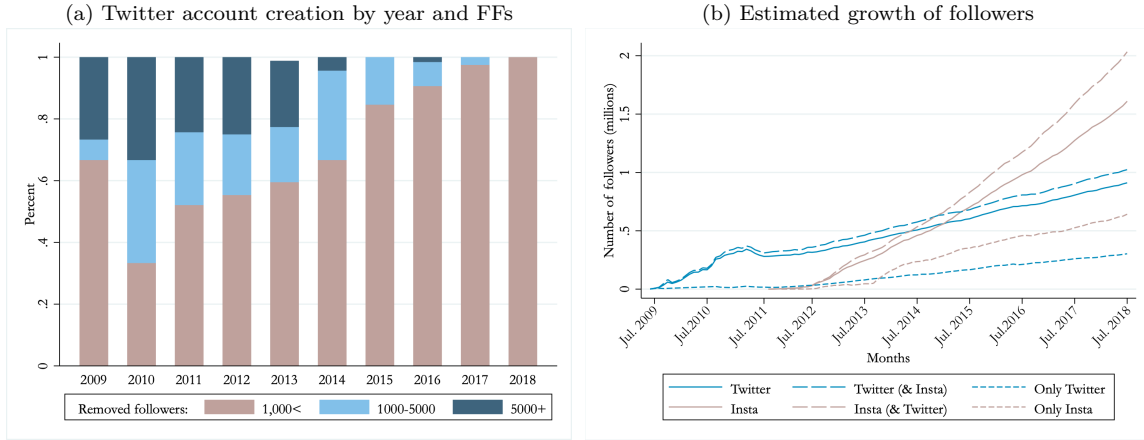
A player’s professional life is quite cyclical. It is paced by phases of competitions and so-called *mercato*, that is, periods during which players can transfer to another club. These latter occur twice a year with the *Summer mercato* in July and August, and the *Winter mercato* in January. Figure 4 provides monthly statistics on Twitter account creation from 2009 to 2018 for players with respectively fewer than 1,000, between 1,000 and 5,000, and more than 5,000 FFs. Since FFs are generally sold in batches of 1,000, we consider that having less than 1,000 is similar to not having FFs.²⁰ Figure 4b highlights that accounts with FFs are over-represented in June, November and December.²¹ These months are special in soccer as they precede the *mercato* periods (July, August and January). It seems that Twitter account creation, and especially those accounts with FFs, occurs more frequently few times before a *mercato*. Table 4 shows, moreover, that transfers with fees are over-represented among the transfers occurring after the creation of Twitter accounts. These

¹⁹In contrast to the other Figures and Tables, Figure 3b includes popular players (i.e. more than 3.2 million followers) on Twitter. These players had a key role in the determination of the dominance of one platform or the other. In Figure 3b, we assume that the number of followers is equal to 0 on the day of an account’s creation and that thereafter it grows linearly until July 2018. This Figure plots average follower evolution for different cases: players present on only one of these two social media (‘Only Twitter’ or ‘Only Insta’), players with a presence on both social media (‘Twitter (& Insta)’ or ‘Insta (& Twitter)’), and followers evolution regardless the presence of the players on one or both social media (‘Twitter’ or ‘Insta’).

²⁰73.6% of players accounting for between 1 and 1,000 FFs have fewer than 500 FFs.

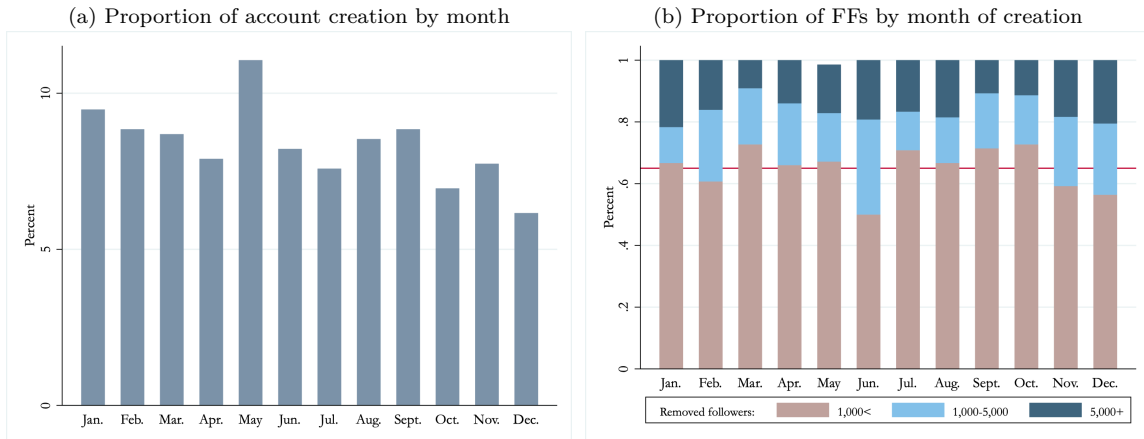
²¹Proportional difference tests show significant over-representation of accounts with FFs at 5% threshold in June ($z = 2.18$; $pr = 0.015$) and at 15% threshold in November and December (resp. $z = 1.12$; $pr = 0.13$ and $z = 1.19$; $pr = 0.12$). There is also a significant under-representation of accounts with FFs in March ($z = -1.12$; $pr = 0.13$).

Figure 3: Twitter account creation, FFs and Instagram growth



Figures and the Table do not indicate, however, if players actually move during the *mercato* following the creation of their Twitter account. Figure 5 fills this gap by providing information on the time between Twitter account creation and the player’s next transfer by transfer type.

Figure 4: Number of Twitter accounts created by month (2009-2018)



Since on average, a player stays at a club for 505 days, Figure 5a shows a strong correlation between Twitter account creation and all transfer types. This trend clearly arises from transfers that involve financial negotiations, that is, transfers with fees, loans with fees and free transfers (see Figures 5b and 5d)²². Loans, which do not involve transfer fees and wage bargaining, do not exhibit different behaviors according to the number of FFs associated with a player. Significant numbers of FFs are associated mainly with accounts created shortly before financial negotiations

²²A free transfer involves that the player (and his agent) negotiates his wage with the buying club. Undefined transfers imply that a new contract has to be agreed and thus include wage negotiations in most cases.

Table 4: Twitter account creation and transfer types

	All transfers	Transfers next to Twitter creation
Transfer with fee	26.8	41.1
Loan with fee	3.8	4.9
Free transfer	12.5	14.5
Loan	16.9	12.8
Loan end	19.8	8.3
Undefined transfer	20.2	18.5
Total # of transfer	4,136	531

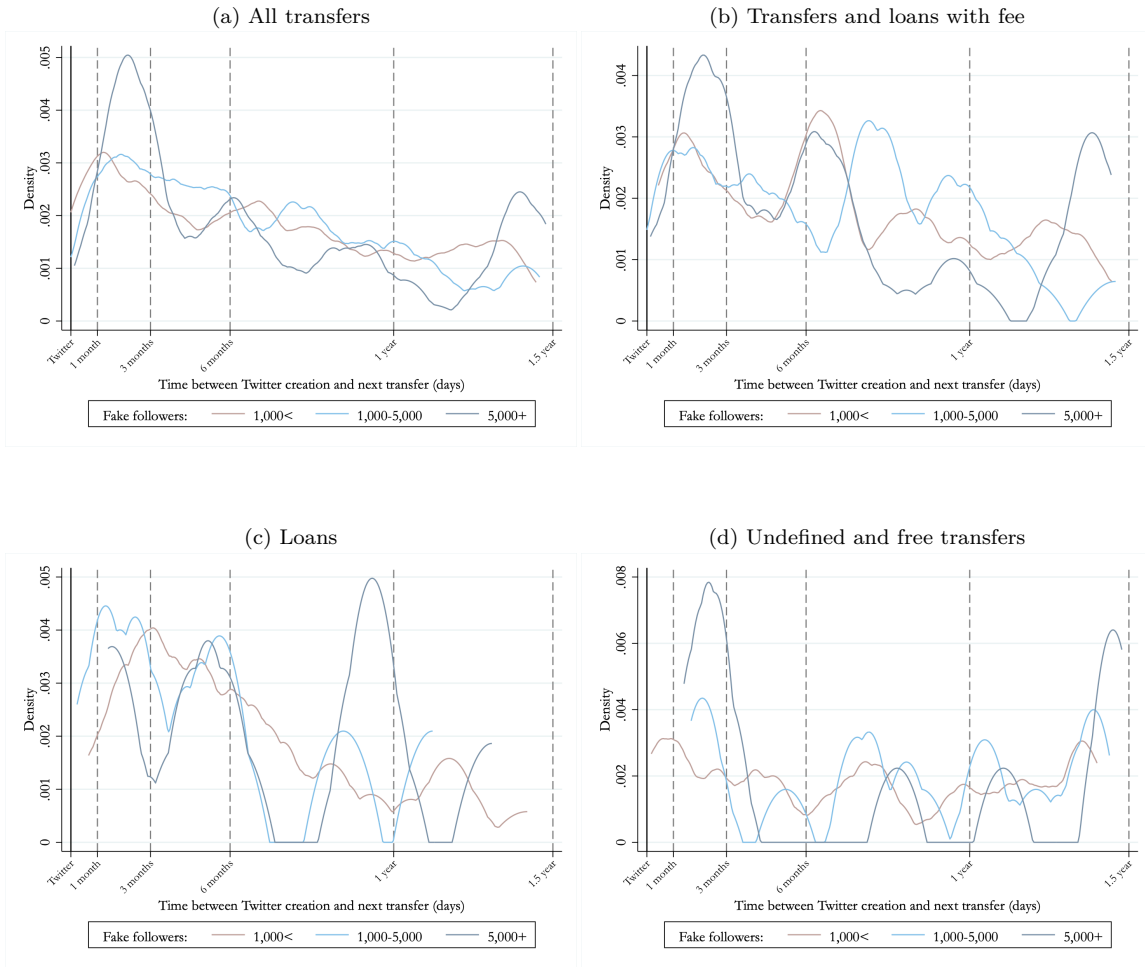
involving the player, the buying club and possibly the selling club. It provides new evidence that popularity is a valuable asset for professional athletes, and especially soccer players, during salary bargaining (Garcia del Barrio and Pujol; 2007; Lehmann and Shulze; 2008; Franck and Nüesch; 2012; Carrieri et al.; 2018). High adoption rates of social media, respectively 61.8% and 76.5% for Twitter and Instagram, underline players' interests into monetizing their online popularity during transfer negotiations.

3.3 Online Popularity Manipulation Strategy

The evidence presented suggest that most FFs have been acquired purposefully to manipulate online popularity. Firstly, the social media spamming explanation does not fit to our data, except for the 5 percent most popular players. The latter have therefore been withdrawn from our analysis. Secondly, recent Twitter accounts are no longer associated with FFs. This evolution results from the rise of Instagram, which offers a larger audience than Twitter. Twitter's FFs are then no longer attractive for manipulating online popularity. Thirdly, Twitter account creation appears to be strongly related to players' transfers shortly after, especially for players with large numbers of FFs. For the latter, transfers involving fees and/or wages negotiations are over-represented.

These findings suggest the following scenario about the manipulation of online popularity. Players keen to be transferred create a Twitter account to monetize their online popularity during transfer negotiations. Indeed, the transfer negotiation includes the player's salary in the new club and possibly the compensation for the selling club for early termination of the contract. The transfer fee paid by the buying club reflects its expectation of the income which will be generated by the recruited players (Carmichael et al.; 1999; Dobson and Gerrard; 1999). The higher a player's performance and popularity are, the better income the buying club can expected from the transfer. More skilled players produce better results and higher match quality which generate more revenue associated to achievements and attendance. Popular athletes generate revenue for their clubs from merchandising, ticketing, TV rights, etc. While a club is able to monitor performance, popularity is more difficult to measure accurately. In this context, players, agents or selling clubs can be interested in boosting popularity artificially. This could enhance the buying club's expected revenue associated with the recruitment of a player and, therefore, increases its willingness to pay a high transfer fee. This strategy is more likely to be used soon after the Twitter account is created, when online popularity is uncertain and the number of followers is limited. Manipulation can lead in this case to a significant increase in online popularity.

Figure 5: Distributions of transfers next to Twitter account creation (2009-2018)



4 Short-term benefits: Online popularity manipulation and players' values

The transfer fee is the main variable of interest in this study. Recruiting a player before the end of his contract involves the buying club compensating the player's current club. The fee is then bargained between the two clubs, including, to some extent, the player's considerations.²³ Two conditions must be satisfied for the transfer to occur. First, the transfer fee must match or exceed the selling club's requirement to let its player leaves. Second, the transfer fee must not exceed the buying club's expected flow of income generated by the potential new player's performance and popularity. This framework thus relies on a *hedonic pricing* approach to players' values by clubs and is frequently used in research on transfer fee valuations (Carmichael et al.; 1999; Dobson and Gerrard; 1999).

4.1 Econometric Model and Descriptive Statistics

Our empirical approach consists in using OLS regression to estimate a transfer fee hedonic price equation which includes performance, popularity, and player bargaining power. We are interested in particular in the impact of FFs on transfers that occur shortly after the creation of Twitter accounts. Therefore, the sample only includes transfers that took place before 12 July 2018, i.e. as long as potential manipulation was not public information.²⁴ Observations are at transfer-player level, where i denotes the individual and j is the transfer. The model is specified as follows:

$$Fee_{ij} = \beta_0 + \beta_1 Timing_{ij} + \beta_2 FF_i \times Timing_{ij} + \beta_3 Pop_i + \beta_4 Perf_{ij} + X_{ij} + \epsilon_{ij} \quad (1)$$

Where X_{ij} is a series of controls variables including year of the transfer, player's usual position, player's age, remaining length of his contract, destination league and buying club.²⁵ For age, we add the corresponding quadratic term in the estimations to allow for non-linear effects.²⁶ ϵ_{ij} is the error term. The performance variables are lagged in order to avoid possible reverse causality problems. These variables measure the player's performance during the 365 days before the transfer. We add variables that capture players' experience with their clubs and national teams.

Table 5 presents summary statistics for the variables used in our estimations.²⁷ The level of observation is per transfer. Our main independent variables of interest are the number of FFs on Twitter, reported as *FF*, and the *Timing* which indicates the time gap between the creation of the Twitter account and the transfer. This variable is composed of four dummy variables (see Figure 6 below). The first one – *Before* – is equal to 1, if the transfer took place before the creation of the Twitter account. The following dummies refer to transfers that occurred after the creation of Twitter accounts. *0-6 months* and *6+ months* dummies refer specifically to the first transfer occurring after the Twitter account creation. If the latter took place within 6 months or after 6 months of Twitter

²³Even if, from a technical viewpoint, transfer fees are basically negotiated by the selling and buying clubs, the players' opinion about joining the new club or staying at his current club affects this negotiation. It is difficult for a club to keep a player who really wants to join another club, as he can threaten to stop playing or decrease his performance.

²⁴Transfers that occur after the "Great Purge" are included in Section 5 to estimate the long-term effect of manipulation.

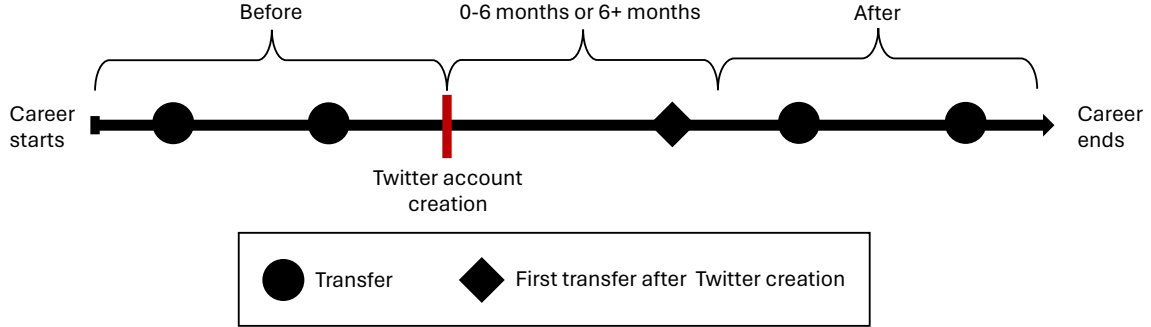
²⁵Buying club fixed effects (FE) are introduced for the 191 clubs that appear at least twice in our sample.

²⁶Lucifora and Simmons (2003) note that North American studies tend not to include age and experience (or appearance) jointly, due to the draft system and the fairly similar age of entry into the professional league just after college graduation. In this context, age and experience then tend to be co-linear. However, soccer players professional careers can begin at many different ages.

²⁷Table C.1 in Appendix C presents summary statistics for the controls variables used in our estimations.

account creation, then *0-6 months* or *6+ months* equals 1, respectively. For all other transfers following the first transfer after Twitter creation, then *After* is equal to 1.

Figure 6: Illustration of the main variables of interest



Players are also characterized using different sets of variables. Bargaining power is the total value in Euros of the players managed by the player's agent. Loan with fees indicates if the transfer is a loan associated with a fee (*vs.* transfer with fees). Age and age squared are computed at the time of the transfer, and position (goalkeeper, defender, midfielder and forward) is the usual position of the player on the field. Championship is the destination championship after the transfer. All performance measurements (goals, assists, etc.), achievements, number of games or justice issues (doping) are computed for a period of one year before the transfer.

Table 5: Summary statistics

Variable	Description	Mean	S. D.	Min.	Max.
Dependent Variable					
Transfer Fee	Log of transfer fee (€)	14.83	1.58	8.99	18.79
Variables of Interest					
Insta.	Equals 1 if the player has an Instagram account	0.84	0.37	0	1
Insta. Foll.	Log of followers on Instagram in July 2018	10.62	4.97	0	16.74
Twitter Foll.	Log of followers on Twitter in July 2018	11.45	2.19	2.4	14.98
FF	Number of Fake Followers on Twitter in thousands	4.39	9.2	0	109.98
Before	Equals 1 if transfer happens before Twitter creation	0.35	0.48	0	1
0-6 months	Equals 1 if next transfer to Twitter creation happens 0 to 6 months after the creation	0.07	0.25	0	1
6+ months	Equals 1 if next transfer to Twitter creation happens 6 months or more after the creation	0.15	0.32	0	1
After	Equals 1 if transfer occurs after the transfer next to Twitter creation	0.42	0.49	0	1
Observations			966		

4.2 Main results and discussion

Our period of interest starts in 2009 when the players in our sample started to create Twitter accounts (See Section 2.2). Our models include transfers and loans with fees that occurred once players reached the age of 18. Table 6 reports the results of our regression according to different measures of popularity. While Models 1 and 3 in Table 6 rely on Twitter followers (corrected from FFs) to measure players popularity, Models 2 and 4 use Instagram followers. The number of followers on Instagram allow us to increase the precision of our measurement of online popularity as well as to control for possible endogeneity in our models between Twitter fake and real followers. All the players in our sample have a Twitter account, but not all have an Instagram account (see Section 2.2). Then, we use in Models 2 and 4 the number of Instagram followers for those who have it and Twitter followers – using an interaction term – for those who do not. Model 3 and 4 controls for timing in addition of the interaction effect and increase precision of our estimation of the effect of the online popularity manipulation.

Whether we consider the number of followers on Twitter or Instagram, online popularity has a significant and positive impact on transfer fees of a similar magnitude, as shown in Table 6. A 1% increase in the number of followers on Twitter and Instagram is associated with a growth of transfer fees around 0.04% and 0.05%, respectively. We can also notice in Models 2 and 4 that for players who have both Twitter and Instagram, followers on Twitter do not have a significant effect on their valuations. For those who have only a Twitter account, a 1% increase in their number of followers has a positive effect on transfer fees ranging between 0.055% and 0.057%.

Besides the impact of online popularity, we focus on the possible impact of FFs on players' valuation. As expected, FFs do not have any effect on transfer that took place before Twitter account creation, as no manipulation is possible. FFs have also no effect on transfers that occur after the first one that follow Twitter account creation. In this case, the true popularity of the player should be better known, and thus, more difficult to manipulate. These results show that FFs do not capture a specific behavior of players that affects all his transfers. FFs only have a significant impact on the first transfer that occurs after the Twitter account is created, if it occurs within 6 months of the account creation. Whether we measure online popularity based on Twitter or Instagram followers, the coefficients are very similar. It highlights again the independence of FFs and real followers on Twitter. In the "Twitter" specification (i.e. Models 1 and 3), a thousand additional FFs is respectively associated with an average increase of 1.2% and 0.9% in transfer fees. The effect of an additional thousand FFs is estimated between 0.9% to 1.3% on the value of transfer fees for the "Instagram" specification (i.e. Models 2 and 4). The mean value of transfer fees and FFs for first transfers after Twitter account creation that occurs within 6 months of the account creation are respectively €9.03 millions and roughly 5,600 FFs. The average effect of FFs is thus about €450,000, which represents 5% of the average transfer fee. This gain far exceeds the cost of acquiring thousands of FFs. This result is comparable to an additional goal scored (1.4% increase in player value) during the previous season.

These results are consistent with a scenario where a player, his agent, and/or the selling club artificially inflates the player's online popularity to monetize it during a transfer negotiation. A transfer generates two main streams of revenue: the selling club and agent are rewarded by the transfer fee, while the player receives the wage negotiated with the buying club, plus possible bonuses. According to the literature on soccer players' value, both revenue streams – wages and transfer fees – are positively impacted by player popularity (Lucifora and Simmons; 2003; Garcia del Barrio and Pujol; 2007; Lehmann and Shulze; 2008; Carrieri et al.; 2018). A (fictitious) rise in online popularity will lead the buying club to overestimate the expected revenue associated to popularity (attendance, audience, merchandising, etc.) generated by a player. The buying club will therefore be more

Table 6: Short-term effect: Main results

Endog. var.: log of transfer fees	(1)	(2)	(3)	(4)
Online popularity:				
Twitter foll.	0.041*		0.044**	
	(0.022)		(0.022)	
Instagram foll.		0.052*		0.053*
		(0.028)		(0.028)
Twitter foll. × Insta. =1		0.010		0.012
		(0.027)		(0.026)
Twitter foll. × Insta. =0		0.055**		0.057**
		(0.028)		(0.027)
Creation Timing:				
0-6 months			0.166	0.192
			(0.134)	(0.134)
6+ months			0.009	0.016
			(0.124)	(0.123)
After			-0.078	-0.070
			(0.121)	(0.121)
Creation Timing and FF:				
Before × FF	0.004	0.004	0.004	0.004
	(0.005)	(0.006)	(0.005)	(0.006)
0-6 months × FF	0.012***	0.013***	0.009***	0.009***
	(0.002)	(0.002)	(0.003)	(0.003)
6+ months × FF	0.011	0.012*	0.010	0.011
	(0.007)	(0.007)	(0.008)	(0.007)
After × FF	0.009	0.009	0.012	0.012
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	7.160***	6.773***	7.223***	6.841***
	(1.816)	(1.980)	(1.812)	(1.972)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	966	966	966	966
Adj R-squared	0.718	0.720	0.718	0.720

Standard errors clustered at player level in parentheses. Reference groups in columns (1) and (2) are players without FF. In columns (3) and (4) reference groups are players without FF that move before their Twitter account creation.

* p<.10, ** p<.05, *** p<.01

inclined to offer a higher wage and agree to pay a higher transfer fee than in a situation where the player is less popular. Therefore, the player, the agent and the selling club have an incentive to artificially inflate the player’s online popularity to achieve higher wages and transfer fees. They can all agree in implementing the manipulation or only some of them can, creating a positive externality for the others. From the perspectives of the selling club and the player’s agent, the higher the transfer fee, the higher their earnings. They will have a direct advantage from manipulating the player’s popularity by allowing them to bargain with the buying club for higher transfer fee. This would imply that the selling club or the agent is in charge of the player’s social media account, which is a frequent situation.²⁸ From the player’s perspective, artificially increasing his online popularity might help him (or his agent) to negotiate a higher wage with the buying club. This (fictitious) rise in online popularity will also have a positive effect on the transfer fee received by the selling club and the player’s agent. Both the transfer fee and the wage are usually negotiated within the same time frame. A higher transfer fee could make the selling club and the agent more likely to support and accept the transfer.

The results for the control variables, detailed in Table C.2, are consistent with previous studies (Lehmann and Shulze; 2008; Franck and Nüesch; 2012; Carrieri et al.; 2018). A player’s experience whether with the club (national or international competitions) or with the national team has a strong positive effect. Age and age squared both have a significant impact on transfer fees which is respectively positive and negative. This inverted U-shape relationship between age and value has been frequently observed. It reflects that greater experience (tactics, ability, knowledge of the game, etc.) – measured by age and appearances – is offset by worsening physical performance (slower speed, more frequent injuries, etc.) when players get older. The number of goals has a positive effect, confirming that players with especially high ability to score are more costly to recruit. In line with the findings of Carrieri et al. (2018), it seems that, in addition to performance and popularity, an agent’s market power is important for negotiating higher transfer fees with buying clubs.

4.3 Robustness checks

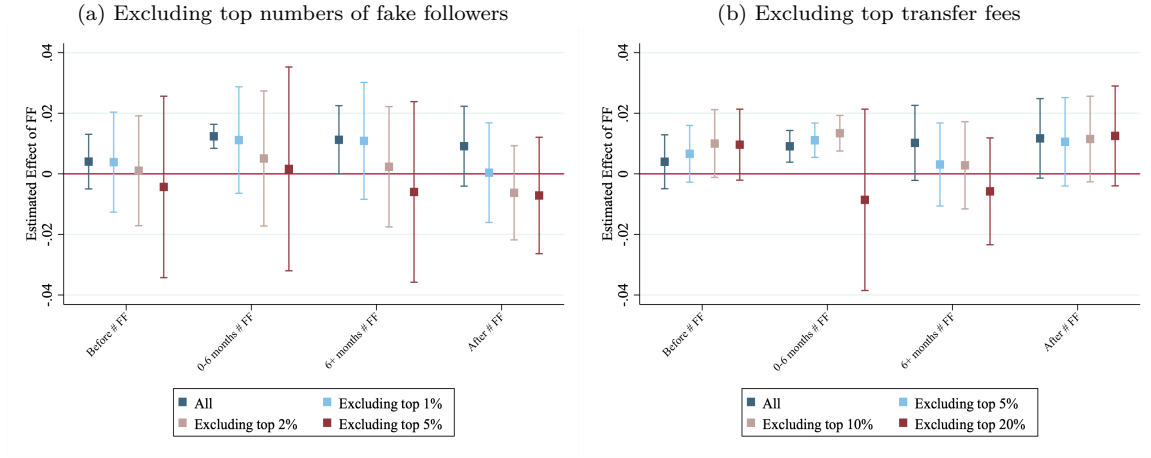
In this subsection, we test whether the FF effect is robust to the withdrawal from the sample of specific players, i.e. those who are likely to derive the greatest benefit from manipulation. In this respect, we check if FF effect persist if we remove players with high numbers of FFs, transfer fees or activity on social media.

Figure 7a illustrates that the positive effect of manipulation is mainly due to players with high number of FFs. If the level of manipulation is below the top 1% threshold (i.e. fewer than 35,878 FFs), we see that the effect fades away and becomes noisier. It indicates that successful manipulation involves the acquisition of a significant number of FFs. Figures 7b and A.5 show that the FF effect remains when removing top transfer fees or high Twitter activity players.²⁹ It highlights that manipulation of online popularity is not a strategy specifically implemented by most talented players or those who are the most active on social media. We also check if our results are robust to different types of Twitter activity: the absolute number of tweets and the number of tweets per day. Table B.4 in Appendix B presents the results for the estimations controlling for these measures of activity on Twitter between the creation of the account and the subsequent transfer. These controls do not affect our main results. It thus seems that producing content on social media and manipulating online popularity can be complementary strategies to increase value, but they are not substitutes.

²⁸See for instance the BBC article available here: <https://www.bbc.com/sport/football/56911978> (last retrieved: May, 2024).

²⁹Figure A.5 is provided in Appendix A.

Figure 7: Persistence of the effect while excluding part of the sample



Note: 90% confidence interval are displayed.

5 Long-term effect of fake followers

Since online popularity has a positive impact on players values, we can expect that losing followers has the opposite effect. Whatever the interpretation of the follower loss – online popularity manipulation or social spamming – the buyer club should be less inclined to pay for a ‘cheater’ or a less popular player than what it was expected. The huge reduction in the number of followers due to the purge of fake accounts on July 12 2018 can be considered as a public signal due to its large media coverage. The removal of fake accounts made on this day involved the loss of millions of followers for some of the most popular persons on Twitter. These large variations in online popularity attracted media attention and generated many comments about the use of fake followers.³⁰ In this section, we investigate the effects of online popularity manipulation disclosure on player values.

5.1 Main results

The signal has been released approximately in the middle of the summer *mercato* 2018 (July-August, 2018). It allows us to measure its impact on player values during this *mercato* and the following ones in a difference-in-differences setting. In this purpose, we estimate the equation below:

$$Fee_{ij} = \beta_0 + \beta_1 foll_loss_i + \beta_2 after12_{ij} + \beta_3 foll_loss_i \times after12_{ij} + X_{ij} + \epsilon_{ij} \quad (2)$$

With X_{ij} a series of controls (age, championship, achievements, buying club, etc.) and fixed effects (year, buying clubs, etc.). ϵ_{ij} denotes the error term. Our main variable of interest is the interaction term combining the dummy variable *after12* – equals to one if the transfer occurs after July 12,

³⁰See for example an article from the Washington Post available here: <https://www.washingtonpost.com/technology/2018/07/13/heres-how-many-followers-trump-obama-others-lost-twitthers-purge-locked-accounts/> (last retrieved: May, 2024).

2018, and 0 otherwise – and the percentage of followers lost (*follow_loss*) on that day. Note that here, we do not use the number of FFs. Losing ten thousands of followers is likely to be insignificant for popular players, while representing a relatively large decrease for less popular ones. Statistics for the distribution of follower losses as a percentage of the total number of followers before the purge are provided in Figure A.6 in Appendix A.³¹ Table 7 below presents the main results of the model.

Table 7: Long-term effect: Main results

Endog. var.: log of transfer fees	Twitter	Instagram
Online popularity:		
Twitter foll.	0.056*** (0.019)	
Instagram foll.		0.058** (0.026)
Twitter foll. × Insta. =0		0.068*** (0.024)
Treatment and time effects:		
% foll. loss	0.018*** (0.004)	0.020*** (0.004)
After 12 July 2018	-0.069 (0.149)	-0.087 (0.147)
% foll. loss × After 12 =1	-0.179** (0.089)	-0.180** (0.090)
Constant	7.325*** (1.542)	6.902*** (1.672)
Controls	Yes	Yes
Time FE	Yes	Yes
Observations	1,153	1,153
Adj R-squared	0.716	0.719

Standard errors clustered at player level in parentheses.

* p<.10, ** p<.05, *** p<.01

Table 7 highlights again the positive impact of online popularity on player values. In both specifications, the magnitude of the coefficients is similar to the previous section³². Regarding our main variable of interest, the share of lost followers has a negative and significant impact on player's value for transfers that took place after July 12, 2018, i.e. the removal of FFs. A 1 percentage point increases in the share of loss followers is associated with a 16% decrease in the transfer fee. However, this larger effect includes both the loss of followers and a possible market sanction for manipulating

³¹We also provide in this Appendix descriptive statistics about the sample in Table B.2. Since we include transfers occurred after July 2018, the sample is slightly larger than the one use in the previous section. The descriptive statistics of both samples are nevertheless very similar.

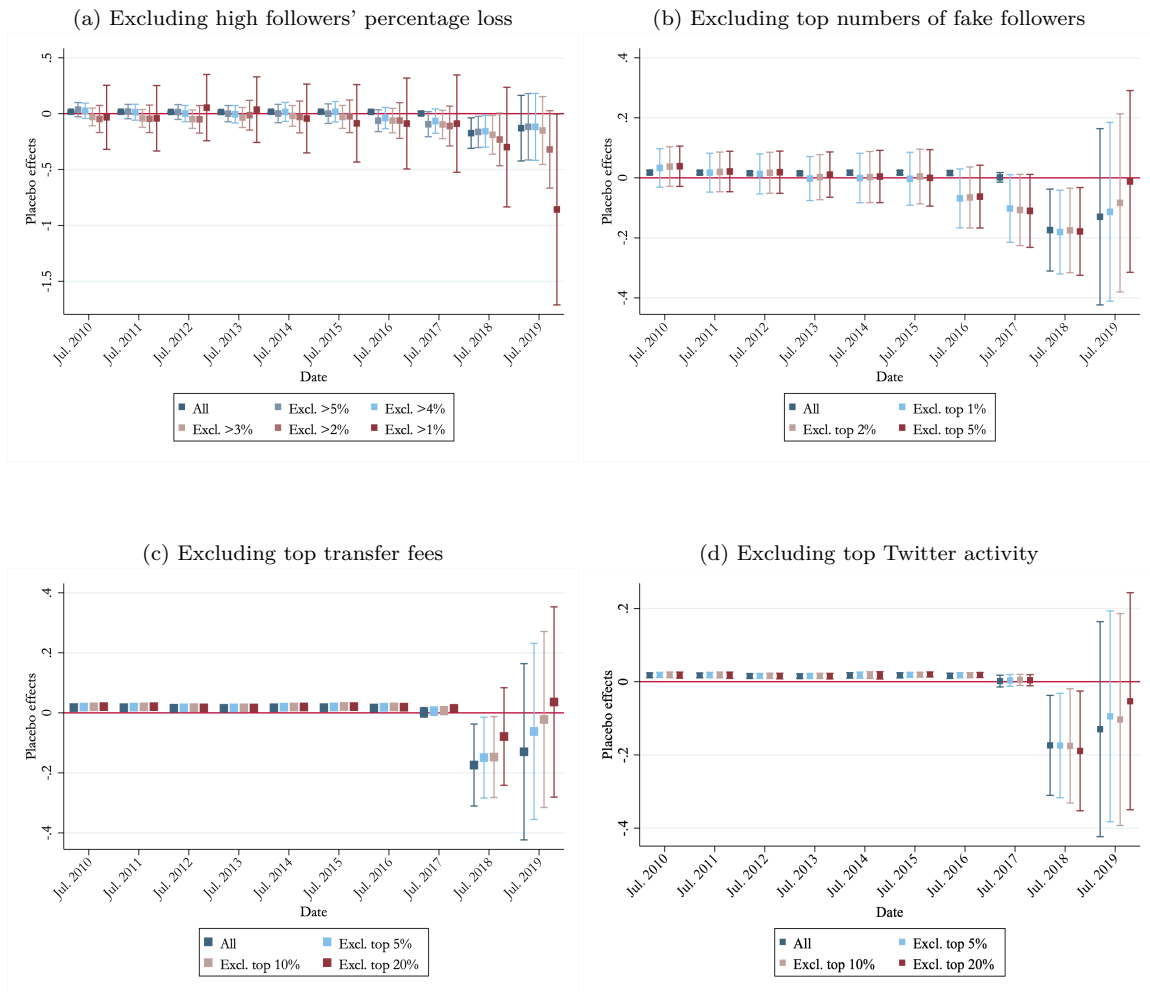
³²The effects of control and fixed effect variables are similar to the effects described in previous section (see Appendix C). Thus, our previous comments apply.

online popularity. The effect of a 1 percentage point loss in the share loss followers is comparable to the effect of 6 months less experience as a professional soccer player (see Table C.3 in Appendix C).

5.2 Placebo tests and robustness checks

In this subsection, we check the robustness of the negative reputation effect highlighted in the previous section. Specifically, we test whether this effect persists if we remove players with higher share of loss followers, larger numbers of FFs, high transfer fees or high levels of Twitter activity. Regarding placebo tests, we check whether this effect is the specific result of the purge of FFs that occurred in July 2018. In that purpose, we consider July 12 – the date of the shock in 2018 – for the years before and after 2018. Figures 8a, 8b, 8c and 8d combine both placebo tests and robustness checks for the above-mentioned cases.

Figure 8: Placebo and robustness checks



Note: 90% confidence interval are displayed.

Placebo tests confirm in all Figures that the negative and significant effect of follower loss holds only during the summer *mercato* 2018, after the 12th of July, as all other years have no significant and negative impacts. The decrease in the number of followers has been interpreted negatively by buyer clubs during this specific period and led to a decrease in the corresponding player values.³³ Figure 8a is interesting as it provides more details about the impact of the negative signal. The effect does not hold anymore when we remove from the sample players who lose more than 2% of their followers. In other words, a drop in online popularity of less than 2% has no significant impact on player value. It seems that a marginal loss of online popularity is not really considered, or perhaps, was rapidly compensated by subsequent gains in followers. Figure 8b shows that the effect is not sensitive to a high number of FFs. It confirms thus the relevance of including in models of this section the share of FFs rather their numbers. Figures 8c and 8d highlight that the signal affects a significant part of the transfer market. In order for the effect to disappear, almost 20% of the largest transfers in terms of fees have to be excluded. Furthermore, the effect remains even if we exclude the top 20% of transfers in terms of player social media activity.

Overall, the placebo tests and the robustness checks confirm the negative and significant effects of follower loss – larger than 2% of the total number of followers – during the summer *mercato* 2018. This event had a wide impact on players’ values that were on the transfer market.

6 Conclusion

Social media metrics can be easily and cheaply manipulated nowadays through the acquisition of FFs, views or comments. Individuals such as professional soccer players who are able to monetize their popularity may be interested in making economic gains by artificially increasing their online popularity. Our results are in line with this scenario. They show that FFs have an impact on player valuations, i.e. transfer fees, but only for the first transfer after Twitter account creation if it occurs within 6 months of account creation. These FF’s are associated with an average increase in the transfer fee of 5% (\approx €450,000), which far exceeds the cost of buying thousands of FFs. The robustness checks point out that only a limited number of transfers involving players with a very high number of FFs have benefited from this manipulation. However, short-term effects of online popularity manipulation, which benefit a few individuals, have major market consequences when publicly revealed. The *“Great Purge”* revealed possible manipulation and resulted in market sanctions. Our results show that a significant share of follower losses, i.e. $>2\%$, has a negative impact on the transfer fee if the transfer occurred soon after the *“Great Purge”*. A 1 percentage point increase in lost the follower share is associated with 16% decrease in the transfer fee. However, this strong effect is the result of followers losses combined with market sanctions in response to detection of online popularity manipulation.

This article provides evidence of online popularity manipulation for economic purposes and measures the *“return on investment”* of such misleading behavior. It thus contributes to two existing strands in the literature. First, it offers a new illustration of (online) popularity as a valuable asset in the case of professional athletes and provides some measures of it. Second, we add to the literature on online information manipulation (Mayzlin et al.; 2014; Luca and Zervas; 2016; Li et al.; 2016; He et al.; 2022). This article documents a new type of online information manipulation, the inflation of online popularity through the acquisition of FFs, in a new context, the labor market. Our results provide some measures of the large positive *“return on investment”* of manipulation in the

³³Small positive effects of FFs are observed until 2016 in some cases. It seems that the share of FFs capture the positive effect they had on players’ valuation. This is in line with what we discuss in the section 3.1 on the rise of Instagram.

short-term, as well as the costs associated with the detection of the manipulation in the long-term.

In terms of policy implications, our findings support the current trend in social media to hide account metrics (number of followers, views, interactions, etc.). While it may be detrimental for users to detect popular people, this policy may reduce the incentives that underlie the manipulation of social media metrics. A second implication relates to the platforms that sell fake metrics (followers, reviews, likes, comments, views, etc.). As they serve no purpose other than to increase the noise in these metrics, at best, and to mislead users, at worst, the legality of this practice may be questioned by regulators.

There are some caveats to this paper. Firstly, while our empirical explorations provide evidence of specific behavior of players with FFs, we do not know precisely when these fake accounts began following soccer players on Twitter. Secondly, our econometric approach does not take into account the potential selection effect among players as to whether they are transferred or not during a *mercato* period. Finally, we found manipulation of Twitter followers, but such manipulation can also occur with Instagram followers.

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Appendix: Figures and Tables

Appendix A Figures

Figure A.1: Screenshot announcement of removal of fake accounts on July 11 2018

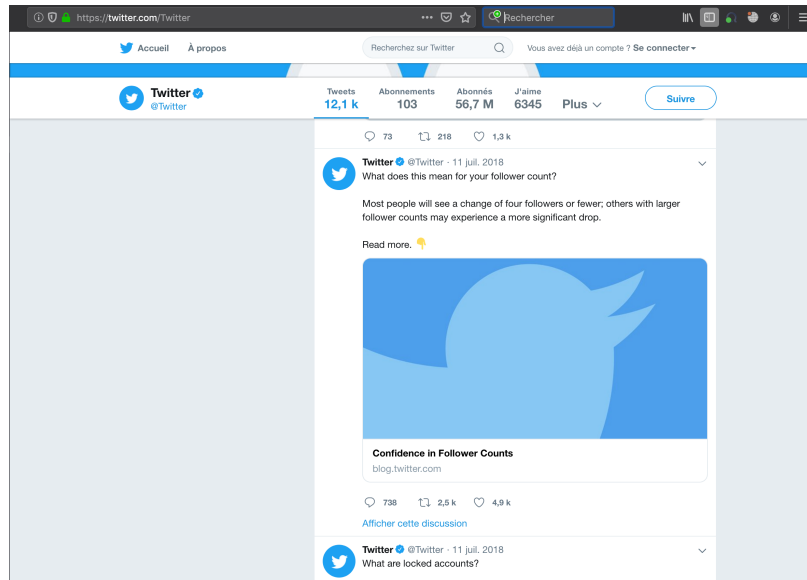


Figure A.2: Transfer types by age or year

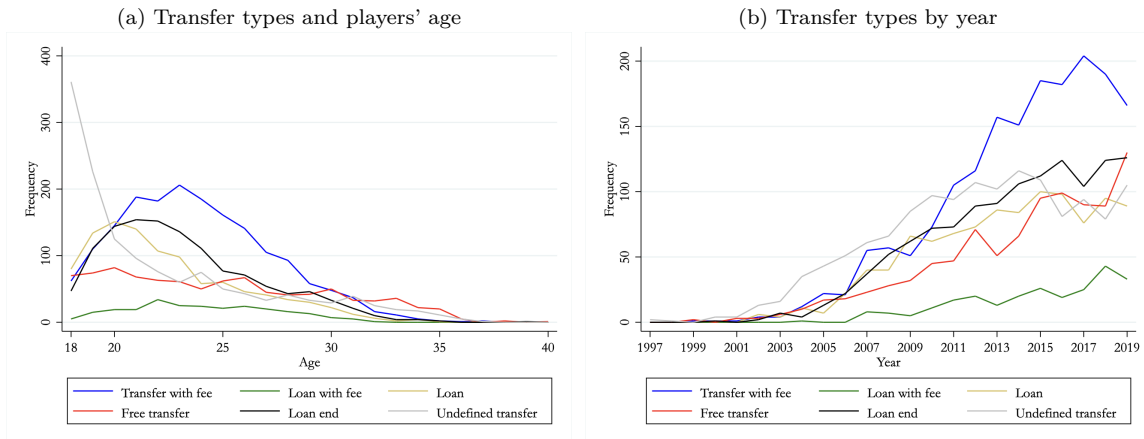


Figure A.3: Evolution of followers in July, 2018

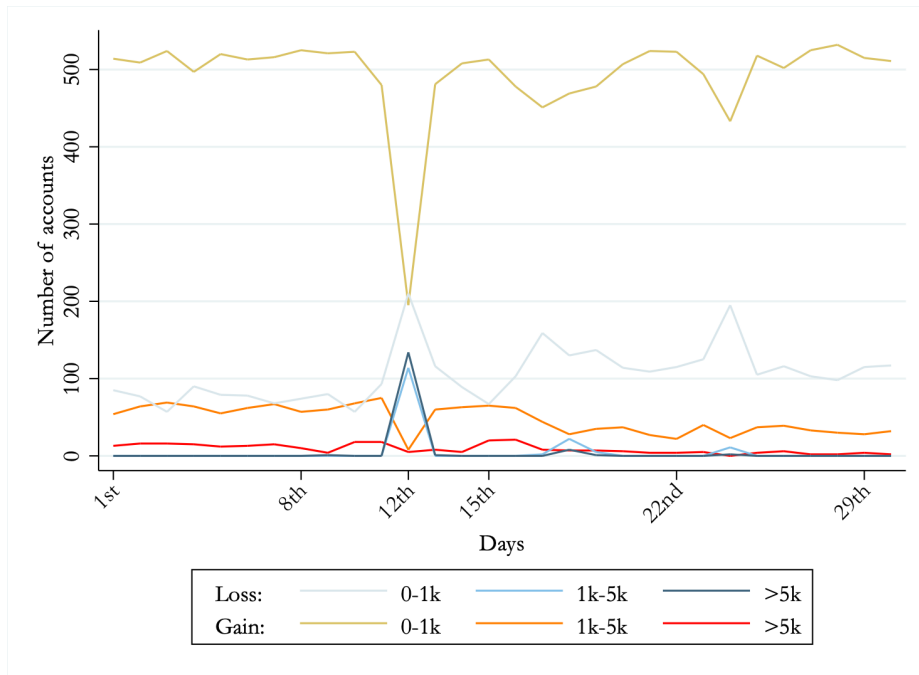


Figure A.4: Date of social media account creation and number of followers

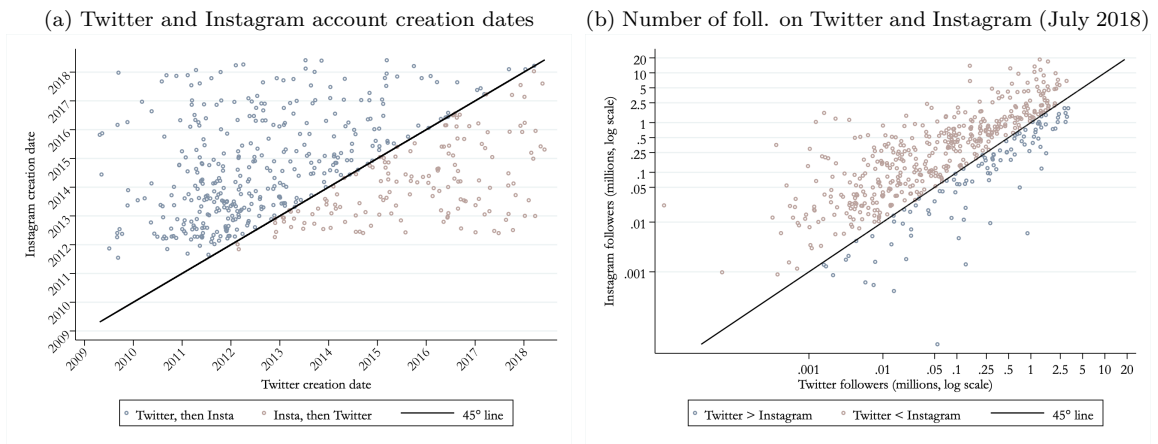


Figure A.5: Persistence of the effect while excluding top twitter activity

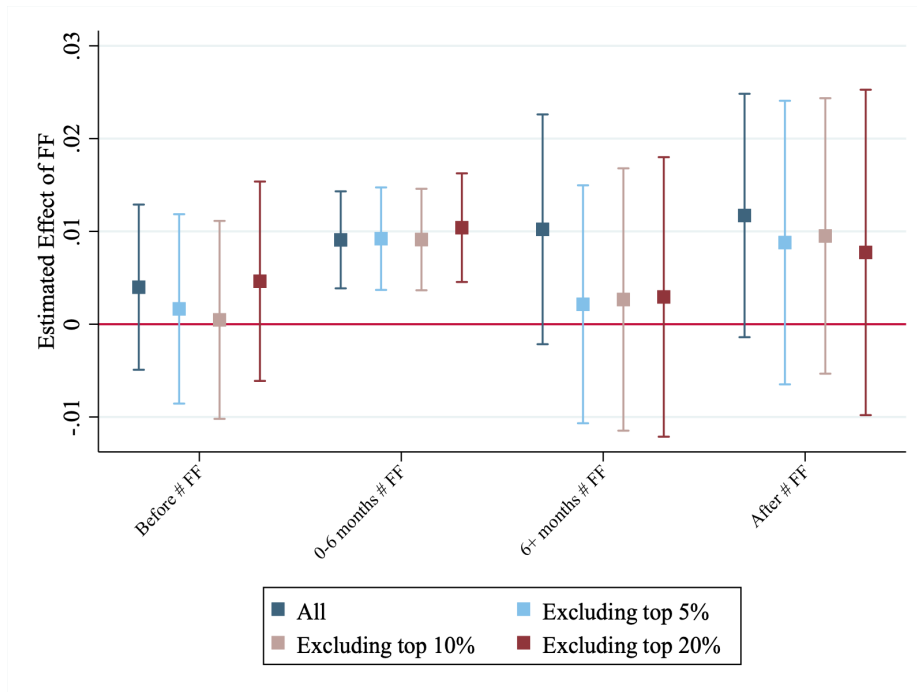
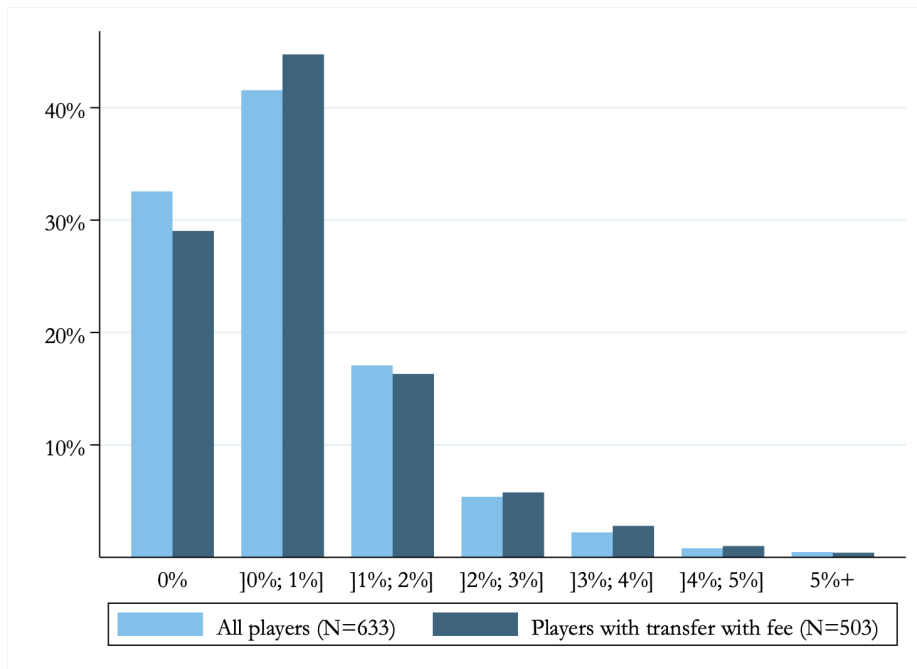


Figure A.6: Distribution of follower's percent loss



Appendix B Tables

Table B.1: Summary statistics of players

	Full sample	Twitter
Age:		
18-19 y.o.	0.3	0.3
20-24 y.o.	18.8	15.9
25-29 y.o.	43.8	45.7
30-34 y.o.	30.5	31.8
35+ y.o.	6.6	6.3
Position:		
Goalkeeper	12.9	12.3
Defender	33.6	33.9
Midfielder	27.3	25.8
Forward	26.2	28.0
Nationality:		
Africa	18.6	17.9
Asia-Pacific	14.3	8.7
Central/North America	8.7	12.9
Eastern Europe	9.6	5.4
Middle East	4.8	3.6
South-America	13.4	15.8
Western Europe	30.6	35.7
Club:		
Africa	4.0	2.4
Asia-Pacific	7.8	3.9
Central/North America	5.9	7.6
Eastern Europe	8.2	3.3
Middle East	7.7	7.1
South-America	5.3	6.0
Western Europe	61.1	69.7
Total no. of players	1,077	666

Table B.2: Summary statistics: Long-term effect sample of transfer

Variable	Description	Mean	S. D.	Min.	Max.
Dependent Variable					
Transfer Fee	Log of transfer fee (€)	14.92	1.57	8.99	18.79
Variables of Interest					
No Insta.	Equals 1 if the player has no Instagram account	0.16	0.37	0	1
Insta. Foll.	Log of followers on Instagram in July 2018	10.65	4.89	0	16.74
Twitter Foll.	Log of followers on Twitter in July 2018	11.38	2.16	2.4	14.98
FF	Number of Fake Followers on Twitter in thousands	4.15	8.84	0	109.98
% foll. loss	Share of Fake Followers removed (%)	1.08	4.33	0	64.08
Observations				1,153	

Table B.3: Correlation between followers and FFs by ventile

Ventile	Corr.	Fake followers		Followers	
		Min.	Max	Min.	Max.
1	.01	0	1	11	1,175
2	.28	0	99	1,178	2,967
3	.02	0	172	3,026	4,413
4	.02	0	188	4,489	7,656
5	.33	0	351	7,671	11,157
6	-.16	0	2,591	11,244	15,418
7	.38	0	514	15,922	23,167
8	-.05	0	1,300	23,189	34,482
9	.12	0	50,382	35,296	54,128
10	-.12	0	109,985	54,130	77,010
11	.23	0	1,553	77,685	100,252
12	.23	0	4,992	103,031	154,127
13	.28	0	7,610	154,131	215,507
14	.03	0	12,396	217,129	310,604
15	-.07	0	13,990	311,016	520,065
16	.18	0	20,027	521,627	767,382
17	-.19	0	32,355	778,131	1,223,102
18	.22	0	35,878	1,241,758	1,646,341
19	.26	114	62,855	1,659,446	3,198,009
20	.97	19,635	1,215,302	3,208,290	73,326,669

Table B.4: Short-Term Effect: Controlling for Twitter Activity

Endog. var.: log of transfer fees	(1)	(2)	(3)
Online popularity:			
Twitter foll.	0.044** (0.022)	0.041* (0.022)	0.040* (0.023)
Twitter Activity:			
Before × Nb Tweets		0.000 (0.000)	
0-6 months × Nb Tweets		0.002** (0.001)	
6+ months × Nb Tweets		0.000** (0.000)	
After × Nb Tweets		0.000 (0.000)	
Before × Tweets per day			-0.037 (0.127)
0-6 months × Tweets per day			0.095 (0.142)
6+ months × Tweets per day			0.435* (0.225)
After × Tweets per day			0.052 (0.116)
Creation Timing:			
0-6 months	0.166 (0.134)	0.137 (0.136)	0.144 (0.136)
6+ months	0.009 (0.124)	-0.015 (0.124)	-0.037 (0.127)
After	-0.078 (0.121)	-0.068 (0.121)	-0.081 (0.123)
Creation Timing and FF:			
Before × FF	0.004 (0.005)	0.004 (0.006)	0.004 (0.006)
0-6 months × FF	0.009*** (0.003)	0.010*** (0.003)	0.009*** (0.003)
6+ months × FF	0.010 (0.008)	0.007 (0.007)	0.007 (0.007)
After × FF	0.012 (0.008)	0.012 (0.008)	0.012 (0.008)
Constant	7.223*** (1.812)	7.271*** (1.831)	7.291*** (1.817)
Controls	Yes	Yes	Yes
Observations	966	966	966
Adj R-squared	0.718	0.719	0.719

Standard errors clustered at player level in parentheses. Reference group are players without FF that move before their Twitter account creation. Controls are the same as in previous estimations.

* p<.10, ** p<.05, *** p<.01

Appendix C Online Appendix

C.1 Controls Variables: Summary Statistics

Table C.1: Summary statistics of controls variables

Variable	Description	Mean	S. D.	Min.	Max.
Player and Contract Characteristics:					
Age	Age of the player at transfer date	23.79	3.26	18	37
Age sq	Squared value of the age	576.68	162.06	324	1369
Value Managed	Log of the total value of the players managed by player's agent	3.78	1.78	0.09	7.12
Loan with Fee	Equals 1 if the transfer is a paid loan	0.12	0.32	0	1
Goalkeeper	Equals 1 if the player is a goalkeeper	0.07	0.25	0	1
Defender	Equals 1 if the player is a defender	0.31	0.46	0	1
Midfielder	Equals 1 if the player is a midfielder	0.26	0.44	0	1
Forward	Equals 1 if the player is a forward	0.26	0.44	0	1
Contract < 1 year	Equals 1 if the remaining contract is less than a year	0.168	0.374	0	1
Contract: 1 year	Equals 1 if the remaining contract is 1 year	0.197	0.398	0	1
Contract: 2 years	Equals 1 if the remaining contract is 2 years	0.135	0.341	0	1
Contract > 2 years	Equals 1 if the remaining contract is more than two years	0.126	0.332	0	1
Performance:					
Goals	Number of goals during last year	5.99	7.26	0	44
Assists	Number of assists during last year	4.07	4.54	0	31
Conceded	Number of goals conceded during last year	61.79	17.84	0	122
Captain	Number of games the player was captain during last year	1.31	5.47	0	53
Yellow	Number of yellow cards given to the player during last year	4.95	3.48	0	18
Red	Number of red cards given to the player during last year	0.17	0.43	0	3
On	Log of the no. of entries in games during last year	1.45	0.93	0	3.61
Club Nat	Log of the no. of national games with club during last year	3.26	0.62	0	3.97
Club Inter	Log of the no. of international games with club during last year	0.92	1.01	0	2.94
Nat	Log of the no. of games with national team during last year	1.35	0.97	0	3.14
Trophies Club	Number of trophies won with club during last year	0.4	0.74	0	5
Trophies Nat	Number of trophies won with national team during last year	0.03	0.16	0	1
Trophies Young	Number of trophies won with club youth team during last year	0.01	0.11	0	1
Justice	Equals 1 if suspended during last year (doping, etc)	0.01	0.12	0	1
Destination:					
England	Equals 1 if the player is transferred to England (<i>EPL</i>)	0.2	0.4	0	1
Spain	Equals 1 if the player is transferred to Spain (<i>LaLiga</i>)	0.12	0.33	0	1
Italy	Equals 1 if the player is transferred to Italy (<i>Serie A</i>)	0.18	0.38	0	1
Germany	Equals 1 if the player is transferred to Germany (<i>Bundesliga</i>)	0.14	0.35	0	1
France	Equals 1 if the player is transferred to France (<i>Ligue 1</i>)	0.1	0.3	0	1
West Europe	Equals 1 if the player is transferred to Western Europe (Top 5 excl.)	0.18	0.38	0	1
Africa	Equals 1 if the player is transferred to Africa	0.03	0.17	0	1
North America	Equals 1 if the player is transferred to Central or North America	0.04	0.19	0	1
South America	Equals 1 if the player is transferred to South America	0.073	0.261	0	1
Asia	Equals 1 if the player is transferred to Asia	0.06	0.24	0	1
Middle East	Equals 1 if the player is transferred to Middle East	0.06	0.24	0	1
East Europe	Equals 1 if the player is transferred to Eastern Europe	0.03	0.16	0	1
Observations				966	

C.2 Controls Variables: Results

Table C.2 shows most of the coefficients for the control variables. The performances are computed for the year before the transfer and league indicates the championship where the player joins. Time FE and Club FE are not reported in this table. Loan with fee has a negative and significant impact on transfer fees as it corresponds to short-term transfers – one year in most cases – compared to the usual contract duration for transfers (three years or more). Winning achievement(s) with their clubs has a positive effect on transfer fees. Attracting a player from a successful team seems to involve higher costs. Frequent goal scorers directly enhance their teams' performance in addition to their own popularity. Scoring goals enhances a club's revenue and thus, increases their willingness to pay for this kind of player. The results show a positive impact of an agent's total market value of their portfolio of players on transfer fees.

Table C.2: **Short-term effect: Control variable results**

Endog. var.: log of transfer fees	(1)	(2)	(3)	(4)
Age	0.360** (0.150)	0.367** (0.160)	0.350** (0.150)	0.356** (0.160)
Age sq	-0.007** (0.003)	-0.007** (0.003)	-0.007** (0.003)	-0.007** (0.003)
Loan with Fee	-1.677*** (0.117)	-1.684*** (0.115)	-1.690*** (0.117)	-1.698*** (0.115)
Africa	-0.545 (0.393)	-0.512 (0.394)	-0.549 (0.398)	-0.514 (0.399)
North America	-0.260 (0.281)	-0.265 (0.277)	-0.256 (0.281)	-0.262 (0.276)
Asia	0.382 (0.290)	0.419 (0.283)	0.383 (0.295)	0.419 (0.287)
Middle East	0.447 (0.385)	0.447 (0.376)	0.440 (0.390)	0.441 (0.380)
East Europe	-0.077 (0.320)	-0.070 (0.301)	-0.074 (0.320)	-0.067 (0.301)
West Europe	-0.633*** (0.139)	-0.614*** (0.139)	-0.626*** (0.141)	-0.607*** (0.141)
France	0.143 (0.215)	0.146 (0.207)	0.167 (0.219)	0.171 (0.211)
Germany	-0.336 (0.278)	-0.300 (0.280)	-0.338 (0.273)	-0.302 (0.274)
Italy	-0.113 (0.182)	-0.117 (0.181)	-0.114 (0.183)	-0.119 (0.183)
Spain	0.134 (0.236)	0.156 (0.236)	0.120 (0.235)	0.141 (0.235)
England	0.271 (0.211)	0.289 (0.206)	0.266 (0.209)	0.282 (0.204)
Trophies Club	0.055 (0.048)	0.052 (0.048)	0.054 (0.049)	0.050 (0.049)
Trophies Nat	0.009 (0.175)	0.046 (0.173)	0.014 (0.175)	0.051 (0.172)
Trophies Young	0.068 (0.222)	0.085 (0.220)	0.074 (0.223)	0.091 (0.220)
On	0.021	0.014	0.029	0.023

	(0.053)	(0.053)	(0.054)	(0.054)
Justice	-0.164	-0.162	-0.154	-0.151
	(0.224)	(0.225)	(0.225)	(0.225)
Amount Managed	0.071***	0.064***	0.072***	0.064***
	(0.024)	(0.024)	(0.024)	(0.024)
Contract < 1 year	-0.267**	-0.267**	-0.267**	-0.267**
	(0.104)	(0.103)	(0.104)	(0.104)
Contract: 1 year	0.131	0.129	0.140	0.138
	(0.100)	(0.100)	(0.101)	(0.101)
Contract: 2 years	0.329***	0.322***	0.335***	0.328***
	(0.110)	(0.111)	(0.111)	(0.112)
Contract > 2 years	0.347***	0.341***	0.356***	0.350***
	(0.114)	(0.114)	(0.116)	(0.115)
Goals	0.014**	0.013**	0.014**	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)
Assists	0.012	0.011	0.011	0.011
	(0.009)	(0.009)	(0.009)	(0.009)
Conceded	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Captain	-0.001	-0.002	-0.001	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)
Yellow	-0.017*	-0.017*	-0.017*	-0.018*
	(0.010)	(0.010)	(0.010)	(0.010)
Red	0.051	0.046	0.047	0.042
	(0.071)	(0.071)	(0.072)	(0.071)
Club Nat	0.307***	0.319***	0.304***	0.317***
	(0.094)	(0.095)	(0.093)	(0.094)
Club Inter	0.106***	0.103***	0.100***	0.098***
	(0.036)	(0.036)	(0.036)	(0.035)
Nat	0.089**	0.087**	0.085*	0.083*
	(0.044)	(0.044)	(0.043)	(0.044)
Winter Mercato	-0.267***	-0.265***	-0.270***	-0.267***
	(0.094)	(0.094)	(0.094)	(0.095)
Constant	7.160***	6.773***	7.223***	6.841***
	(1.816)	(1.980)	(1.812)	(1.972)
Time FE	Yes	Yes	Yes	Yes
Club FE	Yes	Yes	Yes	Yes
Position FE	Yes	Yes	Yes	Yes
Observations	966	966	966	966
Adj R-squared	0.718	0.720	0.718	0.720

Standard errors clustered at player level in parentheses.

* p<.10, ** p<.05, *** p<.01

Table C.3: Long-term effect: Control variable results

Endog. var.: log of transfer fees	(1)	(2)
Age	0.353***	0.361***
	(0.126)	(0.134)
Age sq	-0.007***	-0.007***

	(0.002)	(0.003)
Defender	0.061	0.066
	(0.139)	(0.138)
Midfielder	0.257*	0.249
	(0.153)	(0.153)
Forward	0.230	0.205
	(0.186)	(0.186)
Loan with Fee	-1.744***	-1.749***
	(0.101)	(0.100)
Africa	-0.617	-0.582
	(0.398)	(0.404)
North America	-0.342	-0.338
	(0.268)	(0.261)
Asia	0.298	0.343
	(0.288)	(0.283)
Middle East	0.256	0.257
	(0.300)	(0.297)
East Europe	-0.055	-0.045
	(0.311)	(0.288)
West Europe	-0.643***	-0.635***
	(0.138)	(0.137)
France	0.144	0.143
	(0.197)	(0.189)
Germany	-0.374	-0.342
	(0.234)	(0.234)
Italy	-0.086	-0.100
	(0.158)	(0.157)
Spain	0.117	0.127
	(0.203)	(0.205)
England	0.299	0.300
	(0.187)	(0.184)
Trophies Club	0.107**	0.098**
	(0.042)	(0.041)
Trophies Nat	0.065	0.096
	(0.144)	(0.145)
Trophies Young	0.043	0.059
	(0.209)	(0.206)
On	0.003	-0.002
	(0.047)	(0.046)
Justice	-0.203	-0.195
	(0.195)	(0.198)
Amount Managed	0.048**	0.043**
	(0.021)	(0.022)
Contract < 1 year	-0.244**	-0.243**
	(0.098)	(0.097)
Contract: 1 year	0.148	0.145
	(0.093)	(0.092)
Contract: 2 years	0.355***	0.350***
	(0.096)	(0.096)
Contract > 2 years	0.480***	0.476***
	(0.101)	(0.101)
Goals	0.014**	0.014**

	(0.006)	(0.006)
Assists	0.007	0.007
	(0.009)	(0.009)
Conceded	0.002	0.002
	(0.002)	(0.002)
Captain	0.002	0.001
	(0.005)	(0.005)
Yellow	-0.012	-0.013
	(0.009)	(0.009)
Red	0.060	0.055
	(0.065)	(0.064)
Club Nat	0.281***	0.293***
	(0.085)	(0.086)
Club Inter	0.087***	0.083***
	(0.032)	(0.031)
Nat	0.104***	0.101**
	(0.040)	(0.041)
Winter Mercato	-0.326***	-0.323***
	(0.089)	(0.090)
Constant	7.325***	6.902***
	(1.542)	(1.672)
Time FE	Yes	Yes
Club FE	Yes	Yes
Observations	1,153	1,153
Adj R-squared	0.716	0.719

Standard errors clustered at player level in parentheses.

* p<.10, ** p<.05, *** p<.01