Convergence vs. The Middle Income Trap: The Case of Global Soccer*

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Abstract

Unconditional convergence across countries worldwide is typically rejected in terms of GDP per capita. But when focusing on a specific internationally competitive industry, such as manufacturing, rather than the overall economy, unconditional convergence has been found to hold. As the epitome of competition and globalization, this paper uses the performance of national soccer teams as a further test case. We rely on data of more than 25,000 games between 1950 and 2014 and find clear evidence of unconditional β- and σ-convergence in national team performance, as measured either by win percentages or goal difference. We argue that transfer of technologies, skills and best practices fosters this catch-up process. But there are limits: we show that good teams from Africa and Asia are failing to close the gap with top European or South American teams for reasons that are analogous to the "middle income trap". Lessons for other sectors include the virtues of internationally transferable human capital as well as the mixed blessings of regional integration for worldwide convergence.

JEL Classification: O47, L83, F20, Z2

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1 Introduction

The convergence debate - whether poorer countries are catching up with richer ones - is as old as economics itself. Neoclassical growth theory suggests that countries facing a common technology should converge in terms of income, with poorer ones growing faster than richer ones thanks to the higher marginal productivity of capital in earlier stages of development. However, the empirical evidence regarding unconditional convergence across the worldwide distribution of income per capita is not supportive (Barro, 1991; Mankiw et al., 1992; Islam, 2003; Acemoglu, 2009). The literature has therefore focused on conditional convergence and club convergence, arguing that countries tend to converge towards different steady states (Quah, 1993a, 1996; Durlauf et al., 2009).

Nevertheless, the concept of unconditional convergence may be alive and well. Rodrik (2011, p. 45) comments: "The good news is that there is unconditional convergence after all. But we need to look for it in the right place: in manufacturing industries (and possibly modern services) instead of entire economies." When examining the productivity of manufacturing plants across a global sample of countries, Rodrik (2013) finds unconditional convergence. These results have been confirmed by various other studies with different manufacturing data, including Bénétrix et al. (2012) and Levchenko and Zhang (2011). In many countries the manufacturing sector is small, and different industries may or may not exhibit convergence (Bernard and Jones, 1996), which explains the lack of convergence at the level of the entire economy. Rodrik (2013) argues that the manufacturing sector has a number of features which make it particularly susceptible to unconditional convergence: it produces *tradeable goods* and is integrated into the *global production chain*, which leads to *global competition* and fosters *technological transfer* across borders. Thinking along these lines, we will here focus on another sector which might be considered the embodiment of global competition.

We examine convergence in performance in competitive international soccer,[1] arguably the world's most popular modern service. Soccer exhibits several features Rodrik (2013) has highlighted about the manufacturing industry. First, it is a truly global activity; the world governing body of soccer, FIFA, currently has more members (211) than the United Nations (193). Second, the service is standardized and internationally comparable. At the level of national team competition, performance in soccer is far more accurately measured than most other data series; the game is always the same (rule changes are infrequent and regulation is strict) and large numbers of

[1]"Soccer", widely thought to be a contraction of "Association football" (which is the proper name for the game in English), is generally known outside of the US as simply "football". However, since there are many other codes of football (American football, Australian Rules football, rugby football and Gaelic football), we here prefer the term soccer, which is unambiguous.

games are played (currently around 2000 per year). Comparable data on this scale is simply not available for other industries, and services in particular. Third, international soccer is by definition very competitive, so that small differences in skills, line-ups and preparations can have a big influence on the performance. Apart from the monetary rewards, success in international tournaments is often a source of national pride and well-being, providing a strong incentive to perform well. Fourth, the global nature of soccer facilitates the transfer of technology and skills. Weaker teams can catch up by adopting stronger nations' training and talent selection techniques and by investing in their sports infrastructure. Furthermore, there are direct spillovers when individual players from weaker nations are contracted to play for the world's top leagues and at the same time remain on their national teams. Finally, National soccer associations are organized into continental federations representing Europe, North/Central America, South America, Asia, Oceania and Africa. These play a significant role in organizing competition and represent natural groups around which performance levels may coalesce. Interestingly Africa, whose economic difficulties have been so widely discussed (Easterly, 2009; Sala-i-Martin and Pinkovskiy, 2010), has in recent decades started to emerge as a soccer power, culminating in the hosting of the 2010 FIFA World Cup.

The data used in this paper consists of the results of recorded national teams' soccer games between 1950 and 2014, matched with the Penn World Tables data for GDP and population. Based on more than 25,000 games, our main findings are as follows:
(i) There is consistent evidence of unconditional convergence in national soccer team performance, both β- and σ-convergence. This applies to the percentage of games won as well as the goal difference between the teams. While a country's income per capita, population size and experience help predict the national team's performance, the strong evidence of unconditional convergence in the absence of these factors is striking and robust to different econometric specifications. Apart from manufacturing, this has not yet been found for any other economic sector - and certainly not for a service based on a worldwide comparable dataset.
(ii) Despite this move towards more equal performances in soccer, our rank mobility analysis also shows that the top of the distribution continues to be dominated by a few teams from Europe and South America. Weaker teams from these stronger continents are among those that have made the biggest improvements. While many of the weakest teams from Africa and Asia have also advanced from a low base, the best teams from these continents have failed to catch up with top European and South American teams.

We explain these findings with an analogy to the middle income trap: Thanks to the global nature of soccer, countries with weaker teams can, up to a point, achieve unconditional convergence by adopting the same technology in a broad sense.

The transfer of best practices as well as insights from abroad is fostered by global labor markets for coaches and players, which in the case of soccer are comparatively frictionless thanks to human capital portability and the observability of performance. But the process of catch-up by adoption reaches its limits at the transition to world-class performance levels, when teams have to build up their own long-term talent development techniques and playing styles. Among various lessons for other sectors, we highlight the mixed blessings of regional integration for worldwide convergence. In soccer, as well as in other industries, those countries that find themselves in the same organizational group (here continental federations) as the world's best performers can catch up more quickly, while the gaps with other regional groups might even increase.

The remainder of this paper is organized as follows: Section 2 examines the structure of competitive soccer in light of macroeconomic convergence models. Section 3 presents some summary results of the dataset, while section 4 contains the empirical results on β-, σ-, and club convergence as well as the distributional analysis. Section 5 focuses on the limits of convergence with the analogy to the middle income trap. Section 6 concludes and outlines some lessons for convergence in other globalized industries. Additional tables of results are contained in the Appendix, while an Online Appendix provides supplementary information.

2 Soccer in the Light of Convergence Models

The notion of unconditional convergence, both across entire economies and within specific industries, is based on the idea that entities exhibit a higher marginal productivity of capital at lower level of capital accumulation, and that there exist incentives for cross-border adoption of technology, ideas and best practices. The first point is a simple implication of standard neoclassical growth theory, the second emerges from endogenous growth theory. To see how soccer makes for an insightful case study of the unconditional convergence hypothesis, we have to take a closer look at its structure and organization.

With 211 countries affiliated to FIFA in 2017, it can safely be argued that every nation on the planet participates in international soccer team competition. In many other sectors, tests for convergence in performance across a worldwide sample are troubled by data reliability and comparability problems. Measurement error can be large and potentially correlated with other variables of interest. Soccer is not afflicted by these problems. The result of each international game is a matter of official record and not subject to dispute.[2] National teams play many games a year against different

[2]Fans often dispute whether their team *should* have lost, but not whether it *did* lose.

opponents providing a rich sample of performance in a relatively short time frame.

Soccer has standardized regulations and a long tradition in terms of institutional organization, as the Online Appendix describes in detail.[3] The first "international" match took place between England and Scotland in 1872, but the growth of international competition accelerated significantly in the second half of the 20th century. The end of colonialism in the 1950s and the break-up of the Soviet Union in the 1990s increased the number of countries with national teams. At the same time, the drivers of globalization, which affected many economic sectors, impacted soccer in particular (Sugden and Tomlinson, 1998). Improvements in transport have reduced the time and cost involved in organizing international matches, while the development of international broadcasting enabled matches to be shown live around the world.

Despite the truly global nature of soccer, regional confederations, such as UEFA in Europe and CAF in Africa, play a vital institutional role in the organization of the game. They promote regulations, schedule games and continental cups (the UEFA Euros or CONMEBOL's Copa America) with the consequence that national teams from the same continent play against each other more often than against teams from other continents. There are analogies to the trade literature, where both geography and membership of regional trade deals help to predict bilateral import and export flows between countries (Bergstrand, 1985; Frankel et al., 1995). The interplay between the continental associations and FIFA as the global governing body is embodied in the organization of the FIFA Men's World Cup, the four-yearly pinnacle of international competition.[4] As the Online Appendix describes in more detail, FIFA has expanded the opportunities for the weaker regional federations in order to promote the game in a global context. Yet, European and South American teams have continued to dominate the tournament and no country from outside these associations has ever won it.
In our analysis, however, we will not only look at these few most prestigious matches but at all games between national teams from 1950 to 2014, consisting of (i) competitive games (mostly tournaments such as the World Cup, continental cups and their qualifiers) and (ii) games played outside the framework of competition, termed "friendlies", which are often used as a way of preparing players for formal international competitions.

[3] In this paper we will focus on men's soccer because for women's soccer the time period is too short and the number of countries too few to conduct a meaningful convergence analysis. Women's international soccer was largely ignored or actively discouraged for a long time; for example, the English Football Association rule prohibited members from supporting women's soccer until 1971. The first women's world cup only took place in 1991. Even today, there is a strong correlation between countries' performance in women's soccer and measures of gender equality (Bredtmann et al., 2016), which would point to a selection effect in terms of a global sample.

[4] Organizing the FIFA World Cup is a huge social event for the host country, even if the significance of the economic effects are contested (Feddersen and Maennig, 2012).

We test for unconditional convergence by analyzing national teams' performance over time. For our purposes the industry here can be defined as the national soccer team organization and the measure of industry performance is success in competition against other national teams. In this industry the output of one nation cannot be produced independently of any other nation. Our study is therefore analogous to an assessment of convergence of national education systems by comparing scores in standardized global tests. We posit a conventional production function to define the process by which the skills necessary for soccer competition are created:

$$Y = f(A, K, L) \tag{1}$$

with capital K, labor L and a broadly defined technology A. The country's capital provides the sports infrastructure - stadiums, equipment, medical support and so on - countries with a higher GDP per capita can devote more resources to soccer. A large population L is similarly helpful because soccer talent is drawn from the top end of population distribution. While it might be natural to think of increasing returns to scale (the larger the population, the larger the chance of finding top soccer talent), the world's most populous countries have not proven particularly successful - think of India, China, Pakistan, Indonesia or even the US. In fact, in some of these countries soccer is trumped in popularity by cricket (India, Pakistan), or baseball and American football (the US), which underlines the importance of widespread public support in developing successful national teams. Total factor productivity A, defined in a broad sense, therefore subsumes all cultural and institutional factors fostering a national team's performance, from establishment as a national pastime and young talent development systems to best practices in training, and well-functioning institutions running the game at all levels.[5] Many of the ingredients of technology spread easily across borders and we argue that the globalized and competitive nature of soccer makes it amenable to a best-practice adoption. For the economy in general, Barro and Xavier Sala-i-Martin (2004), Caselli and Coleman (2001) as well as Howitt (2000) discuss the factors facilitating and hindering the technology diffusion across countries. In the context of soccer the following seem relevant:

(i) *Technology in the strict sense.* Match recording and slow-motion replay, satellite TV live broadcasting and information availability via the internet has allowed teams to analyze their own games more thoroughly, but also those of other countries. Specialized software can help to break down the tactical behavior into individual actions (Kempe

[5] China has remained stuck at middling performance results in recent decades; as of 2017 it was 77th in the FIFA national team rankings. But the country is investing heavily, and in 2015 President Xi Jinping announced a series of initiatives aimed at turning China into a soccer superpower in the same way the nation has reached the top of the Olympics medal table.

et al., 2014). Consequently, a team can anticipate its opponents' tactical set-up and better prepare for games. This spread of information allows teams to adopt the successful strategies of others, so that weaker teams learn from the best.

(ii) *Institutions.* The convergence debate has long focused on the role of countries' institutional quality, including property rights and the rule of law (North and Thomas, 1973; Hall and Jones, 1999; Acemoglu et al., 2005). In soccer, institutions in a broad sense range from the continental associations to the organization of soccer at all competitive levels on the ground. There have been scandals of corruption in associations' governing bodies; see Maennig (2002) and Manoli et al. (2017) for discussions from an economic point of view. Nevertheless, institutions play a vital role in the process of technology diffusion by setting standards and spreading best practices across countries in the whole organizational process, from game scheduling to resource distribution.

(iii) *Human Capital (coaches).* A good coach can help to improve the performance of the players as a team (Frick and Simmons, 2008). While players need to have the nationality of the country in order to play for a national team, no such rules apply to coaches. Therefore, there is substantial international mobility in what is a global labor market for coaches. FIFA data show that 14 of the 32 national teams participating in the 2014 World Cup had a foreign coach and these include many of the comparatively weaker teams, see Table A-1. Coaches from abroad can bring in new training techniques, change the tactical set-up and, more generally, spread insights gained in other countries.

(iv) *Human Capital (players).* While our interest is in the results of national teams' games, most players make a living from playing for clubs in a national league, some of which have become substantial enterprises in recent years. Since the Bosman ruling from 1995 delivered freedom of contract to professional soccer players in the EU irrespective of their home country, European leagues have experienced a huge internationalization (Szymanski, 1999; Antonioni and Cubbin, 2000). Club soccer plays a vital role in the development of talent, transfer of skills and the adoption of best practices. Most of the world's best players play 50-60 competitive games per season, typically for clubs located in the wealthiest European leagues (Spain, England, Germany and Italy) and only 10 or so of these games are played for the national team. Thus when a player join a foreign club, his national team may directly benefit from the skills he acquires while working for his employer. Indeed, FIFA rules require every club to release their employees to represent their national team in all forms of international competition.[6] Table A-1 gives

[6]FIFA Regulations on the Status and Transfer of Players 2016, Annexe 1, Paragraph 1: "Clubs are obliged to release their registered players to the representative teams of the country for which the player is eligible to play on the basis of his nationality if they are called up by the association concerned. Any agreement between a player and a club to the contrary is prohibited."

some evidence of the internationalization of top players by listing how many players of each 2014 World Cup squad played in their home league or a European league. In only eight of the thirty-two countries did more than half of the squad members play for a club in their country, and four of these were countries with top national leagues.[7] At the other extreme, only one player from each of Bosnia-Herzegovina, Uruguay, Ivory Coast and Ghana played for domestic clubs. Generally, it has been shown that the share of foreign players is the highest in the leagues that pay the highest wages, which are also the leagues considered to play the highest quality soccer (Besson et al., 2008).

While knowledge transfer and skill development resulting from migration is in general a significant transmission mechanism among economies, there are reasons to think it is especially important in the soccer world, see e.g. Milanovic (2005). There are three key features to note:

(a) Because the player remains on his national team while playing for a club in the foreign league, the skill transfer effect can be thought to be much stronger and more immediate than that of migrants returning to their country of origin (see Dustmann (2003) and Wahba (2014) on return migration). There is a discussion whether this so-called 'foot drain' of the best national players, analogous to the 'brain drain' in other industries, hampers the development of domestic leagues.[8] But for the performance of the national team, the skill transfer effects of migration are unambiguously positive. For instance, Bauer and Lehmann (2007) provide evidence that teams with a higher percentage of players under contract abroad performed better in the 2006 World Cup than others, and Berlinschi et al. (2013) use 2010 FIFA rankings to find that migration of national team players improves international soccer performance for weaker national teams.

(b) The labor market for players exhibits hardly any information asymmetries. In contrast to other global labor markets, workers' performance is very transparent and is measured almost exclusively in the objective terms of game success (Kahn, 2000). Comparability is facilitated with match analysis technology, continuously adding information to databases on player characteristics and individual performance statistics over time (Kempe et al., 2014).

(c) Finally, it is a particular feature of soccer that the skills acquired in one country are directly transferable, whereas human capital might not be portable for many other industries and jobs (Friedberg, 2000).

[7]Cases such as Russia, whose national team players exclusively play domestically, underlines the importance of political and institutional factors in player migration, see Leeds and Leeds (2009).

[8]Beine et al. (2001) argues that the migration prospects provide incentives for a skills investment which might mitigate the actual loss due to migration. In soccer, top players which stay on the national team continue to act as a role model and can therefore show a possible way out of poverty for talented children in poorer countries (Berlinschi et al., 2013).

Our hypothesis is therefore that the global transfer of skills and technology in the soccer industry will lead to unconditional convergence in teams' performance over time which should be visible in the data.

3 The Dataset

Our original dataset contains more than 32,000 results of all the matches played between national teams from 1950 to 2014.[9] We have information on the date and the venue of the game, the number of goals scored by each team as well as the type of the match, ranging from 'Friendly' to World Cup. Such a worldwide dataset of industry performance is unique to soccer.

In the convergence literature, the economic growth performance of a nation is typically judged relative to that of other countries, with the 'productivity gap' (Rodrik, 2011) or 'distance to the technological frontier' (Acemoglu et al., 2006). In sporting competitions such as soccer, the agreed performance benchmark is also a relative measure of success: Winning is everything. The inherent zero-sum nature makes our study more akin to a comparison of countries' relative rather than absolute income or productivity levels, in line with the literature. Whether at the individual game level or at the multi-year aggregate, we will work with two relative performance measures for national teams: (a) the winning percentage (in terms of points with 1 for a victory, 0.5 for a draw and 0 for a loss), and (b) the average goal difference. The two measures can be thought to be complementary: The winning percentage reflects the decisive outcome (win, lose or draw), while the goal difference gives an indication of the scale of the victory (Koopman and Lit, 2014).

Following the discussion of the previous section, we can identify a number of factors contributing to the outcome of the game between countries i and j at time t:[10]

$$outcome_{ijt} = dummy_i + home_{it} + away_{it} + lpopratio_{ijt} + lgdpratio_{ijt} + lexpratio_{ijt} + \epsilon_{ijt} \quad (2)$$

$home_{it}$ is a dummy for the home advantage for country i if the game takes place in their country in front of their own supporters, $away_{it}$ is equal to 1 if the game takes place in country j, with neutral ground serving as the reference category. $lpopratio_{ijt}$ and $lgdpratio_{ijt}$ denote the logarithms of, respectively, the population ratio and GDP

[9]The data for this paper is based on a database of international games from 1871 to 2001 compiled by Russell Gerrard (http://www.staff.city.ac.uk/~sc397/football/aifrform.htm) and updated using data kindly provided by Christian Muck (http://laenderspiel.cmuck.de/index.php?2e2abc971121d3382a78a6f5fbccea2e).

[10]This is also in line with the statistical literature on forecasting soccer results of clubs within national leagues, which assumes, for instance, that match results come from a bivariate Poisson distribution dependent on clubs' latent attack and defense strength as well as the home advantage (Maher, 1982; Koopman and Lit, 2014).

per capita ratio between the two countries, with GDP per capita serving as an indicator of a country's potential spending power on soccer (Hoffmann et al., 2002). Population and GDP per capita data are taken from the from the Penn World Tables, version 9.0 (Feenstra et al., 2015). Finally, $lexpratio_{ijt}$ is the logarithm of the countries' ratio of the experience proxies. Experience reflects the familiarity with the competitive environment, but also the extent to which soccer is established as a national pastime (Macmillan and Smith, 2007). Our proxy for experience at time t is the number of international games played by the country since 1872, the year of the first recognized international soccer game.[11] After this matching process of the explanatory variables, about 25,000 games are still left.[12]

Table A-2 presents summary statistics of the outcome and explanatory variables for the whole sample period as well as various sub-periods. Overall, the variables look stable over time; only the slight increase in the standard deviation of the population and GDP per capita ratios indicate that in later years larger and richer countries played more often against smaller ones. We will see if convergence in performance holds nevertheless. In fact, if our hypothesis of absolute convergence is correct, the importance of the explanatory variables should have decreased.

We start by estimating (2), using the win percentage as a measure of outcome, for all games from 1950 to 2014 with clustered standard errors at the team level. Column 1 of Table 1 shows that all the explanatory variables are statistically significant at the 1% level and enter with the expected sign in explaining the winning percentage. For instance, a 100% increase, hence a doubling, of the population ratio of the two countries increases the win percentage by 3.4 percentage points. Columns 2 to 5 of Panel A divide the games by competitiveness into 'friendly' and 'competitive' games, with the latter consisting of the qualifiers for World and Continental Cups (Column 4) as well as the tournaments themselves (Column 5). There are slight differences between specifications; for example, home advantage is most pronounced for World and Continental Cup tournament games and it is stronger than the disadvantage of playing in the opponent's country. The converse holds for the qualifiers. In World and Continental Cups, population size also plays less of a role than for friendlies or qualifiers, and the fit of the regression is less good. Overall, however, we conclude that across all types of games the explanatory variables are highly significant and of comparable importance. This is corroborated by Table A-

[11]Our reasoning builds upon Macmillan and Smith (2007), who conduct a cross-sectional regression of countries' soccer performance and who use the year of a country's first international football match as a proxy for experience. The two indicators are highly correlated. However, the total number of matches played can better capture the activity throughout the years and produces fewer outliers.

[12]Note that the matching process with GDP per capita results in this loss of 7000 of the 32000 matches. These involve (i) small territories with national FIFA status but without national income accounts, e.g. several Caribbean islands, Scotland and Zanzibar, (ii) nations which no longer exist, e.g. West Germany, Czechoslovakia and the USSR. Given these nations were also strong soccer nations (especially West Germany), their omission is likely to understate the variance of performance in the early decades and therefore understate any tendency toward convergence.

Table 1: Game Outcome (Win Percentage) Regressed on Explanatory Factors

Panel A: By Types of Games

Dependent Var: Win Percentage	(1) All Games	(2) Friendlies	(3) Competitive	(4) Qualifiers	(5) World + Cont. Cup
home	0.121***	0.102***	0.152***	0.093***	0.167***
	(0.007)	(0.009)	(0.010)	(0.015)	(0.023)
away	-0.122***	-0.120***	-0.116***	-0.173***	-0.131***
	(0.006)	(0.008)	(0.010)	(0.014)	(0.022)
lgdppcratio	0.031***	0.027***	0.035***	0.032***	0.045***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)
lpopratio	0.034***	0.031***	0.038***	0.040***	0.025***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
lexpratio	0.100***	0.100***	0.093***	0.089***	0.098***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.012)
Constant	0.451***	0.537***	0.397***	0.449***	0.372***
	(0.006)	(0.006)	(0.010)	(0.015)	(0.007)
Country Dummies	Yes	Yes	Yes	Yes	Yes
R2	0.215	0.171	0.277	0.313	0.163
Obs.	50804	27708	23096	17784	5312
Countries	182	181	182	182	132

Panel B: By Time Period

Dependent Var: Win Percentage	(1) All Games	(2) 1950-1966	(3) 1967-1982	(4) 1983-1998	(5) 1999-2014
home	0.121***	0.122***	0.129***	0.138***	0.112***
	(0.007)	(0.026)	(0.018)	(0.011)	(0.008)
away	-0.122***	-0.120***	-0.159***	-0.126***	-0.103***
	(0.006)	(0.025)	(0.015)	(0.010)	(0.008)
lgdppcratio	0.031***	-0.024*	0.031***	0.040***	0.033***
	(0.003)	(0.013)	(0.008)	(0.005)	(0.004)
lpopratio	0.034***	0.035***	0.029***	0.036***	0.035***
	(0.003)	(0.008)	(0.005)	(0.004)	(0.003)
lexpratio	0.100***	0.126***	0.117***	0.086***	0.117***
	(0.005)	(0.012)	(0.007)	(0.006)	(0.007)
Constant	0.451***	0.510***	0.515***	0.376***	0.486***
	(0.006)	(0.022)	(0.019)	(0.011)	(0.007)
Country Dummies	Yes	Yes	Yes	Yes	Yes
R2	0.215	0.221	0.245	0.245	0.216
Observations	50804	2970	7990	14866	24978
Countries	182	86	130	175	182

Notes: The table presents OLS regression results of (2) with the winning percentage as the dependent variable. Standard errors clustered at the country level are given in parentheses: *** p<0.01, ** p<0.05, * p<0.1. In terms of observations, every game is counted twice, once from the perspective of country i and once from country j, to capture both the home advantage and disadvantage of playing in the opponent's country. Neutral venue serves as the reference category. Columns 2 to 4 in Panel A break the games down by type, friendly and competitive, with the latter consisting of World Cup and Continental Cup qualifiers (col 4) and tournaments (col 5).

3, which uses the goal difference rather than the winning percentage as the outcome variable. In the main specification of our convergence analysis, we will therefore pool all these games.

Panel B of Table 1 and Table A-3 shows how the explanatory factors have influenced the performance variable in different time periods. The sample from 1950 to 2014 is split into four sixteen-year periods.[13] In particular since 1982, when the impact of globalization on soccer has become stronger (Sugden and Tomlinson, 1998), the importance of the variables *home* and *away* decreased, as has the impact of countries' GDP per capita. By contrast, the population and experience ratios remain as game-decisive as ever and might even have become more important. The fact that we are working with an unbalanced panel, with many new nations entering international competition in recent decades, may account for these mixed results. The decrease in the model R^2 - for the goal difference it decreased from 0.32 to 0.28 in the last two sample periods - is in line with our convergence prediction of explanatory factors becoming less important. Let us therefore now subject this hypothesis to a plethora of formal tests.

4 Empirical Results on Convergence

To investigate convergence between countries, we now turn from the individual game to national team level. We will work with four-year World Cup cycles (i.e. four-year periods ending in a FIFA World Cup year, for instance 2011-2014) to average out seasonal and cyclical effects as well as one-off events such as playing against a particularly strong opponent. Hence, we define the performance of country i in cycle t as the average outcome, in terms of either win percentages (points) or goal differences, over the four-year cycle.[14] At the country and cycle rather than game level, the ratio variables of GDP per capita, population and experience refer to the ratio between the given team and its average opponent over the cycle. Countries playing fewer than five games over the cycle were omitted to avoid a small sample bias. At this level, we are left with an unbalanced panel of 1,644 country-cycle observations, roughly 15 games per country per cycle.

[13] Different cutoff years yield very similar results, as does a regression which interacts the explanatory variables with a time trend.

[14] When averaging across win percentages, draws are treated as half a win. Note that starting in 1950 means that the first cycle comprises five years (1950-1954). Robustness checks with other periods than four-year cycles, such as eight-year periods spanning two FIFA World Cups, lead to comparable results.

4.1 Beta-Convergence

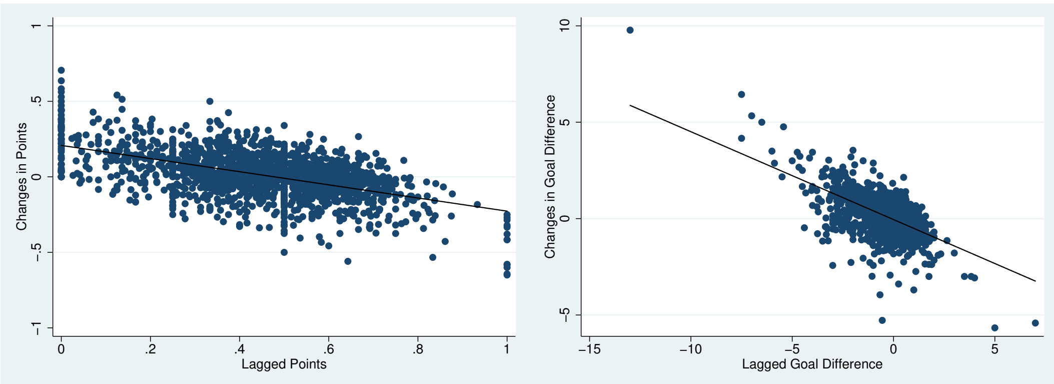
In the economic growth literature, β-convergence is defined as a negative coefficient of the lagged level term in a growth rate regression

$$\Delta y_{it} = \alpha + \beta \cdot y_{i,t-1} + \epsilon_{it}, \tag{3}$$

where the error term ϵ_{it} fulfills the usual assumptions. Based on country i's performance in cycle t, y_{it} (win percentage and goal difference), we calculate lags and changes. If unconditional convergence holds, weaker teams in the previous cycle should show performance increases even in the absence of other explanatory variables. The scatter plots in Figure 1 suggest that this is indeed the case: The plot of changes versus lagged performance levels across all 1,644 country-cycle observations exhibits a negative slope, slightly more strongly for goal differences than for win percentages.

Figure 1: Changes vs. Lagged Levels of Win Percentages and Goal Differences over 16 World Cup Cycles (1950-2014)

(a) Win Percentage **(b)** Goal Difference



Using the win percentage (points) per cycle as the performance variable, Table 2 shows the regression results. The main unconditional convergence regression (3) in Panel A, col. (1) shows a negative coefficient of -0.435, which is statistically significant at the 1% level. This is a striking result. Unconditional convergence in a particular industry has until now only been found in manufacturing (Rodrik, 2013; Bénétrix et al., 2012), but, to our knowledge, it has not yet been empirically established in any other sector, and certainly not for any activity in which the performance of all nations is measured and compared.

The rest of Table 2 tests this results with various econometric specifications and robustness checks. By including the ratios of GDP per capita, population and experience of country i against its average opponent in that cycle in Panel A, col. (2), we can test for conditional convergence. The R^2 increases from 0.29 to 0.39, but the β-coefficient becomes even larger in absolute value. This is robust to the inclusion of regional confederation dummies in col. (3), implying that the development is not confined to one particular continent. We then include country fixed effects to examine the unconditional (4) and conditional (5) convergence hypothesis. The $\hat{\beta}$-coefficient stays highly significant and doubles in size to -0.82 (-0.87).

A possible concern with these fixed effects estimations is the relatively short T setting, given that the number of four-year cycles a country has played is at most 16. With the model specification being dynamic by construction, the estimation might suffer from the Nickell bias (Nickell, 1981). Rewriting (3) (with fixed effect α_i) as

$$y_{it} = \alpha_i + \underbrace{(\beta + 1)}_{\rho} \cdot y_{i,t-1} + \epsilon_{it}, \tag{4}$$

we employ specific short T dynamic panel data model estimation methods in Panel B. The Arellano-Bond GMM results (Arellano and Bond, 1991) in col. (1) and col. (2) show a $\hat{\rho}$-parameter of close to 0, which suggests a $\hat{\beta}$-coefficient of close to -1.[15] Similarly, the Unconditional Quasi-Maximum Likelihood results (Hsiao et al., 2002) in col. (3) and col. (4) are around 0.2 for $\hat{\rho}$, hence -0.8 for $\hat{\beta}$, and therefore of the same magnitude as the fixed effects results in Panel A.

There might still be other concerns. In the dataset, there is a lot of heterogeneity across time periods and countries in terms of the number of games played and average opponent strength. Panel C therefore conducts two different weighted regressions. The first addresses the problem that the number of games per team has increased over time, contributing towards a decreasing variation. In col. (1) and col. (2), we control for this by running regression (3) with time weights $w_{it} = (\bar{n}_i/n_{it})^{1/2}$, where n_{it} is the number of games played by country i in cycle t and $\bar{n}_i$ is the average number of games by i over all cycles. The regression coefficient remains negative and highly significant. Finally, in col. (3) and col. (4) we use so-called dominance weights. With the European and South American continental confederations generally presumed to be the strongest ones, the weights reflect how often country i played against an opponent from those two confederations.[16] Even under this specification, we have a $\hat{\beta}$-coefficient of -0.31 in the unconditional convergence regression and -0.49 for conditional convergence.

We conclude that all the results from the β-convergence analysis agree in their prediction that weaker teams have caught up with stronger ones. In the Online Appendix,

[15] The residuals also pass the Arellano-Bond test for serial correlation in the first-differenced errors and of no serial correlation in the second-differenced errors, see the reported test statistics $AR1$ and $AR2$ in Table 2, Panel B.

[16] This specification also addresses the possible concern that mediocre teams which barely manage to qualify for the World Cup and lose against stronger opponents from other continents might potentially show a worse average performance than teams that did not qualify at all.

Table 2: Beta-Convergence Regression Results, Main Specification

Panel A: Panel Data Regression

Dep Var: Δ points	(1)	(2)	(3)	(4)	(5)
l.points	-0.435***	-0.590***	-0.597***	-0.818***	-0.872***
	(0.027)	(0.031)	(0.030)	(0.032)	(0.032)
lgdppcratio		0.012**	0.012**		0.017*
		(0.005)	(0.005)		(0.010)
lpopratio		0.018***	0.019***		0.006
		(0.004)	(0.004)		(0.009)
lexpratio		0.057***	0.056***		0.073***
		(0.007)	(0.007)		(0.010)
Constant	0.208***	0.288***	0.280***	0.383***	0.417***
	(0.013)	(0.016)	(0.018)	(0.015)	(0.015)
Confed Dummies	No	No	Yes	No	No
Country FE	No	No	No	Yes	Yes
R2	0.291	0.394	0.395	0.503	0.543
Observations	1644	1644	1644	1644	1644
Countries	178	178	178	178	178

Panel B: Fixed Effects Short T Dynamic Panel Estimation

	(1)	(2)	(3)	(4)
Dep Var: points	(GMM)	(GMM)	(QML)	(QML)
L.points	-0.043	0.021	0.254***	0.189***
	(0.048)	(0.049)	(0.039)	(0.033)
lgdppcratio		0.031**		0.026**
		(0.012)		(0.011)
lpopratio		0.029***		0.008
		(0.009)		(0.009)
lexpratio		0.055***		0.064***
		(0.013)		(0.011)
Constant	0.486***	0.469***	0.361***	0.395***
	(0.024)	(0.023)	(0.022)	(0.019)
AR1	-6.136	-7.076		
AR2	-0.751	0.396		
Observations	1484	1484	1372	1372
Countries	176	176	139	139

Panel C: Weighted Regressions

	(1)	(2)	(3)	(4)
Dep Var: Δ points	(Time W)	(Time W)	(Dom W)	(Dom W)
l.points	-0.454***	-0.617***	-0.306***	-0.493***
	(0.028)	(0.031)	(0.040)	(0.042)
lgdppcratio		0.010*		0.020*
		(0.005)		(0.011)
lpopratio		0.019***		0.031***
		(0.004)		(0.005)
lexpratio		0.060***		0.033***
		(0.008)		(0.011)
Constant	0.214***	0.290***	0.163***	0.268***
	(0.014)	(0.019)	(0.022)	(0.026)
R2	0.304	0.409	0.178	0.301
Observations	1644	1644	599	599
Countries	178	178	56	56

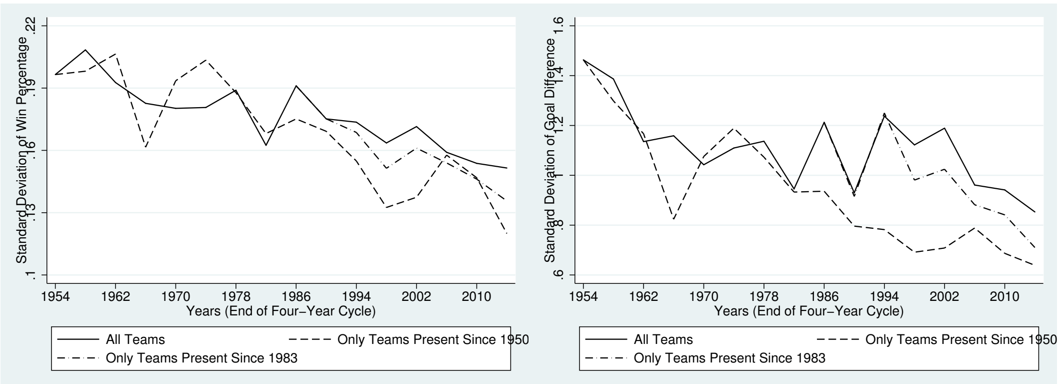
Notes: The table presents the regression results of (3) (Panels A and C) and (4) (Panel B). Standard errors clustered at the country level are given in parentheses: *** p<0.01, ** p<0.05, * p<0.1. $points_{it}$ denotes the average points country i has obtained per game during the four-year cycle t. Panel C uses observation weights as explained in the text.

we repeat the complete analysis with other performance variables and subsamples. The negative sign in the $\hat{\beta}$-coefficient is robust to (i) the use of goal difference rather than winning percentages, (ii) limiting the sample to competitive games, (iii) considering only teams that were active from the first cycle (1950-1954) onwards,[17] (iv) splitting the sample into the time periods 1950-1982 (the first eight cycles) and 1983-2014 (the last eight cycles). While we find significant convergence results throughout time, there is no indication that they have become stronger in later years. We will return to this point, when we analyze limits of the convergence between weaker and stronger teams.

4.2 Sigma-Convergence

A negative β-coefficient in the growth-initial-level regression (3) is well-grounded in growth theory and widely viewed as evidence for convergence (Islam, 2003). However, Quah (1993b) and Friedman (1992) argue that convergence must also be visible in a declining dispersion of the cross-sectional distribution. This so-called σ-convergence does not necessarily follow from β-convergence. Due to random shocks, a negative $\hat{\beta}$ in (3) might result from a general reversion to the mean and might not imply that poorer or weaker individuals are systematically catching up ('Galton's Fallacy'). With random shocks playing an important role in an essentially unpredictable sport such as soccer, we solidify our β-convergence result by checking for σ-convergence.

Figure 2: The Standard Deviation of (a) Win Percentage and (b) Goal Difference over 16 World Cup cycles 1950-2014



Simple descriptive statistics suggest that σ-convergence, defined as a reduction in the variance of the performance variable, is present. Figure 2 shows that the standard deviation of both win percentages and goal differences decreased by one third to one half over the sample period (1950-2014). This is true whether one considers all the countries

[17] Obviously, the national teams entering the international stage and catching up has contributed to the overall convergence effect, but we also observe unconditional and conditional convergence among the teams which were present throughout the years.

in each four-year cycle (the solid line), only the small group of football nations active since 1950 (the dashed line), or the countries that have been continuously present in the second half of the sample (since 1983, the dash-dotted line). The formal σ-convergence test suggested by Carree and Klomp (1997) computes a test statistic

$$R = \frac{\sqrt{N}(\frac{\hat{\sigma}_0^2}{\hat{\sigma}_1^2} - 1)}{2\sqrt{1-(\hat{\beta}+1)^2}}, \tag{5}$$

based on the adjusted ratio of estimated variances, $\hat{\sigma}_0^2$ and $\hat{\sigma}_1^2$, at the beginning and end of the sample. $\hat{\beta}$ is the coefficient estimate from the β-convergence regression (3) for the respective time period. R has asymptotically a standard normal distribution. In Table 3 we use it to test for σ-convergence across various time periods, both for the whole sample and different sub-periods. Whether we look at the win percentages or goal differences, the R test statistic is nearly always highly significant. The test is typically applied at medium to long horizons, but even if we test for σ-convergence within each four-year cycle in Table A-4 we obtain many significant results, in particular in cycles in the 1960s and 1980s/1990s.[18] Our overall conclusion is therefore not only in favor of unconditional β-convergence but also σ-convergence in terms of national teams' performance.

Table 3: Ratio Test Statistics for σ-Convergence in Win Percentage and Goal Difference

Period	N	Win Percentages			Goal Difference		
		$\hat{\beta}$	$\hat{\sigma}_1^2$	R-stat	$\hat{\beta}$	$\hat{\sigma}_1^2$	R-stat
Convergence over 65 years (16 cycles)							
1950-2014	31	-0.7576	0.0144	7.1762***	-0.8506	0.4081	11.9581***
Convergence over 32 years (8 cycles)							
1950-1982	30	-0.4357	0.0283	1.1147	-0.5065	0.8701	4.6002***
1983-2014	111	-0.5574	0.0184	6.2461***	-0.6072	0.5045	10.9664***
Convergence over 16 years (4 cycles)							
1950-1966	26	-0.7336	0.0261	1.8002**	-0.7407	0.6785	5.6914***
1966-1982	80	-0.5278	0.0219	2.5305***	-0.5273	0.6878	2.9425***
1983-1998	108	-0.4832	0.0229	3.5227***	-0.4628	0.9621	3.2548***
1999-2014	167	-0.3905	0.0227	2.0910**	-0.5304	0.7318	6.8239***

Notes: The table presents the variables and results of (5), computed for the respective periods. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Distributional Analysis

How has the shape of the performance distribution evolved over time, as weaker national teams have caught up with stronger ones? In line with σ-convergence, the histograms and kernel densities for the win percentage and goal difference in each four-year cycle have

[18] The lack of significance within the latest four-year cycles is mirrored in the flattening of the standard deviation graphs in Figure 2.

become taller and thinner, as described in the Online Appendix. But a full distributional analysis has to abstract from the increasing number of teams and work with a balanced panel. As a trade-off between the number of countries and the number of time periods we construct our baseline Sample 1, which contains 76 countries across 10 four-year cycles (1975-2014). It is restricted to countries with more than 1m inhabitants because it can be argued that tiny countries lack the human and financial resources to make significant performance improvements against their more populous peers (Hoffmann et al., 2002). As robustness checks, the Online Appendix works with a shorter Sample 2 (127 countries and 6 four-year cycles, 1990-2014) as well as an extended Sample 3 (Sample 1 including countries with less than 1m inhabitants).[19]

Table 4: Distribution of Win Percentages and Goal Difference Sample 1 (76 countries)

Panel a) Distribution of Win Percentage

	(1) Mean	(2) St.Dev.	(3) Skew	(4) Kurt	(5) JB pval.	(6) Unimod pval.	(7) CC Ind.	(8) Pola	(9) Gini
1975-78	0.5002	0.1683	-0.3445	2.8710	0.3564	0.6567	0.3024	0.1594	0.1885
1979-82	0.5134	0.1371	-0.1872	3.1298	0.5000	0.4733	0.3142	0.1059	0.1473
1983-86	0.5258	0.1316	-0.6700	3.1216	0.0436	0.9400	0.2265	0.1038	0.1379
1987-90	0.5159	0.1465	-0.5679	2.7126	0.0698	0.1533	0.4125	0.1180	0.1574
1991-94	0.5224	0.1341	-0.4842	2.4387	0.0812	0.5133	0.3499	0.1314	0.1442
1995-98	0.5326	0.1226	-0.3149	3.1776	0.4086	0.9633	0.2070	0.0971	0.1277
1999-02	0.5451	0.1001	-0.1941	2.1501	0.1514	0.5833	0.3563	0.0992	0.1045
2003-06	0.5432	0.1177	-0.2323	2.2168	0.1656	0.2200	0.4314	0.1181	0.1231
2007-10	0.5408	0.1188	0.1811	2.9808	0.5000	0.8733	0.2527	0.0980	0.1227
2011-14	0.5431	0.1052	-0.0154	2.3663	0.4338	0.3467	0.3781	0.0959	0.1099

Panel b) Distribution of Goal Differences

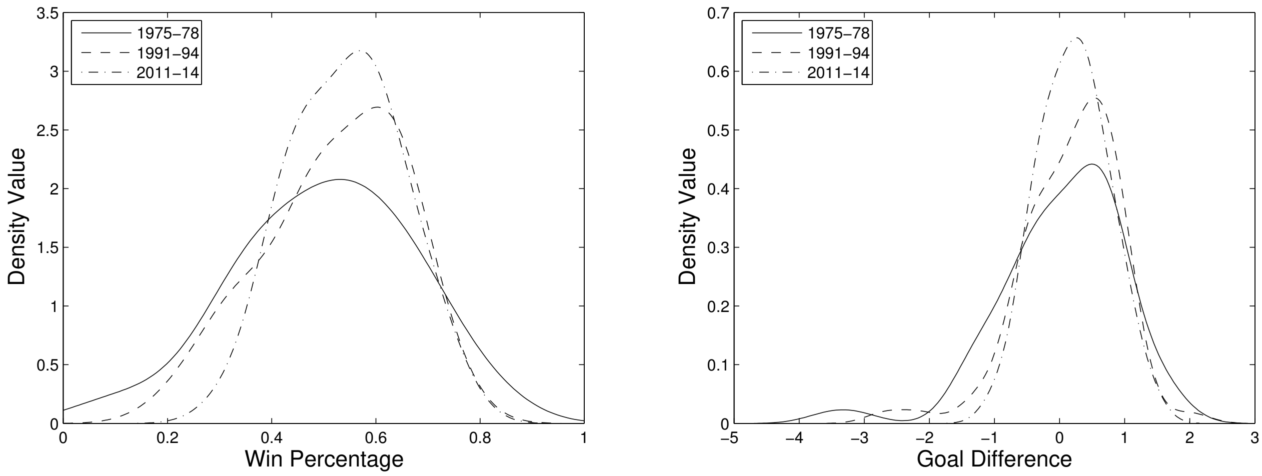
	(1) Mean	(2) St.Dev.	(3) Skew	(4) Kurt	(5) JB pvalue	(6) Unimod pvalue	(7) CC Ind.
1975-78	0.0352	0.9450	-1.1445	5.4890	0.0010	0.7733	0.2466
1979-82	0.0708	0.7895	-0.6210	4.1080	0.0205	0.8200	0.2422
1983-86	0.1985	0.6819	-0.4944	3.0985	0.1217	0.3933	0.3525
1987-90	0.0637	0.7217	-0.7806	3.5111	0.0215	0.5400	0.3127
1991-94	0.1647	0.7554	-1.0087	5.2635	0.0014	0.6467	0.2844
1995-98	0.2251	0.6279	-0.1753	3.1777	0.5000	0.9533	0.2167
1999-02	0.2837	0.5343	0.0838	2.6192	0.5000	0.3067	0.3798
2003-06	0.2494	0.5706	-0.1930	2.6359	0.5000	0.3633	0.3698
2007-10	0.2084	0.5749	-0.3756	3.3441	0.2289	0.7600	0.2539
2011-14	0.2108	0.5273	0.0416	2.5391	0.5000	0.8233	0.2614

Notes: The analysis is based on a balanced sample of 76 countries (Sample 1) with more than 1m inhabitants throughout the sample period. Columns 1-4 report the distributional moments mean, standard deviation, skewness and kurtosis. Column 5 contains the p-values of the Jarque Bera test with the null hypothesis as the Gaussian distribution. Column 6 shows the p-values of Silverman's (1981) multimodality test with the null hypothesis as a unimodal distribution. Column 7 presents the club convergence indicator by Krause (2017), Column 8 the bi-polarization index by Wolfson (1994) and Column 9 the Gini coefficient as a measure of inequality. Due to the presence of negative values in the goal differences, the latter two cannot be computed for this data.

[19] All samples are restricted to countries which played more than 5 games in every cycle in order to avoid a small sample bias in calculating win percentage averages.

The evolution of various distributional statistics for Sample 1 in Table 4 underpin the convergence evidence. Apart from the large decreases in the standard deviation of win percentages and goal differences (column 2), we also note decreases in, respectively, skewness and kurtosis (columns 3 and 4), particularly since the 1990s. This makes the distribution less skewed and flattens the tails, specifically the left one where the worst performing teams are located. Countries' positions move closer together as weaker teams catch up. According to the Jarque-Bera p-value (column 5), in recent years we cannot reject the hypothesis that win percentages and goal differences follow a Gaussian distribution, which is symmetric and light-tailed. This is also illustrated in Figure 3a for win percentages and Figure 3b for goal differences: the distributions clearly appear less skewed, less dispersed and more Gaussian since the 1980s. The disappearance of the long left tails of weak countries in the distribution of goal difference is particularly striking.[20]

Figure 3: Densities of Performance Measures in Various Years, Sample 1 (76 Countries)



That the distribution of countries' soccer performance has moved towards a Gaussian distribution stands in stark contrast to the evolution of countries' (relative) GDP per capita distribution, which is characterized by continued asymmetry and multimodality. For GDP per capita, the literature has failed to find unconditional convergence in the global distribution and attention has focused on the narrower notion of club convergence, which denotes convergence only within certain groups of countries (Baumol, 1986; Quah, 1993a, 1996). If the distribution is multimodal, one can test for club convergence by measuring if the various peaks become more pronounced over time (Krause, 2017).

[20] Only for Sample 3, which includes tiny country with less than 1m inhabitants, the left tail stays rather long, as the Online Appendix explains. This suggests that while there is convergence, very small nations face significant obstacles to improving their performance due to scarce resources in terms of population and wealth.

However, we find little or no evidence of multimodality at any point in time either for the distribution of win percentage or goal difference. Even for the years before the move towards a symmetric, Gaussian distribution, the continental groupings do not become visible in multiple modes in the performance distribution. Silverman's (1981) test never rejects the unimodality hypothesis at any reasonable significance level; the p-values never go below 0.15 for the win percentage distribution (column 6 of Table 4).[21] Accordingly, the dynamic club convergence indicator shows no clear pattern across time periods (column 7). While the relative GDP per capita distribution has gone through various periods of club convergence and de-clubbing (Krause, 2017), in terms of soccer performance countries have clustered more and more around a 0.5 win percentage and a goal difference close to zero. We conclude that the convergence results in countries' soccer performance holds across the worldwide distribution. This is further underlined by a steady decrease in Wolfson's (1994) bi-polarization index (Column 8), which measures the size of the distribution at both ends compared to the middle. Lastly, the Gini coefficient of inequality in performance (Column 9) also decreases significantly across all time periods.

5 The Limits of Convergence and the Middle Income Trap Analogy

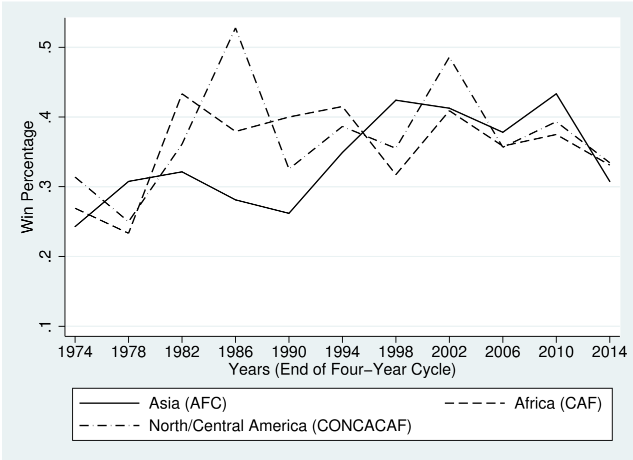
5.1 Country Analysis

While our evidence strongly suggests that there has been convergence in men's soccer national team performance since 1950, it is also obvious that significant differences remain. The prediction by the celebrated Brazilian player Pele in the 1980s that "An African nation will win the World Cup before the year 2000" has proved to be wide of the mark. Only European and South American teams have achieved this feat so far. This leads us to question how teams from other continents have fared against European and South American teams: are they catching up and winning more often in direct encounters? Figure 4 reports the average win percentage per 4-year cycle of the newer confederations (Asia, Africa and Central/North America) against the established powers of Europe and South America since the 1970s.[22] The graph suggests that each continent has enjoyed some periods of catch-up, but that in all three cases convergence toward the elite confederations has stalled in the last decade and might even be going into reverse. The win percentage seems stuck at just below the 40% level, significantly below equality with European and South American teams.

[21] We follow the version of Silverman's (1981) unimodality test with the sample variance adjustment by Efron and Tibshirani (1993). For the bootstrap procedure we use 2500 replications.

[22] In the years before, there were rather few direct encounters between the particular confederations per four-year cycle. Also note the sixth confederation, Oceania (OFC), is omitted here since it largely consists of small Pacific islands struggling to compete outside of the confederation.

Figure 4: Win Percentages of Countries from Other Continental Confederations Against Teams from Europe (UEFA) or South America (CONMEBOL), per Four-Year Cycle



Further evidence is provided by a decomposition of performance inequality into inequality within and between continental confederations. Using the 76 countries from Sample 1 (ten four-year cycles from 1975-2014), Table 5 shows that the Theil index of global inequality in win percentage decreased markedly over the years (col 1), but this evolution has been driven by the strong decrease in performance inequality within continental confederations (col 2).[23] This holds for inequality within all the individual confederations except North/Central America; in particular, performance inequality within Europe decreased by 75% (Table A-5). By contrast, between-continent inequality in performance (col 4) stood at the same value as at the beginning of the sample. Its share of global performance inequality has therefore increased considerably (col 5). While most of the differences in performance can still be attributed to within-continent inequality (col 3), the relatively increasing gaps between continents are worth investigating.

In order to square the results of unconditional convergence across the worldwide soccer performance distribution with the remaining rift between the top national teams and the rest, let us analyze which countries have caught up the most. For our mobility analysis, we rank the 76 countries from Sample 1 based on their win percentage. The relatively low correlation coefficients of 0.5-0.7 from cycle to cycle in Table A-6 shows that there is a lot of mobility in the distribution, much more than is typically found in, say, the distribution of countries' income per capita. Nevertheless, there are clearly some limits to the catch-up process and we see big differences across continental federations. This is revealed by Table 6. Across the whole period (1975-2014), European countries had the highest rank on average (32.1 out of 76), while the average Asian, African and South American teams were on similar levels. But looking at changes from the beginning to the end, we see that the average countries from Europe and South America managed to improve their ranks

[23]The Theil index of inequality is used because it can be decomposed into its within- and between-group components, unlike the Gini index (Cowell, 2009).

Table 5: Inequality in Win Percentage and its Decomposition Within and Between Continental Confederations, Sample 1 (76 countries)

	Theil Index of Inequality	*Within Continents*		*Between Continents*	
		Theil-Index	Share of Total	Theil-Index	Share of Total
	(1)	(2)	(3)	(4)	(5)
1975-1978	0.0630	0.0604	0.9588	0.0026	0.0412
1979-1982	0.0373	0.0357	0.9551	0.0017	0.0449
1983-1986	0.0340	0.0324	0.9506	0.0017	0.0494
1987-1990	0.0440	0.0408	0.9285	0.0031	0.0715
1991-1994	0.0350	0.0324	0.9270	0.0026	0.0730
1995-1998	0.0277	0.0244	0.8793	0.0033	0.1207
1999-2002	0.0170	0.0145	0.8491	0.0026	0.1509
2003-2006	0.0240	0.0195	0.8140	0.0045	0.1860
2007-2010	0.0241	0.0223	0.9274	0.0017	0.0726
2011-2014	0.0188	0.0163	0.8638	0.0026	0.1362

(from 34.3 to 30.8 and 44.6 to 38.9).[24] The average African team fell further behind in relative terms (from 37.5 to 39.6). This becomes even clearer when focusing on the countries starting out from the bottom half of ranks in the beginning (rows 6 to 9), which therefore had the biggest catch-up potential: Both weak teams from Europe and South America made big improvements - by 15 ranks for the average European bottom-half team -, while the average African bottom-half team fell slightly further behind. This leads us to conclude that the biggest beneficiaries of worldwide convergence have been second-tier national teams from Europe and South America. Some African and Asian teams have also advanced, but many are still struggling to close the continental gap.

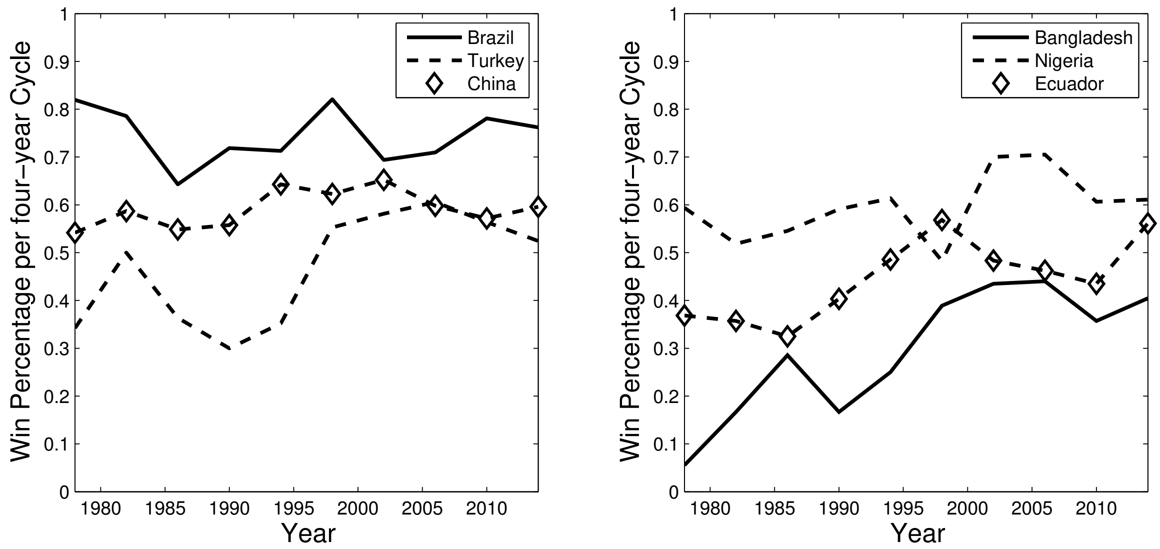
Table 6: Countries' Ranks in the Win Percentage Distribution over Four-Year Cycles by Continental Federation, Sample 1 (76 countries)

	Asia	Africa	America (N,C)	South America	Pacific	Europe
Mean Rank	39.3	40.2	44.2	41.5	58.0	32.1
St.Dev. of Rank	16.7	14.2	14.5	12.2	23.6	14.6
Rank in 1975-86	41.8	37.5	38.9	44.6	35.0	34.3
Rank in 2003-14	41.4	39.6	47.3	38.9	75.0	30.8
No. of Countries	15	23	6	10	1	21
Bottom Half: Rank in 1975-86	57.1	50.9	45.6	55.3		52.7
Bottom Half: Rank in 2003-14	48.4	52.3	51.6	50.6		37.6
No. of Bottom Half Countries	9	11	4	7	0	9

Figure 5 illustrates some cases in point: The world's dominant national teams like Brazil kept an empirical winning percentage at 0.7 throughout the sample period. Turkey in the left panel and Ecuador in the right panel are examples of formerly weaker European and South American countries which showed big improvements. Bangladesh, the world's 8th most populous country, was among the weakest teams overall with a win percentage

[24]The beginning (1975-86) and end (2003-2014) here encompass three four-year cycles to ease out random variation in ranks over cycles.

Figure 5: The Evolution of Selected Countries' Win Percentages per four-year Cycle



of 0.1 in the 1970s. With a huge catch-up potential, it has shown performance increases. But the better national teams from Africa and Asia, such as China and Nigeria, have failed to make long-lasting improvements and remain at middling performance levels. In order to understand why, we will consider the parallels to an empirical phenomenon in the GDP per capita growth literature: the Middle Income Trap.

5.2 The Middle Income Trap Analogy

Coined by two World Bank economists (Gill and Kharas, 2007), the term 'middle income trap', refers to the challenge countries face after prolonged periods of economic catch-up growth. As the returns to capital diminish and wages rise, export-based growth strategies based on abundant labor reach their limits. At the same time, they do not yet have the technological and human capital resources to compete with richer countries on innovation.[25] Obviously, when drawing analogies to football performance, the countries involved differ. In terms of income per capita, the Asian Tiger countries (Korea, Taiwan etc), have been more successful in making the transition than some stagnating Latin American countries. Brazil and Argentina owe their position in the middle income trap partly to a resource-dependent economy, slow industrialization and inefficient institutions (Lee, 2013), while soccer has a long history in these countries, and they are continually investing in their talent to stay among the top teams. Still, looking at other teams which are failing to close the rift with these best European and South American countries elucidates mechanisms of a 'middle performance gap'.

[25] Gill and Kharas (2015) lament that no economic growth model has yet been developed particularly for middle-income countries to fill the gap been the Solow-Swan capital accumulation model for poorer economies and endogenous growth theory for richer ones.

First, it is obvious that for very weak teams, performance improvements are easier to achieve than for teams in the middle. Starting at low levels, better sports infrastructure, better nutrition and fitness plans, more effective training techniques, expanded knowledge of tactics and insights from abroad, gained by players or a foreign coach, can go a long way (Yamamura, 2009). Directed initiatives reflecting the soccer equivalent of foreign aid and foreign direct investment can also help to lay the groundwork. For instance, FIFA gives grants to emerging continental associations paid out of the profits generated by the FIFA World Cup; clubs from rich countries and philanthropists support training and cooperation facilities in African countries.[26] From a low level, the win percentages of the world's weakest teams can therefore increase rather easily. But once these low-hanging fruits have been picked, sustained performance improvements are harder, all the more so if their opponents have advanced in similar ways.

The development of new talent becomes decisive if teams aspire to be among the world's best. According to Acemoglu et al. (2006), the closer an economy gets to the technology frontier, the more important it is not only to improve the performance of existing firms and managers, but to broaden the talent pool. Applied to soccer, maximizing the potential of the national population requires a national network of scouting and training schemes for young players. It is well-known that the physiological predictors for developing soccer talent have to be combined with the right sociological factors in terms parental support, child-coach interaction and hours of training, see Williams and Reilly (2000). Germany is widely admired for its youth development system; 121 regional training centers allow every aspiring German teenager to have access to intensive training programs within 25 km of their hometown. The creation of a national league for players under the age of 17 further helps young talents to gain competitive experience.[27] Other countries are adopting these initiatives; in 2017 China announced plans to create 50,000 football youth academies by 2025. Establishing a talent development system can in the long run be expected to help countries escape the 'middle performance trap'.

For the continued growth of rich economies, innovation plays a vital role (Romer, 1990; Grossman and Helpman, 1991). Eichengreen et al. (2013) find that countries with more high-tech production were less likely to have growth slowdowns at the

[26] Examples are the Dutch clubs of Feyenoord Rotterdam and Ajax Amsterdam, which have established youth training camps and cooperation facilities in African countries. George Weah, the FIFA World Footballer of the Year in 1995, has invested considerably in soccer development of his native Liberia.

[27] For the discussion of the German youth development system by the international press, see for instance https://www.theguardian.com/football/2015/sep/05/germany-football-team-youth-development-to-world-cup-win-2014 .

typical transition level of the middle income trap. In soccer, the adoption of best-practices from abroad has helped many teams to catch up, but beyond a certain point it might be important for a team to develop its own style. In fact, successful playing styles which spread quickly across countries typically originate in the world's leading football nations, see Menéndez et al. (2013). One example is the 'Tiki Taka' style of short passes and movements associated with the Spanish team's victory in the UEFA Euro 2008 and 2012 as well as the FIFA World Cup 2010 (Gyarmati et al., 2014).[28]

A final, but crucial factor helping to explain the 'middle performance trap' in soccer is the network effect from regional integration. According to Ayiar et al. (2013), countries from Central and Eastern Europe, such as Poland and Hungary, have avoided the middle income trap thanks to frequent interactions, via trade and technology spillovers, with richer European neighbors. In soccer, regional blocks are particularly vital because teams from the same federation most often play against each other (see Table A-7). Out of all international pairings from 1950 to 2014, 82% pitted two teams from the same regional federation against each other. European teams played against other European teams 84% of the time. This is not only due to geographical proximity but underlines the role of the continental confederations in organizing games and setting standards.
Our mobility analysis has revealed that weaker teams from Europe and South America have improved their performance a lot. They are benefiting from playing against the world's best teams on a regular basis as well as sharing the same institutional environment, which facilitates the technology transfer. By contrast, relatively good teams from Africa or Asia can gain less from regional integration where they meet even weaker peers. They simply have fewer opportunities to hone their skills against the world's top national teams, becoming stuck in the soccer analogue of the middle income trap. This leads us to conclude that the strong role of regional associations in soccer has come with a mixed blessing in terms of helping weaker teams to catch up.

6 Conclusion

Examining the performance of national soccer teams from 1950 to 2014, this paper has found strong evidence of unconditional convergence. The results of the β- and σ-convergence tests suggest that weaker teams have made improvements and caught up with better ones. Unlike countries' income per capita distribution, worldwide soccer performance in terms of win percentages and goal differences has evolved towards a

[28] There is a big discussion among sports commentators to what extent the adoption of 'Tiki Taka' by other teams is proving successful or long-lasting, see https://www.supersport.com/football/blogs/sunday-oliseh/Why_Tiki_Taka_still_rules_the_world and http://bleacherreport.com/articles/1391050-barcelonas-tiki-taka-4-teams-whove-tried-to-emulate-them.

Gaussian distribution, as countries have moved towards each other. We identify the biggest beneficiaries as (i) the world's weakest teams with huge catch-up potential and (ii) second-tier teams from Europe and South America, benefiting from regional integration into the world's top soccer continents. By contrast, the stronger teams from Africa and Asia are failing to close the gap with the world's best national teams and, with continued middling performances, remain in the soccer analogue of the middle income trap.

Our study is the first to find unconditional convergence in a particular sector other than manufacturing and the first of its kind to use a truly global dataset. Conducting a similar exercise in other service industries, from banking to tourism, would be more difficult, given the challenge of constructing a consistent measure of performance across countries. While international soccer obviously has some unique idiosyncracies, the fact that we find unconditional convergence in such a competitive and regionally-integrated service has implications for other sectors. Two conclusions are particularly noteworthy:
(i) Technological transfer by way of best-practice adoption can facilitate convergence if the product/service involved is standardized, globally traded and performance is easily observable. Global labor markets for soccer players and coaches ensure the transfer of skills and insight, which is helped by the portability of human capital and low information asymmetries (Kahn, 2000; Milanovic, 2005). It has been shown before that national teams with more players contracted by foreign leagues do better than their peers (Bauer and Lehmann, 2007; Berlinschi et al., 2013); this paper provides the link to global convergence. Obviously, labor markets function differently and with more frictions in other sectors. However, our results can be seen under the light of general discussions about how to better recognize migrants' skills, to foster industry-specific experience abroad and to internationalize the talent pool of skilled workers.
(ii) Regional integration fosters trade, common standards and the diffusion of best practices between the countries involved. Regional associations are important in soccer, but they have played an ambiguous role for worldwide convergence in performance: Our results show that weaker teams from Europe and South America have gained from the continued exposure to top teams and their institutional environment, at the expense of teams from other continents. This calls for stronger integration not only within but also between regions, an argument which can easily be made for other industries as well.

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Appendix A More Tables and Figures

Table A-1: Squads of 32 National Teams Participating in the 2014 FIFA World Cup

Team	Coach	Players (out of 23)	
	Foreign	Home League	(Other) European League
UEFA (Europe)			
Germany	No	16	7
Spain	No	14	9
Italy	No	20	3
England	No	22	1
France	No	8	15
Portugal	No	8	15
Greece	Yes	14	9
Russia	Yes	23	0
Netherlands	No	10	13
Belgium	No	3	20
Switzerland	Yes	7	16
Croatia	No	2	21
Bosnia & Herzegovina	No	1	22
CONMEBOL (South America)			
Brazil	No	4	18
Argentina	No	3	19
Chile	Yes	5	15
Colombia	Yes	3	16
Uruguay	No	1	16
Ecuador	Yes	8	4
CONCACAV (North/Central American + Caribbean)			
United States	Yes	9	13
Mexico	No	15	8
Costa Rica	Yes	9	11
Honduras	Yes	11	5
AFC (Asia)			
Australia	No	7	13
Japan	Yes	11	12
Iran	Yes	14	6
South Korea	No	6	10
CAF (Africa)			
Nigeria	No	4	19
Cameroon	Yes	2	21
Ivory Coast	Yes	1	22
Ghana	No	1	18
Algeria	Yes	2	19

Notes: Each official squad consists of 23 players. Players which neither play in the home league nor in a European league make up the difference to 23. The data are from http://resources.fifa.com/mm/document/tournament/competition/02/36/33/44/fwc_2014_squadlists_neutral.pdf

Table A-2: Summary Statistics of the Outcome and Explanatory Variables

	All Years	1950-1966	1967-1982	1983-1998	1999-2014
Winning Percentages (Points)					
Mean	0.5000	0.5000	0.5000	0.5000	0.5000
St.Dev.	0.4336	0.4490	0.4384	0.4297	0.4325
Min	0.0000	0.0000	0.0000	0.0000	0.0000
Max	1.0000	1.0000	1.0000	1.0000	1.0000
Obs	50804	2970	7990	14866	24978
Goal Difference					
Mean	0.0000	0.0000	0.0000	0.0000	0.0000
St.Dev.	2.1868	2.5762	2.2716	2.1455	2.1326
Min	-20.0000	-14.0000	-14.0000	-17.0000	-20.0000
Max	20.0000	14.0000	14.0000	17.0000	20.0000
Obs	50804	2970	7990	14866	24978
Log Population Ratio					
Mean	0.0000	0.0000	0.0000	0.0000	0.0000
St.Dev.	2.0940	1.7661	1.9321	2.0823	2.1849
Min	-9.1152	-6.9764	-8.6362	-9.1152	-8.4066
Max	9.1152	6.9764	8.6362	9.1152	8.4066
Obs	50804	2970	7990	14866	24978
Log GDP per capita Ratio					
Mean	-0.0000	-0.0000	0.0000	-0.0000	-0.0000
St.Dev.	1.2194	0.8994	1.1123	1.2150	1.2861
Min	-5.7318	-3.4041	-5.1160	-4.9244	-5.7318
Max	5.7318	3.4041	5.1160	4.9244	5.7318
Obs	50804	2970	7990	14866	24978
Log Experience Ratio					
Mean	0.0000	0.0000	0.0000	0.0000	0.0000
St.Dev.	1.0290	1.0613	1.0296	1.1804	0.9227
Min	-6.4877	-4.0678	-5.5910	-6.4877	-6.1092
Max	6.4877	4.0678	5.5910	6.4877	6.1092
Obs	50804	2970	7990	14866	24978

Notes: The table presents summary statistics of the match-level data presented in the text. The years from 1950 to 2014 can be divided into 4 four-year World Cup cycles. In terms of observations, every game is counted twice, once from the perspective of country i and once from country j, to capture the both the home advantage and the disadvantage of player in the opponent's country in the subsequent regressions.

Table A-3: Game Outcome (Goal Difference) Regressed on Explanatory Factors

Panel A: By Types of Games

Dependent Var: Goal Difference	(1) All Games	(2) Friendlies	(3) Competitive	(4) Qualifiers	(5) World + Cont. Cup
home	0.589***	0.465***	0.766***	0.407***	0.774***
	(0.035)	(0.042)	(0.051)	(0.090)	(0.102)
away	-0.629***	-0.561***	-0.675***	-1.042***	-0.582***
	(0.031)	(0.037)	(0.047)	(0.083)	(0.095)
lgdppcratio	0.136***	0.123***	0.147***	0.134***	0.192***
	(0.016)	(0.019)	(0.023)	(0.025)	(0.031)
lpopratio	0.168***	0.146***	0.205***	0.224***	0.111***
	(0.015)	(0.013)	(0.020)	(0.022)	(0.024)
lexpratio	0.657***	0.589***	0.675***	0.637***	0.716***
	(0.031)	(0.030)	(0.041)	(0.042)	(0.070)
Constant	-0.016	0.346***	-0.195***	0.145	-0.557***
	(0.033)	(0.030)	(0.053)	(0.090)	(0.039)
Country Dummies	Yes	Yes	Yes	Yes	Yes
R2	0.274	0.213	0.356	0.388	0.252
Observations	50804	27708	23096	17784	5312
Countries	182	181	182	182	132

Panel B: By Time Period

Dependent Var: Goal Difference	(1) All Games	(2) 1950-1966	(3) 1967-1982	(4) 1983-1998	(5) 1999-2014
home	0.589***	0.693***	0.678***	0.617***	0.538***
	(0.035)	(0.147)	(0.088)	(0.051)	(0.035)
away	-0.629***	-0.694***	-0.853***	-0.633***	-0.538***
	(0.031)	(0.141)	(0.073)	(0.046)	(0.040)
lgdppcratio	0.136***	-0.142*	0.161***	0.198***	0.131***
	(0.016)	(0.082)	(0.041)	(0.023)	(0.019)
lpopratio	0.168***	0.214***	0.160***	0.182***	0.168***
	(0.015)	(0.045)	(0.023)	(0.020)	(0.017)
lexpratio	0.657***	0.892***	0.726***	0.552***	0.748***
	(0.031)	(0.072)	(0.036)	(0.037)	(0.052)
Constant	-0.016	0.380***	0.675***	-0.357***	0.093**
	(0.033)	(0.127)	(0.104)	(0.053)	(0.036)
Country Dummies	Yes	Yes	Yes	Yes	Yes
R2	0.274	0.305	0.317	0.320	0.277
Observations	50804	2970	7990	14866	24978
Countries	182	86	130	175	182

Notes: Analogous to Table 1, the table presents OLS regression results of (2) with the goal difference rather than the winning percentage as the dependent variable. See Table 1 for more details.

Table A-4: Ratio Test Statistics for σ-Convergence in Win Percentage and Goal Difference Within 4-year Cycles

Period	N	Win Percentages			Goal Difference		
		$\hat{\beta}$	$\hat{\sigma}_1^2$	R-stat	$\hat{\beta}$	$\hat{\sigma}_1^2$	R-stat
1955-1958	26	-0.4829	0.0393	-0.0473	-0.4169	1.6862	0.8472
1959-1962	29	-0.2975	0.0406	0.1944	-0.3812	1.2688	1.7653**
1963-1966	44	-0.7092	0.0274	1.6663**	-0.6390	0.6218	3.8155***
1967-1970	61	-0.5349	0.0316	0.2524	-0.5413	0.9812	1.6188**
1971-1974	80	-0.4409	0.0279	0.8135	-0.3567	0.9621	0.7557
1975-1978	88	-0.3801	0.0344	-0.2552	-0.2816	1.2167	0.0799
1979-1982	95	-0.4344	0.0268	1.8086**	-0.4320	0.8802	2.7708***
1983-1986	103	-0.2962	0.0310	-0.7965	-0.2788	1.1284	-1.5246
1987-1990	107	-0.2749	0.0307	1.0206	-0.2902	0.8378	5.5443***
1991-1994	111	-0.3816	0.0287	0.3875	-0.1547	1.5515	-4.3673
1995-1998	146	-0.3783	0.0249	1.3643*	-0.4231	0.9565	4.4460***
1999-2002	165	-0.4177	0.0260	0.2007	-0.3885	1.0789	1.3555*
2003-2006	169	-0.3263	0.0246	1.3327*	-0.3764	0.9171	4.5074***
2007-2010	169	-0.3059	0.0233	0.5907	-0.2509	0.8761	0.5310
2011-2014	172	-0.3390	0.0227	0.2989	-0.2992	0.7239	2.0603**

Notes: The table presents the variables and results of (5), computed for the respective periods. *** p<0.01, ** p<0.05, * p<0.1.

Table A-5: Theil-Index of Inequality in Win Percentage Within Continental Confederations, Sample 1 (76 countries)

	Asia	Africa	America (N,C)	America (South)	Europe
1975-1978	0.1430	0.0439	0.0081	0.0764	0.0358
1979-1982	0.0805	0.0259	0.0140	0.0423	0.0233
1983-1986	0.0437	0.0155	0.0290	0.0683	0.0311
1987-1990	0.0630	0.0160	0.0764	0.0809	0.0310
1991-1994	0.0509	0.0233	0.0122	0.0540	0.0254
1995-1998	0.0249	0.0199	0.0180	0.0459	0.0207
1999-2002	0.0121	0.0127	0.0104	0.0334	0.0114
2003-2006	0.0165	0.0218	0.0431	0.0216	0.0135
2007-2010	0.0206	0.0237	0.0123	0.0301	0.0217
2011-2014	0.0139	0.0175	0.0137	0.0334	0.0097

Notes: In this sample Oceania only consists of one country (New Zealand), so that within-continental inequality in performance is zero.

Table A-6: Correlation of Countries' Ranks in the Win Percentage Distribution over Four-Year Cycles, Sample 1 (76 countries)

Variables	1975-78	1979-82	1983-86	1987-90	1991-94	1995-98	1999-02	2003-06	2007-10	2011-14
1975-78	1.00									
1979-82	0.54	1.00								
1983-86	0.54	0.51	1.00							
1987-90	0.50	0.36	0.61	1.00						
1991-94	0.39	0.27	0.47	0.62	1.00					
1995-98	0.53	0.36	0.53	0.43	0.61	1.00				
1999-02	0.43	0.22	0.39	0.46	0.57	0.57	1.00			
2003-06	0.52	0.33	0.52	0.57	0.60	0.57	0.73	1.00		
2007-10	0.41	0.17	0.46	0.45	0.57	0.53	0.70	0.73	1.00	
2011-14	0.48	0.37	0.48	0.59	0.63	0.58	0.55	0.68	0.65	1.00

Table A-7: Regional Matches Involving Teams from the Various Federations, 1950-2014

	Asia	Africa	America (N,C)	America (S)	Oceania	Europe
Asia	9586	691	161	202	130	788
Africa	691	12524	99	124	9	460
America (N,C)	161	99	4214	666	17	456
America (S)	202	124	666	3454	15	711
Oceania	130	9	17	15	32	26
Europe	788	460	456	711	26	11884

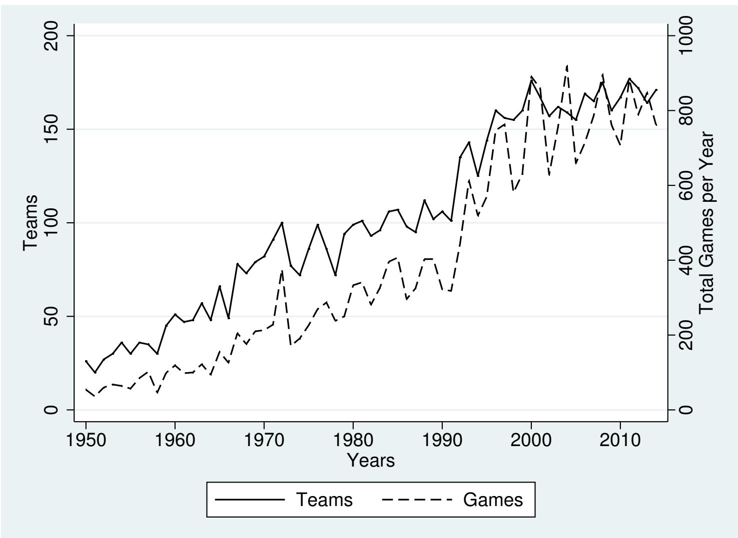
Notes: The table shows the number of international matches pitting Team 1 from the regional federation in the row against Team 2 from the regional federation in the column. The continental confederations are AFC (Asia), CAF (Africa), CONCACAF (North and Middle America and the Caribbean), CONMEBOL (South America), OFC (Oceania) and UEFA (Europe).

Appendix B Online Appendix

B.1 The Growth of International Competition

Association football (soccer) is a game whose rules were first written down in 1863 in England. Originally played only between local clubs, the first "international" match was played between England and Scotland in 1872. The game spread rapidly and by the end of the nineteenth century most European and South American nations had established national associations to administer the game, thus facilitating competition between national teams. In 1904 FIFA was created as an organization to manage soccer relations between countries, and in 1930 the FIFA World Cup was first played, with 13 national teams competing. In the first half of the 20th century, there were still rather few international games; under 2,200 were recorded between 1900 and 1940, an average of 54 per year, and almost all of these involved European and South American countries. But in the second half of the 20th century, this has changed, turning soccer into a truly global industry: Since 1950 there have been over 36,000 games played between men's national soccer teams, an average of over 500 per year, see Figure B-1.

Figure B-1: The Growth of International Soccer Competition



Notes: The graph shows yearly figures on the number of international games played between national teams as well as the number of internationally active national teams. Apart from the steady increase the graphs exhibit cyclical peaks in the years of a FIFA World Cup.

Table B-1 lists the years since 1950 in which a FIFA World Cup took place and the number of participating teams from each continental association. Teams from CONMEBOL, the South American association, and UEFA, the European one, where the game first took root, have tended to dominate the World Cup; in fact, no team from outside these associations has ever won the Cup. Teams from outside the big two regional confederations have reached the semi-finals twice: the USA in the first World Cup in 1930 (contested by only 13 nations), and South Korea in 2002. But FIFA has consciously tried to expand opportunities for the smaller associations. While each continent controls its own qualifying process, the number of slots allocated to each continental association is agreed centrally. The share allocated to UEFA and CONMEBOL has shrunk considerably over time, largely through expansion of the number of participating teams. A further expansion of 16 teams has been agreed for the 2026 World Cup, which will reduce the European and South American share further, possibly to as little as 46 %. Critics have argued that the distribution remains unfair and should reflect global population shares more accurately. The counter argument is that for a given quality of team it is harder to qualify through UEFA or CONMEBOL than any other federation.

Table B-1: Number of Countries Qualifying for the FIFA World Cup 1950-2014

World Cup	AFC (Asia)	CAF (Africa)	CONCACAF (Central+ North Am.)	CONMEBOL (South America)	OFC (Oceania)	UEFA (Europe)	Total	UEFA + CONMEBOL share
1950	1	0	2	5*	0	7	15	0.800
1954	1	0	1	2	0	12*	16	0.875
1958	0	0	1	3	0	12*	16	0.938
1962	0	0	1	5*	0	10	16	0.938
1966	1	0	1	4	0	10*	16	0.813
1970	0	1	2*	3	0	10	16	0.813
1974	1	1	1	4	0	9*	16	0.813
1978	1	1	1	3*	0	10	16	0.813
1982	1	2	2	4	1	14*	24	0.750
1986	2	2	2*	4	0	14	24	0.750
1990	2	2	2	4	0	14*	24	0.750
1994	2	3	2*	4	0	13	24	0.708
1998	4	5	3	5	0	15*	32	0.625
2002	4*	5	3	5	0	15	32	0.625
2006	4	5	4	4	1	14*	32	0.563
2010	4	6*	3	5	1	13	32	0.563
2014	4	5	4	6*	0	13	32	0.594

Notes: For each FIFA World Cup, the table lists the number of participating teams by continental federation. The * indicates the host federation. The CONCACAF federation includes Central and North America as well as the Caribbean. Note that the table shows the number of teams that actually qualified; in some cases the final slots were allocated by inter-continental play-offs.

B.2 Beta-Convergence Results: Other Performance Variables and Subsamples.

Analogous to the test for β-convergence countries' winning percentages as explained in Section 4.1 in the text, we here conduct the analysis with other performance variables and subsamples. The following tables are all structured similarly and regress the change in performance of country i in cycle t on its past performance:

$$\Delta y_{it} = \alpha + \beta \cdot y_{i,t-1} + \epsilon_{it}, \tag{B-1}$$

Panel A, col. (1) runs this regression for unconditional convergence, col. (2) tests for conditional convergence by including additional controls. Col. (3) includes regional confederation dummies. Col. (4) and Col. (5) test for, respectively, unconditional and conditional convergence using country fixed effects.
Panel B estimates

$$y_{it} = \alpha_i + \underbrace{(\beta + 1)}_{\rho} \cdot y_{i,t-1} + \epsilon_{it}, \tag{B-2}$$

with specific short T dynamic panel data model estimation techniques, Arellano-Bond GMM in col. (1) and col. (2) and Unconditional Quasi-Maximum Likelihood in col. (3) and col. (4).
Panel C conducts weighted regressions. Col. (1) and col. (2) use time weights $w_{it} = (\bar{n}_i/n_{it})^{1/2}$, where n_{it} is the number of games played by country i in cycle t and $\bar{n}_i$ is the average number of games by i over all cycles. In col. (3) and col. (4) dominance weights are used, reflecting how often country i played against an opponent from the two confederations, Europe and South America.

In particular, we conduct the analysis with different performance variables and subsamples and compare the results to those in the main text. Using the goal difference (Table B-2) yields very similar coefficients as the winning percentage. Concerns that convergence results might be driven by stronger teams' anecdotically worse performance at friendlies, when they often give weaker players a chance, can be alleviated by Table B-3: restricting the sample to competitive games gives even stronger convergence results, in line with our previous analysis that 'friendlies' and competitive games are mostly decided by the same factors. In Table B-4 we consider only the teams that were active from the first cycle (1950-1954) onwards, to exclude the effect of newcomers. Obviously, the national teams entering the international stage and catching up has contributed to the overall convergence effect, but we also observe unconditional and conditional convergence among the 42 teams which were present throughout the years. Finally, we split the sample into the time periods 1950-1982 (the first eight cycles, Table B-5) and 1983-2014 (the last eight cycles, Table B-6). While we find significant convergence results throughout time, there is no indication that they have become stronger in later years. This is confirmed by Table B-7, which shows that the regression coefficients are clearly negative in each four-year cycle but their magnitude has slightly decreased rather than increased.

We conclude from this analysis that our results of β-convergence in national teams' performance is a result that is robust across econometric specifications, performance variables, sub-samples and time periods.

Table B-2: Beta-Convergence Regression Results, Goal Difference (GD)

Panel A: Panel Data Regression

Dep Var: Δ GD	(1)	(2)	(3)	(4)	(5)
l.GD	-0.456***	-0.587***	-0.594***	-0.796***	-0.859***
	(0.030)	(0.033)	(0.033)	(0.030)	(0.032)
lgdppcratio		0.043	0.048		0.083
		(0.029)	(0.030)		(0.054)
lpopratio		0.095***	0.098***		0.026
		(0.024)	(0.023)		(0.063)
lexpratio		0.337***	0.334***		0.502***
		(0.044)	(0.044)		(0.065)
Constant	-0.049*	-0.032	-0.113*	-0.140***	-0.098***
	(0.026)	(0.024)	(0.066)	(0.008)	(0.011)
Confed Dummies	No	No	Yes	No	No
Country FE	No	No	No	Yes	Yes
R2	0.367	0.453	0.454	0.554	0.600
Observations	1644	1644	1644	1644	1644
Countries	178	178	178	178	178

Panel B: Fixed Effects Short T Dynamic Panel Estimation

Dep Var: GD	(1) (GMM)	(2) (GMM)	(3) (QML)	(4) (QML)
l.GD	0.234***	0.128**	0.267***	0.187***
	(0.057)	(0.058)	(0.045)	(0.038)
lgdppcratio		0.062		0.148**
		(0.074)		(0.057)
lpopratio		0.114*		0.045
		(0.060)		(0.047)
lexpratio		0.597***		0.433***
		(0.079)		(0.066)
Constant	-0.132***	-0.077*	-0.055	-0.046
	(0.047)	(0.041)	(0.045)	(0.040)
AR1	-6.692	-6.072		
AR2	2.596	1.807		
Observations	1484	1484	1372	1372
Countries	176	176	139	139

Panel C: Weighted Regressions

Dep Var: Δ GD	(1) (Time W)	(2) (Time W)	(3) (Dom W)	(4) (Dom W)
l.GD	-0.474***	-0.068***	-0.287***	-0.463***
	(0.030)	(0.005)	(0.037)	(0.043)
lgdppcratio		0.007		0.048
		(0.005)		(0.057)
lpopratio		0.012***		0.149***
		(0.003)		(0.027)
lexpratio		0.046***		0.186***
		(0.007)		(0.060)
Constant	-0.065**	-0.007	0.046	0.092*
	(0.029)	(0.008)	(0.028)	(0.052)
R2	0.381	0.223	0.187	0.307
Observations	1644	1644	599	599
Countries	178	178	56	56

Notes: Analogous to Table 2 in the paper, the table presents beta convergence regressions of (B-1) (Panel A and C) and (B-2) (Panel B) when the goal difference is used as performance variable. See the text in this Online Appendix for more details.

Table B-3: Beta-Convergence Regression Results, Competitive Games

Panel A: Panel Data Regression

Dep Var: Δ points	(1)	(2)	(3)	(4)	(5)
l.points	-0.453***	-0.609***	-0.617***	-0.918***	-0.947***
	(0.029)	(0.033)	(0.033)	(0.030)	(0.029)
lgdppcratio		0.024***	0.024***		0.015
		(0.006)	(0.006)		(0.010)
lpopratio		0.018***	0.018***		0.009
		(0.005)	(0.005)		(0.008)
lexpratio		0.066***	0.067***		0.075***
		(0.008)	(0.008)		(0.011)
Constant	0.219***	0.294***	0.277***	0.431***	0.447***
	(0.016)	(0.018)	(0.021)	(0.014)	(0.014)
Confed Dummies	No	No	Yes	No	No
Country FE	No	No	No	Yes	Yes
R2	0.276	0.386	0.388	0.527	0.563
Observations	1530	1530	1530	1530	1530
Countries	176	176	176	176	176

Panel B: Fixed Effects Short T Dynamic Panel Estimation

Dep Var: points	(1) (GMM)	(2) (GMM)	(3) (QML)	(4) (QML)
l.points	0.045	0.101*	0.151***	0.116***
	(0.052)	(0.052)	(0.035)	(0.033)
lgdppcratio		0.036***		0.017
		(0.014)		(0.010)
lpopratio		0.016*		0.005
		(0.009)		(0.007)
lexpratio		0.069***		0.068***
		(0.014)		(0.011)
Constant	0.448***	0.427***	0.416***	0.431***
	(0.027)	(0.025)	(0.022)	(0.020)
AR1	-5.742	-6.221		
AR2	-1.130	-0.449		
Observations	1354	1354	1292	1292
Countries	168	168	140	140

Panel C: Weighted Regressions

Dep Var: Δ points	(1) (Time W)	(2) (Time W)	(3) (Dom W)	(4) (Dom W)
l.points	-0.479***	-0.652***	-0.349***	-0.570***
	(0.031)	(0.036)	(0.048)	(0.057)
lgdppcratio		0.023***		0.021
		(0.007)		(0.014)
lpopratio		0.019***		0.036***
		(0.005)		(0.007)
lexpratio		0.073***		0.049***
		(0.010)		(0.014)
Constant	0.230***	0.296***	0.185***	0.301***
	(0.017)	(0.023)	(0.029)	(0.031)
R2	0.287	0.406	0.205	0.349
Observations	1530	1530	579	579
Countries	176	176	56	56

Notes: Analogous to Table 2 in the paper, the table presents beta convergence regressions of (B-1) (Panel A and C) and (B-2) (Panel B) when the sample is restricted only to competitive games, excluding 'friendlies'. See the text in this Online Appendix for more details.

Table B-4: Beta-Convergence Regression Results, Only National Teams Present Since 1950

Panel A: Panel Data Regression

Dep Var: Δ points	(1)	(2)	(3)	(4)	(5)
l.points	-0.384***	-0.537***	-0.553***	-0.753***	-0.790***
	(0.058)	(0.057)	(0.053)	(0.054)	(0.057)
lgdppcratio		-0.002	-0.001		-0.003
		(0.011)	(0.012)		(0.016)
lpopratio		0.015**	0.020***		-0.005
		(0.006)	(0.006)		(0.019)
lexpratio		0.080***	0.077***		0.096***
		(0.012)	(0.014)		(0.019)
Constant	0.203***	0.262***	0.234***	0.392***	0.394***
	(0.033)	(0.031)	(0.037)	(0.028)	(0.026)
Confed Dummies	No	No	Yes	No	No
Country FE	No	No	No	Yes	Yes
R2	0.234	0.339	0.345	0.433	0.473
Observations	574	574	574	574	574
Countries	42	42	42	42	42

Panel B: Fixed Effects Short T Dynamic Panel Estimation

Dep Var: points	(1) (GMM)	(2) (GMM)	(3) (QML)	(4) (QML)
l.points	-0.006	-0.011	0.265***	0.201***
	(0.059)	(0.056)	(0.056)	(0.045)
lgdppcratio		0.018		0.014
		(0.022)		(0.017)
lpopratio		-0.001		0.001
		(0.015)		(0.015)
lexpratio		0.084***		0.095***
		(0.025)		(0.024)
Constant	0.521***	0.505***	0.397***	0.403***
	(0.037)	(0.037)	(0.037)	(0.029)
AR1	-4.729	-4.885		
AR2	0.116	-0.0618		
Observations	538	538	483	483
Countries	42	42	34	34

Panel C: Weighted Regressions

Dep Var: Δ points	(1) (Time W)	(2) (Time W)	(3) (Dom W)	(4) (Dom W)
l.points	-0.439***	-0.778***	-0.339***	-0.583***
	(0.117)	(0.129)	(0.067)	(0.063)
lgdppcratio		0.083		0.004
		(0.045)		(0.022)
lpopratio		0.069**		0.031***
		(0.020)		(0.006)
lexpratio		0.028		0.077***
		(0.036)		(0.019)
Constant	0.237***	0.295***	0.193***	0.308***
	(0.067)	(0.046)	(0.039)	(0.037)
R2	0.193	0.365	0.187	0.318
Observations	112	112	398	398
Countries	8	8	27	27

Notes: Analogous to Table 2 in the paper, the table presents beta convergence regressions of (B-1) (Panel A and C) and (B-2) (Panel B) when the sample is restricted to the countries which played matches from the first four-year cycle onwards. See the text in this Online Appendix for more details.

Table B-5: Beta-Convergence Regression Results, Period 1 (1950-1982)

	Panel A: Panel Data Regression				
Dep Var: Δ points	(1)	(2)	(3)	(4)	(5)
l.points	-0.565***	-0.735***	-0.741***	-0.993***	-1.011***
	(0.043)	(0.038)	(0.040)	(0.044)	(0.045)
lgdppcratio		0.008	0.007		0.049*
		(0.010)	(0.010)		(0.026)
lpopratio		0.021***	0.022***		0.034*
		(0.007)	(0.007)		(0.019)
lexpratio		0.092***	0.093***		0.053**
		(0.012)	(0.013)		(0.021)
Constant	0.274***	0.362***	0.349***	0.474***	0.490***
	(0.023)	(0.021)	(0.027)	(0.020)	(0.022)
Confed Dummies	No	No	Yes	No	No
Country FE	No	No	No	Yes	Yes
R2	0.403	0.532	0.530	0.648	0.667
Observations	474	474	474	474	474
Countries	108	108	108	108	108

	Panel B: Fixed Effects Short T Dynamic Panel Estimation			
	(1)	(2)	(3)	(4)
Dep Var: points	(GMM)	(GMM)	(QML)	(QML)
l.points	-0.106	-0.045	0.093**	0.067
	(0.076)	(0.085)	(0.045)	(0.044)
lgdppcratio		0.032		0.038
		(0.031)		(0.029)
lpopratio		0.020		0.021
		(0.018)		(0.019)
lexpratio		0.074***		0.065***
		(0.027)		(0.021)
Constant	0.527***	0.506***	0.441***	0.455***
	(0.038)	(0.040)	(0.027)	(0.025)
AR1	-2.989	-2.998		
AR2	-1.608	-1.081		
Observations	386	386	425	425
Countries	100	100	87	87

	Panel C: Weighted Regressions			
	(1)	(2)	(3)	(4)
Dep Var: Δ points	(Time W)	(Time W)	(Dom W)	(Dom W)
l.points	-0.547***	-0.734***	-0.412***	-0.740***
	(0.053)	(0.047)	(0.066)	(0.081)
lgdppcratio		0.020*		0.007
		(0.012)		(0.019)
lpopratio		0.022***		0.039***
		(0.008)		(0.011)
lexpratio		0.085***		0.094***
		(0.014)		(0.019)
Constant	0.265***	0.354***	0.217***	0.375***
	(0.029)	(0.038)	(0.036)	(0.044)
R2	0.388	0.512	0.237	0.420
Observations	346	346	215	215
Countries	78	78	36	36

Notes: Analogous to Table 2 in the paper, the table presents beta convergence regressions of (B-1) (Panel A and C) and (B-2) (Panel B) when the sample period is restricted 1950-1982, the first eight four-year cycles. See the text in this Online Appendix for more details.

Table B-6: Beta-Convergence Regression Results, Period 2 (1983-2014)

	Panel A: Panel Data Regression				
Dep Var: Δ points	(1)	(2)	(3)	(4)	(5)
lagpts	-0.355***	-0.494***	-0.503***	-0.902***	-0.959***
	(0.028)	(0.038)	(0.038)	(0.040)	(0.037)
(mean) lgdppcratio		0.012**	0.013**		0.019**
		(0.005)	(0.005)		(0.009)
(mean) lpopratio		0.015***	0.016***		0.021**
		(0.004)	(0.004)		(0.009)
(mean) lexpratio		0.041***	0.040***		0.066***
		(0.007)	(0.007)		(0.012)
Constant	0.170***	0.241***	0.238***	0.417***	0.456***
	(0.013)	(0.019)	(0.021)	(0.018)	(0.017)
Confed Dummies	No	No	Yes	No	No
Country FE	No	No	No	Yes	Yes
R2	0.223	0.304	0.305	0.516	0.558
Observations	1170	1170	1170	1170	1170
Countries	177	177	177	177	177

	Panel B: Fixed Effects Short T Dynamic Panel Estimation			
	(1)	(2)	(3)	(4)
Dep Var: points	(GMM)	(GMM)	(QML)	(QML)
l.points	-0.109	-0.019	0.230***	0.180***
	(0.081)	(0.078)	(0.051)	(0.047)
lgdppcratio		0.024*		0.013
		(0.014)		(0.010)
lpopratio		0.031***		0.018**
		(0.011)		(0.009)
lexpratio		0.049***		0.054***
		(0.016)		(0.013)
Constant	0.510***	0.483***	0.363***	0.393***
	(0.036)	(0.035)	(0.026)	(0.024)
AR1	-4.266	-5.528		
AR2	0.459	1.211		
Observations	897	897	1007	1007
Countries	175	175	161	161

	Panel C: Weighted Regressions			
	(1)	(2)	(3)	(4)
Dep Var: Δ points	(Time W)	(Time W)	(Dom W)	(Dom W)
lagpts	-0.353***	-0.493***	-0.259***	-0.417***
	(0.027)	(0.038)	(0.038)	(0.048)
(mean) lgdppcratio		0.012**		0.019
		(0.006)		(0.012)
(mean) lpopratio		0.015***		0.027***
		(0.004)		(0.006)
(mean) lexpratio		0.040***		0.024**
		(0.008)		(0.011)
Constant	0.168***	0.236***	0.138***	0.234***
	(0.013)	(0.022)	(0.021)	(0.031)
R2	0.218	0.292	0.150	0.257
Observations	1170	1170	384	384
Countries	177	177	56	56

Notes: Analogous to Table 2 in the paper, the table presents beta convergence regressions of (B-1) (Panel A and C) and (B-2) (Panel B) when the sample period is restricted 1983-2014, the last eight four-year cycles. See the text in this Online Appendix for more details.

Table B-7: Beta-Convergence Regression Results For Each Four-Year Cycle

Dep Var: Δ points	1955-1958	1959-1962	1963-1966	1967-1970	1971-1974	1975-1978	1979-1982	
lagpts	-0.573**	-0.643***	-0.805***	-0.572***	-0.524***	-0.429***	-0.519***	
	(0.208)	(0.105)	(0.087)	(0.065)	(0.081)	(0.093)	(0.073)	
Constant	0.284**	0.319***	0.408***	0.284***	0.258***	0.196***	0.250***	
	(0.127)	(0.056)	(0.050)	(0.037)	(0.045)	(0.044)	(0.034)	
R2	0.214	0.537	0.582	0.431	0.343	0.248	0.428	
Observations	29	39	50	74	91	92	99	
Countries	29	39	50	74	91	92	99	
	1983-1986	1987-1990	1991-1994	1995-1998	1999-2002	2003-2006	2007-2010	2011-2014
lagpts	-0.309***	-0.336***	-0.436***	-0.369***	-0.395***	-0.326***	-0.297***	-0.339***
	(0.076)	(0.068)	(0.061)	(0.051)	(0.073)	(0.067)	(0.049)	(0.060)
Constant	0.153***	0.160***	0.217***	0.178***	0.190***	0.150***	0.138***	0.160***
	(0.040)	(0.036)	(0.033)	(0.025)	(0.035)	(0.034)	(0.024)	(0.031)
R2	0.134	0.214	0.335	0.261	0.238	0.190	0.172	0.191
Observations	105	110	119	155	170	169	170	172
Countries	105	110	119	155	170	169	170	172

Notes: The table presents the unconditional beta regression results of (B-1) analogous to Table 2, Panel A, column (1), for each four-year cycle separately.

B.3 Histograms and Kernel Densities

We plot the histograms and kernel densities of both win percentage and goal difference for each four-year cycle. The scale is the same for comparison. As the Figure B-2 and Figure B-3 show, the histograms mostly seem unimodal. Over time, they become taller and thinner, which is in accordance with our finding on σ-convergence. Note that the number of countries varies. For a complete distributional analysis with balanced samples of countries, see the main text.

Figure B-2: Histograms and Kernel Density Plots: Win Percentage per World Cup Cycle (varying numbers of countries)

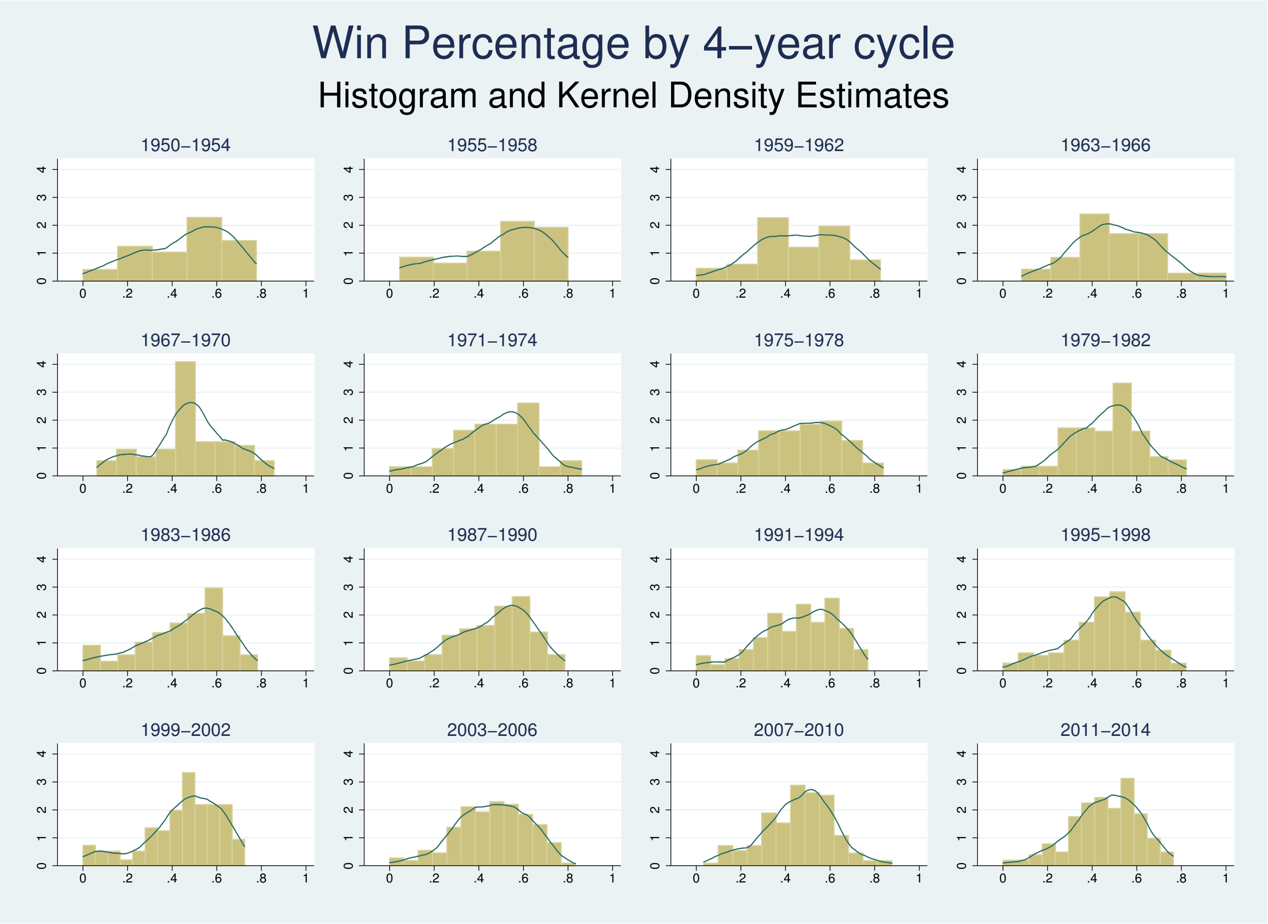
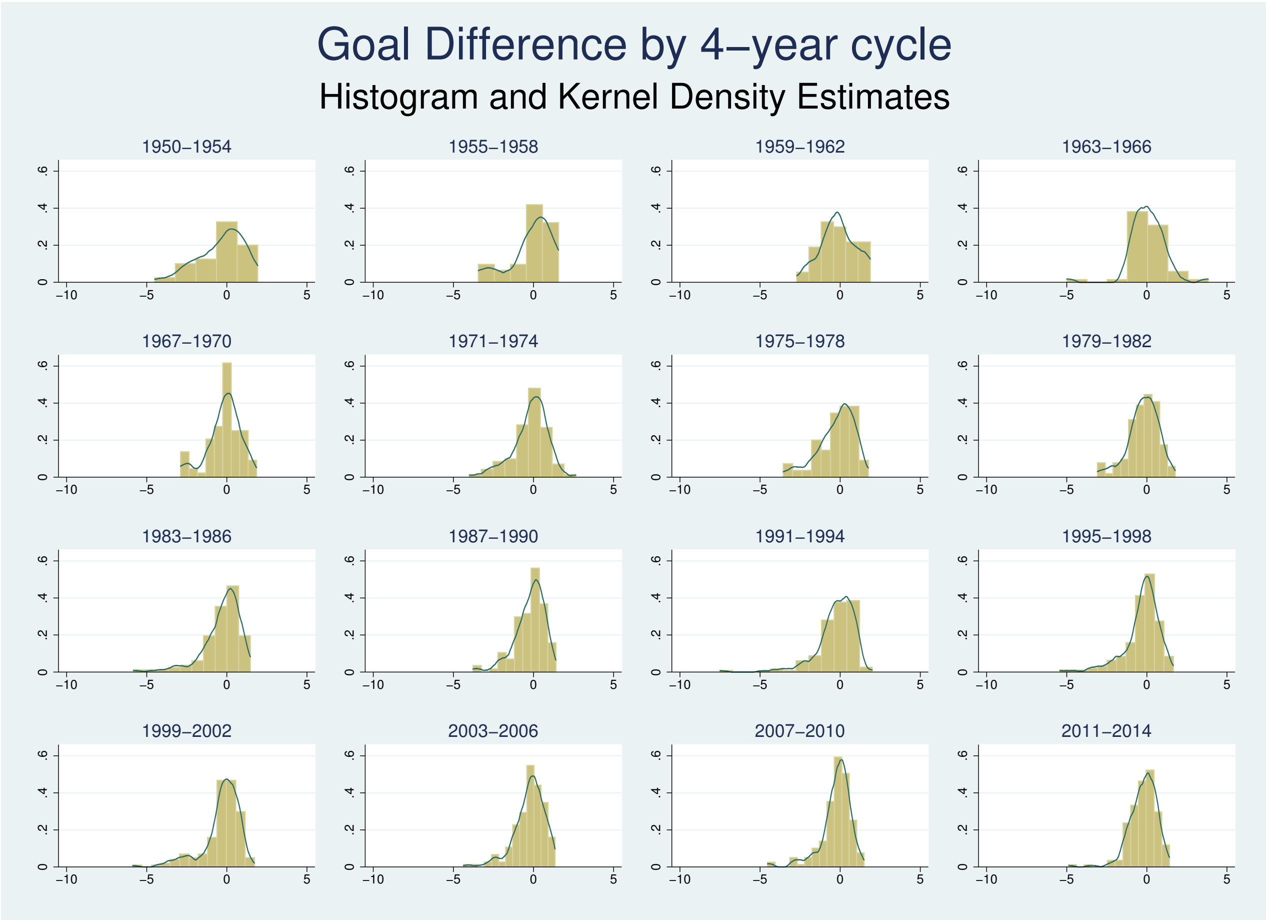


Figure B-3: Histograms and Kernel Density Plots: Goal Difference per World Cup Cycle (varying numbers of countries)



B.4 Distributional Analysis with Different Samples

Here we repeat the distributional analysis, which the main text conducted with Sample 1 (76 countries and 10 four-year cycles, 1975-2014). We consider the shorter Sample 2 (127 countries and 6 four-year cycles, 1990-2014) as well as an extended Sample 3 (Sample 1 including countries with less than 1m inhabitants, in total 86 countries).

Table B-8 and Table B-9 describe the evolution of the distribution of win percentages and goal differences for both samples according to various characteristics. While Sample 2 behaves very similarly to Sample 1 from the main text in terms of the reduction of standard deviation, skewness and kurtosis, we see that the higher moments remain high for Sample 3. The distribution including tiny countries remains relatively skewed and long-tailed so that the Jarque-Bera null hypothesis of Gaussianity is rejected. This is also visible in the kernel densities Figure B-4. Still, we have observed convergence across all countries, and also within Sample 3, there is a clear decrease in performance inequality in terms of the Gini coefficient (last column of Table B-9). Our conclusion is therefore that very small football nations face significant obstacles due to scarce resources in terms of population and wealth. This effect is, however, not strong enough to affect the overall result of worldwide convergence in performance.

Table B-8: Distribution of Points and Goal Difference Sample 2 (127 countries)

Panel a) Distribution of Win Percentage

	(1) Mean	(2) St.Dev.	(3) Skew	(4) Kurt	(5) JB pvalue	(6) Unimod pvalue	(7) CC Ind.	(8) Pola	(9) Gini
1991-94	0.4752	0.1668	-0.5967	2.9474	0.0280	0.1433	0.3313	0.1482	0.1963
1995-98	0.4858	0.1480	-0.4899	3.3679	0.0460	0.9567	0.1948	0.1071	0.1686
1999-02	0.4986	0.1356	-0.7987	3.5606	0.0062	0.3633	0.3473	0.1110	0.1498
2003-06	0.4959	0.1394	-0.2458	2.2911	0.0941	0.3667	0.3403	0.1328	0.1602
2007-10	0.5007	0.1310	0.0276	3.2144	0.5000	0.5067	0.2732	0.1073	0.1459
2011-14	0.5003	0.1301	-0.2388	2.5107	0.2149	0.5300	0.2967	0.1168	0.1474

Panel b) Distribution of Goal Differences

	(1) Mean	(2) St.Dev.	(3) Skew	(4) Kurt	(5) JB pvalue	(6) Unimod pvalue	(7) CC Ind.
1991-94	-0.1545	1.0823	-1.4467	6.0484	0.0010	0.3267	0.3006
1995-98	-0.0451	0.8217	-0.7569	3.8306	0.0057	0.2700	0.3563
1999-02	0.0427	0.7578	-1.0645	5.1369	0.0010	0.4567	0.2709
2003-06	-0.0177	0.7381	-0.5354	3.2609	0.0379	0.8633	0.2246
2007-10	0.0188	0.6426	-0.5112	3.6708	0.0255	0.7667	0.2219
2011-14	0.0020	0.6497	-0.1382	2.3739	0.2141	0.4900	0.2899

Notes: The analysis is based on a balanced sample of 127 countries (Sample 2) with more than 1m inhabitants throughout the sample period. Columns 1-4 report the distributional moments mean, standard deviation, skewness and kurtosis. Column 5 contains the p-values of the Jarque Bera test with the null hypothesis being the Gaussian distribution. Column 6 shows the p-values of Silverman's (1981) multimodality test with the null hypothesis being a unimodal distribution. Column 7 present the club convergence indicator by Krause (2017), Column 8 the bi-polarization index by Wolfson (1994) and Column 9 the Gini coefficient as a measure of inequality. Due to the presence of negative values in the goal differences, Wolfson's (1994) bi-polarization index and the Gini coefficient cannot be computed for this data.

Table B-9: Distribution of Points and Goal Difference Sample 3 (86 countries, including those with less than 1m inhabitants)

Panel a) Distribution of Win Percentage

	(1) Mean	(2) St.Dev.	(3) Skew	(4) Kurt	(5) JB pvalue	(6) Unimod pvalue	(7) CC Ind.	(8) Pola	(9) Gini
1975-78	0.4690	0.1888	-0.3993	2.7193	0.1802	0.7333	0.2848	0.1807	0.2260
1979-82	0.4856	0.1573	-0.4490	3.4461	0.0988	0.6300	0.2738	0.1263	0.1781
1983-86	0.5045	0.1537	-0.9286	3.6328	0.0082	0.8933	0.2383	0.1183	0.1651
1987-90	0.4970	0.1582	-0.6722	3.0560	0.0359	0.4567	0.3186	0.1321	0.1757
1991-94	0.5074	0.1443	-0.6202	2.9253	0.0473	0.3700	0.3535	0.1385	0.1584
1995-98	0.5159	0.1341	-0.4774	3.2503	0.1045	0.9733	0.2086	0.1059	0.1437
1999-02	0.5292	0.1160	-0.8369	4.7137	0.0033	0.1967	0.3952	0.1061	0.1199
2003-06	0.5253	0.1360	-0.7245	3.7247	0.0182	0.1300	0.4101	0.1232	0.1431
2007-10	0.5222	0.1356	-0.3753	3.7377	0.0839	0.9900	0.1797	0.1048	0.1422
2011-14	0.5272	0.1232	-0.5948	3.4196	0.0450	0.4667	0.3361	0.1020	0.1289

Panel b) Distribution of Goal Differences

	(1) Mean	(2) St.Dev.	(3) Skew	(4) Kurt	(5) JB pvalue	(6) Unimod pvalue	(7) CC Ind.
1975-78	-0.1622	1.1141	-0.9871	3.8775	0.0053	0.2033	0.4277
1979-82	-0.0947	0.9184	-0.7554	3.9015	0.0130	0.3000	0.3348
1983-86	0.0685	0.8227	-1.0952	4.9705	0.0011	0.6333	0.2617
1987-90	-0.0241	0.7702	-0.8152	3.5144	0.0147	0.4600	0.3250
1991-94	0.1020	0.7827	-0.9667	4.7886	0.0020	0.7833	0.2518
1995-98	0.1257	0.7142	-0.5727	3.7947	0.0317	0.9633	0.1934
1999-02	0.1973	0.6291	-0.7496	4.9710	0.0028	0.2033	0.3495
2003-06	0.1614	0.6953	-1.0305	5.2054	0.0010	0.8167	0.2348
2007-10	0.1124	0.6660	-0.7816	4.0398	0.0099	0.4967	0.2991
2011-14	0.1359	0.6138	-0.5612	3.6389	0.0415	0.5800	0.2843

Notes: The analysis is based on a balanced sample of 86 countries (Sample 3), which, in contrast to Sample 1 includes those with less than 1m inhabitants. See Table B-8 for more details.

Figure B-4: Densities of Win Percentage and Goal Differences in Various Years, Sample 3 (86 Countries)