Economics Bulletin

Volume 46, Issue 2

Wage dispersion and team performance: Lessons learned from major league soccer

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Abstract

Given the potential positive and negative relationship between wage dispersion and team performance signaled by economic theory, empirical analyses are crucial for furthering understanding of this relationship. I use Major League Soccer (MLS) as a case to study the relationship of wage dispersion with team performance, relying on 2007-2023 data. Across all estimations, I find a consistently significant negative relationship between wage dispersion and team performance, evidence lending support to the cohesiveness theory relating less wage dispersion, team harmony, and cohesion to increased productivity. Furthermore, I find the novel result that first-year expansion teams suffer a smaller negative effect from increased wage dispersion than teams that have existed for multiple years in MLS. My findings provide potential benefit in the specific context of team management in MLS (or sports more broadly), but perhaps more importantly, they also provide insight into the wider context of team management in labor markets outside the sports world. Understanding the factors that contribute to team performance is central to improving team productivity and any associated outcomes, so this research benefits the body of literature and researchers within labor economics but also has clear benefits and applicability for team management in general.

Funding: This work was supported by the University of North Georgia Mike Cottrell College of Business Summer 2024 Research Grant.
Citation: Michael Gove, (2026) "Wage dispersion and team performance: Lessons learned from major league soccer", *Economics Bulletin*, Volume 46, Issue 2, pages 461-473
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Submitted: February 10, 2025. **Published:** June 30, 2026.

1. Introduction

Researchers have studied the relationship between wage dispersion and team performance in professional sports since initial studies 25 years ago (see Sommers (1998), Richards and Guell (1998), Bloom (1999), and Depken (2000)), contributing to a literature of empirical anlayses with important implications for the areas of labor economics as well as business management. Economic theory points to the possibility of both a positive (Lazear & Rosen, 1981) and negative (Akerlof & Yellen, 1990, and Levine, 1991) relationship between wage dispersion and team performance. Wage dispersion may benefit a team if it incentivizes team members to put forth greater effort as a means to a higher payoff; however, dispersion could also harm team outcomes if it demoralizes team members, leading to lower productivity. These conflicting potential outcomes from economic theory result in the need for more empirical studies to further understanding.

I use Major League Soccer (MLS) as a case to study the relationship of wage dispersion with team performance. MLS, the professional soccer league spanning the United States and Canada, provides an especially useful environment for analyzing the connection between compensation and team performance, given the changes in salary structure of teams in the league in recent years (see Coates et al. (2016) for a discussion of why MLS is particularly useful in the study of labor market outcomes). In this paper, I estimate the contribution that wage dispersion makes to team performance in MLS, and subsequently develop counterfactual performance outcomes based on varying selected levels of wage dispersion. I find that wage dispersion is indeed statistically significant in affecting team performance, including the novel finding that first-year expansion teams suffer a smaller negative effect from increased wage dispersion than teams that have existed for multiple years in MLS.

My findings provide potential benefit in the specific context of team management in MLS (or sports more broadly), but perhaps more importantly, they also provide insight into the wider context of team management in labor markets outside the sports world. Understanding the factors that contribute to team performance is central to improving team productivity and any associated outcomes, so I see this study ultimately benefiting the body of literature and researchers within labor economics but also having clear benefits and applicability for team management in general.

2. Wage Dispersion and Soccer: Theory & Literature

Given the potential positive and negative relationship between wage dispersion and team performance signaled by economic theory, empirical analyses are crucial in furthering understanding. Two main theories shape much of the discussion in this literature. On the one hand, tournament theory (Lazear & Rosen, 1981) posits a positive relationship between dispersion and performance, one where greater dispersion incentivizes greater effort from team members, leading to increase productivity and performance. In contrast, cohesiveness theory (Akerlof & Yellen, 1988, Akerlof & Yellen, 1990, Levine, 1991) posits a negative relationship, focusing on how less salary dispersion leads to better harmony and cohesiveness within a team, ultimately resulting in increased productivity and performance. More recent theories also exist, including what is described as "congruence in resource and pay dispersion" in Hill et al. (2017). This theory posits that as there is more congruence between wage disparities and the dispersion of individual contributions, team members are more satisfied, leading to better individual and team performance.

Gove (2024) reviews the literature regarding the relationship between wage dispersion and team performance in professional sports, a commonly used "laboratory" by researchers highlighted by Kahn (2000) and Bar-Eli *et al.* (2020). The existing literature reflects a lack of consensus in the relationship between wage dispersion and team performance across studies examining professional sports, however within research focused specifically on soccer, studies generally find a significant negative effect of dispersion on team performance – arguably an expected result for a larger-team sport such as soccer, where eleven players play for a team at once, compared to a sport such as basketball, where only five players play for a team at once. Of the sports highlighted in Gove (2024), soccer stands out as the sport with the most variation in leagues studied and the most variation in measures of performance and wage dispersion. Research examining this relationship using data from Major League Soccer includes Sonntag & Sommers (2014), Coates *et al.* (2016), and Bykova & Coates (2020) – focusing on the periods of 2011-2012, 2005-2013, and 2005-2017, respectively.

3. Data, Results, and Discussion

I analyze publicly-available data for MLS salaries, available annually going back to 2007 through the MLS Players' Association. I focus on the reported "annual average guaranteed compensation" figures. According to the Players' Association, this includes "a player's base salary and all signing and guaranteed bonuses annualized over the term of the player's contract, including option years." Following the literature, I use points per game as the measure for team performance, obtained for all MLS teams from sports-reference.com.[1] In addition, I use two varied measures for capturing wage dispersion, the Gini coefficient and the coefficient of variation. The unbalanced sample consists of 344 observations, reflecting a sports league that has undergone considerable transformation during the sample period examined, expanding from 12 teams to the current 29. In Tables 1, 2, and 3 below I report mean performance and salary structure by year, mean performance and salary structure by team, and descriptive statistics of the relevant variables in the sample, respectively.

Table 1. Mean Performance and Salary Structure by Year

Year	Observations	PPG (ln)	Gini	Coeff. Var.	Rel. Wage*
2023	29	0.277	0.502	1.159	0.903
2022	28	0.299	0.507	1.167	0.925
2021	27	0.276	0.510	1.163	0.937
2020	26	0.288	0.498	1.105	0.972
2019	24	0.305	0.516	1.194	0.915
2018	23	0.292	0.521	1.212	0.849
2017	22	0.303	0.521	1.285	0.830
2016	20	0.280	0.521	1.306	0.743
2015	20	0.318	0.525	1.409	0.703
2014	18	0.297	0.500	1.327	0.710
2013	18	0.306	0.429	1.090	0.777
2012	18	0.310	0.455	1.123	0.681

[1] This measure is the prevailing measure used in the relevant literature examining wage dispersion and team performance in professional soccer (see, for example, Bykova & Coates (2020) or Coates *et al.* (2016)).

2011	17	0.267	0.434	1.079	0.693
2010	15	0.311	0.450	1.138	0.583
2009	14	0.267	0.477	1.314	0.834
2008	13	0.293	0.505	1.358	0.810
2007	12	0.264	0.501	1.344	0.748

*Yearly means of relative wage are 1, so median values are reported here.

Table 2. Mean Performance and Salary Structure by Team

Team	PPG (ln)	Gini	Coeff. Var.	Rel. Wage
ATL	0.380	0.521	1.179	1.115
AUS	0.182	0.519	1.184	0.987
CLT	0.223	0.463	1.058	0.783
CHI	0.188	0.559	1.628	1.071
CIN	-0.031	0.482	0.971	0.946
CLB	0.377	0.435	0.931	0.797
COL	0.214	0.430	0.930	0.716
DAL	0.357	0.429	0.965	0.738
DC	0.168	0.468	1.090	0.797
HOU	0.242	0.393	0.847	0.724
KC	0.370	0.437	0.911	0.802
LAFC	0.504	0.555	1.537	1.135
LA	0.343	0.701	2.187	2.100
MIA	0.143	0.638	1.841	1.410
MIN	0.278	0.425	0.902	0.777
MTL	0.246	0.496	1.212	0.795
NE	0.302	0.490	1.205	0.788
NSH	0.386	0.490	1.009	0.908
NYC	0.423	0.568	1.469	1.462
NYRB	0.379	0.571	1.542	1.420
ORL	0.268	0.558	1.644	1.039
PHI	0.333	0.435	0.910	0.697
POR	0.355	0.466	1.065	0.878
RSL	0.334	0.418	0.854	0.722
SEA	0.474	0.580	1.507	1.203
SJ	0.176	0.398	0.817	0.747
STL	0.501	0.557	1.171	0.664
TOR	0.117	0.628	1.691	1.743
VAN	0.245	0.463	1.064	0.804

Table 3. Descriptive Statistics of the Sample

Variable	Mean	Median	Std. Dev.	Min.	Max.
PPG (ln)	0.292	0.344	0.241	-0.755	0.765

Gini coefficient	0.496	0.473	0.123	0.236	0.813
Coefficient of variation	1.212	1.014	0.558	0.452	3.299
Relative wage	1	0.834	0.529	0.430	3.581
National	0.157	0.154	0.123	0	0.476
Expansion	0.046	0	0.209	0	1

Number of observations = 344.

I follow Coates *et al.* (2016) in estimating a model that considers the influence on team performance of wage dispersion. This approach allows for nonlinearities (given the included squared terms), also considering the influence of team quality (proxied by the relative team wage bill and the fraction of a team's players playing on their respective national teams) and a team's first year in the league (the expansion dummy variable)[2]. In addition, I allow for the possibility that wage dispersion's effect on team performance varies as teams become more established, including an interaction variable where wage dispersion and the expansion dummy interact. The model is as follows:

$$\ln(PPG)_{it} = \alpha_0 + \alpha_1 Disp_{it} + \alpha_2 Disp_{it}^2 + \alpha_3 RelWage_{it} + \alpha_4 RelWage_{it}^2 + \alpha_5 Nat_{it} + \alpha_6 Exp_{it} + \alpha_7 Disp_{it}\, Exp_{it} + \varepsilon_{it}\ ,$$

where the dependent variable is the natural log of points per game for team *i* in year *t*; independent variables include a measure of wage dispersion and of relative wages, both of which enter the equation linearly and squared, the percentage of a team's players who also play on their respective national teams for at least one game during a given year, a dummy variable for expansion teams playing in their first year in MLS, and the previously mentioned interaction variable. Following the literature, I conduct estimations using two different measures to proxy wage dispersion – a team Gini coefficient and a team coefficient of variation. The relative wage measure equals the total wage bill of team *i* in year *t* divided by the average team wage bill in the league in year t. Estimations include a full set of team and year fixed effects. While the expected direction of effects on the wage dispersion variables represent the principal effect under investigation, other independent variables have the following expected effects:

(1) relative wage – positive, as this is a measure of team quality,
(2) national – positive, as this is another measure of team quality; however, it is also the case that when club players report for national team duty, they may miss a certain number of club games, leading to some detrimental effect on team performance, and
(3) expansion team – negative, as more established teams/players often have an experience advantage.

Table 4 reports the main results of the estimations, (1) with the team Gini coefficient as the wage dispersion measure and (2) with the team coefficient of variation as the wage dispersion measure.

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[2] A topic investigated to a certain extent in the literature, the "newness" of an expansion team could potentially spill over to more than one year. For purposes of this study, I conducted estimations varying the definition of expansion team to include more than just the first year in exploring when an expansion team becomes "established." Full treatment of this topic, along with the related question of how the wage dispersion-franchise age interaction evolves with franchise age, is presented in Appendix A.

Table 4. Results of Model Estimations

Variable	(1)	(2)
Gini coefficient	-2.867 (0.993)***$^{+++}$	
Gini coefficient squared	2.622 (1.025)**	
Coefficient of variation		-0.278 (0.132)**$^{++}$
Coefficient of variation squared		0.057 (0.039)
Relative wage	0.036 (0.162)	0.162 (0.153)
Relative wage squared	-0.006 (0.036)	-0.014 (0.036)
National	0.588 (0.169)***	0.547 (0.180)***
Expansion	-0.312 (0.180)*	-0.277 (0.108)**
Interaction variable	0.264 (0.147)*	0.210 (0.082)**
Constant	1.131 (0.301)***	0.494 (0.175)***
R^2	0.265	0.253
Observations	344	344

Dependent variable is ln(PPG). Models include year and team dummies, and robust standard errors are in parentheses. The interaction variable is the interaction of the expansion dummy variable with the corresponding measure of wage dispersion. *Coefficient significant at 10% level, **coefficient significant at 5% level, and ***coefficient significant at 1% level. $^{++}$Linear and squared terms jointly significant 5% level, and $^{+++}$linear and squared terms jointly significant 1% level.

Both estimations (1) and (2) give evidence of a significant negative relationship between wage dispersion and team performance in MLS. Gini coefficient linear and squared terms are both significant at the 1% level, respectively; the coefficient of variation linear term is significant at the 5% level. Both wage dispersion measures' linear and squared terms are jointly significant. These results give more support overall for cohesiveness theory, rather than tournament theory, in explaining the effect of wage dispersion on a team in Major League Soccer. However, interestingly, given the interaction variable estimate, there is some evidence that wage dispersion's effect on team performance varies depending on how long a team has been in MLS. While the estimation results do not reflect a clear pattern in which wage dispersion's effect on team performance varies systematically as a team has more years since being established, the interaction variable's estimate does point to first-year expansion teams specifically suffering a smaller negative effect from increased wage dispersion than teams that have existed for multiple years in MLS. In addition, as expected, a team's performance is negatively associated with being an expansion team and participating for the first year in the league. Furthermore, the two measures of team quality have the expected positive coefficient estimates. While relative wages have the expected positive association with a team's performance, it is unexpected that the relative wages variable's coefficient is quite small and insignificant in both estimations. Finally, the fraction of a team's players playing on their respective national teams in a given year has a significant positive relationship with team performance.[3]

[3] While it is reasonable to expect that some wages are paid to players in part because of their particular marketing appeal and potential for driving higher team revenues, there are multiple other factors in addition to on-field team performance that also affect revenues (front office management, market size, etc.). In this paper I do not attempt to separate wages for an individual player as corresponding to either marketing appeal

Table 5. Team Performance with Varied Wage Dispersion						
Gini Coefficient Percentile	Relative Wage & National Team Percentile	Predicted ln PPG	Predicted PPG	PPG Percentile	2023 Table Rank (Western Conference)	2023 Table Rank (Eastern Conference)
Non-expansion team:						
25th	50th	0.516	1.68	85th	1st	3rd
50th	50th	0.482	1.62	79th	2nd	4th
75th	50th	0.467	1.60	77th	2nd	6th
Expansion team:						
25th	50th	0.276	1.32	40th	8th	8th
50th	50th	0.265	1.30	39th	8th	8th
75th	50th	0.264	1.30	39th	8th	8th

Putting into context the effect of a team's potential change in wage dispersion, the difference in associated team performance is clear. Assuming a median relative wage and national team fraction for a non-expansion team, a decrease in wage dispersion from the median to the 25th percentile of observed team Gini coefficients would result in an increase from 1.62 to 1.68 points per game, an improvement from the 79th to the 85th percentile of observed points per game, respectively. Assuming the same median relative wage and national team fraction for an expansion team, a similar decrease in wage dispersion from the median to the 25th percentile of observed team Gini coefficients would result in an increase from 1.30 to 1.32 points per game, an improvement from the 39th the 40th percentile of observed points per game, respectively. Table 5 highlights these results, along with the hypothetical scenarios of a non-expansion (expansion) team with a median relative wage and national team fraction moving from a median wage dispersion to a higher level of inequality at the 75th percentile of observed Gini team coefficients. For perspective, columns 6 and 7 of Table 5 show how the points per game change would have changed the team's final standing in the 2023 table for each MLS conference.

4. Conclusion

Examining 2007-2023 data, I find evidence from Major League Soccer that gives more support overall to cohesiveness theory, that is, a negative relationship between wage dispersion and team performance. This inverse relationship is consistently significant across the estimations performed. Furthermore, I also find a novel result associated with wage dispersion – the estimation evidence points to first-year expansion teams suffering a smaller negative effect from wage dispersion than those teams that are more established in MLS. While more work is needed across a variety of professional sports, these findings contribute to both labor economics and team management in general. Potential for further work examining this relationship between wage dispersion and team performance includes further work on this novel result, evaluating alternative measures to PPG for "team success" that incorporates playoff performance, and considering whether the matching of wage dispersion measures with the relevant economic theory could be improved.

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or actual on-field performance, however I do examine the possibility that dispersion effects are driven by a small number of extreme earners (generally with high marketing appeal) in Appendix B with robustness tests.

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Appendix A

Expansion teams often perform more poorly before becoming a more established team within a respective professional sports league, with a wide variety of factors such as roster limitations (affecting player quality), a lack of team cohesion, and a lack of organizational maturity (front office, coaching staff, facilities, team culture, etc.) contributing to this difficulty. However, the question of at what point exactly the franchise becomes "established" is an important one. Here, I explain the process that I used for exploring this question, and how I arrived at the "one-year" definition of an expansion team used in the estimations highlighted above.

In exploring this question, I employed two sets of estimations. First, I sequentially added dummy variables beyond the first-year dummy variable for a franchise's second, third, fourth, and fifth years, respectively. If a franchise faces difficulty associated with the newness of the franchise beyond the first year, this difficulty should show up as significant coefficients estimated for any of these independent variables added to the estimation equation. I highlight results of this set of estimations below in Table A1. Estimations are conducted (1) excluding the interaction variable (Panel A) and (2) including a continuous wage dispersion-franchise age interaction variable (Panel B), as specifying the interaction variable also potentially depends on the outcome of these tests related to the expansion variable (see discussion related to Table A3 below).

Table A1. Results of Model Estimations – Testing First Five Years

Panel A: Excluding interaction independent variable

Variable	(1)	(2)	(3)	(4)	(5)
Gini coefficient	-2.826***$^{+++}$	-2.846***$^{+++}$	-2.822***$^{+++}$	-2.790***$^{+++}$	-2.817***$^{+++}$
	(0.984)	(0.989)	(0.997)	(0.998)	(1.018)
(Gini coefficient)^2	2.602**	2.631**	2.589**	2.549**	2.586**
	(1.022)	(1.027)	(1.040)	(1.033)	(1.055)
Relative wage	0.038	0.027	0.046	0.053	0.043
	(0.161)	(0.161)	(0.161)	(0.160)	(0.163)
(Relative wage)^2	-0.006	-0.004	-0.008	-0.010	-0.008
	(0.036)	(0.035)	(0.035)	(0.035)	(0.036)
National	0.594***	0.613***	0.600***	0.593***	0.595***
	(0.168)	(0.173)	(0.173)	(0.171)	(0.172)
Year 1 dummy	-0.180***	-0.169***	-0.186***	-0.194***	-0.185***
	(0.057)	(0.059)	(0.063)	(0.064)	(0.065)
Year 2 dummy		0.040	0.024	0.016	0.025
		(0.061)	(0.063)	(0.064)	(0.065)
Year 3 dummy			-0.060	-0.067	-0.059
			(0.073)	(0.074)	(0.075)
Year 4 dummy				-0.027	-0.018
				(0.069)	(0.069)
Year 5 dummy					0.034
					(0.066)
Constant	1.112***	1.111***	1.119***	1.117***	1.116***
	(0.296)	(0.295)	(0.300)	(0.299)	(0.301)

R^2	0.264	0.265	0.267	0.268	0.268
Observations	344	344	344	344	344

Panel B: Including continuous interaction independent variable

Variable	(1)	(2)	(3)	(4)	(5)
Gini coefficient	-2.906***$^{+++}$ (1.088)	-2.932***$^{+++}$ (1.094)	-2.916***$^{+++}$ (1.103)	-2.890***$^{+++}$ (1.105)	-2.908***$^{+++}$ (1.126)
(Gini coefficient)^2	2.634** (1.056)	2.666** (1.062)	2.626** (1.070)	2.588** (1.069)	2.621** (1.091)
Relative wage	0.037 (0.161)	0.026 (0.162)	0.045 (0.161)	0.052 (0.160)	0.042 (0.164)
(Relative wage)^2	-0.006 (0.035)	-0.004 (0.035)	-0.008 (0.036)	-0.010 (0.036)	-0.008 (0.036)
National	0.594*** (0.168)	0.613*** (0.173)	0.600*** (0.173)	0.593*** (0.171)	0.595*** (0.172)
Year 1 dummy	-0.181*** (0.058)	-0.170*** (0.060)	-0.188*** (0.063)	-0.196*** (0.065)	-0.186*** (0.065)
Year 2 dummy		0.040 (0.061)	0.024 (0.063)	0.016 (0.064)	0.025 (0.065)
Year 3 dummy			-0.060 (0.073)	-0.068 (0.074)	-0.059 (0.075)
Year 4 dummy				-0.027 (0.069)	-0.019 (0.069)
Year 5 dummy					0.033 (0.066)
Interaction variable	0.004 (0.018)	0.004 (0.018)	0.005 (0.018)	0.005 (0.018)	0.005 (0.018)
Constant	1.163*** (0.389)	1.165*** (0.389)	1.179*** (0.393)	1.182*** (0.392)	1.117*** (0.394)
R^2	0.264	0.265	0.268	0.268	0.269
Observations	344	344	344	344	344

Dependent variable is ln(PPG). Models include year and team dummies, and robust standard errors are in parentheses. The interaction variable is the continuous interaction of the Gini coefficient with a team's years in existence. **Coefficient significant at 5% level, and ***coefficient significant at 1% level. $^{+++}$Linear and squared terms jointly significant at 1% level.

Highlighted in columns (1)-(5), only the dummy variable for a franchise's first year demonstrates significance of the five dummy variables included, consistently showing high statistical significance across all estimations (while excluding and including the interaction variable).

Second, I expanded the "definition" of an expansion team to sequentially include additional years beyond just one year. In the estimation results presented in table A2 below, "Expansion" is defined differently for franchises in each column: only for one year in column (1), for the first two years in column (2), for the first three years in column (3), for the first four years in column (4), and for the first five years in column (5). This again allows for testing if the difficulty associated with the newness of the franchise lasts for a certain amount of time beyond just one year. As in Table A1, results are reported in Panel A for estimations excluding the interaction variable, while results in Panel B are for estimations including the continuous interaction variable as an independent variable.

Table A2. Results of Model Estimations – Testing Expansion Definition

Panel A: Excluding interaction independent variable					
Variable	(1)	(2)	(3)	(4)	(5)
Gini	-2.826***$^{+++}$	-2.524**$^{+++}$	-2.489**$^{+++}$	-2.310**$^{+++}$	-2.428**$^{+++}$
coefficient	(0.984)	(1.002)	(1.014)	(1.014)	(1.020)
(Gini	2.602**	2.288**	2.235**	2.149**	2.183**
coefficient)^2	(1.022)	(1.040)	(1.054)	(1.049)	(1.056)
Relative wage	0.038	0.056	0.075	0.079	0.062
	(0.161)	(0.161)	(0.160)	(0.158)	(0.163)
(Relative	-0.006	-0.008	-0.012	-0.013	-0.009
wage)^2	(0.036)	(0.035)	(0.035)	(0.035)	(0.036)
National	0.594***	0.597***	0.586***	0.587***	0.614***
	(0.168)	(0.172)	(0.170)	(0.168)	(0.171)
Expansion	-0.180***	-0.055	-0.066	-0.059	-0.027
	(0.057)	(0.053)	(0.051)	(0.048)	(0.042)
Constant	1.112***	1.009***	1.013***	0.997***	0.984***
	(0.296)	(0.295)	(0.300)	(0.296)	(0.294)
R^2	0.264	0.248	0.250	0.249	0.246
Observations	344	344	344	344	344
Panel B: Including continuous interaction independent variable					
Variable	(1)	(2)	(3)	(4)	(5)
Gini	-2.906***$^{+++}$	-2.539**$^{+++}$	-2.512**$^{+++}$	-2.443**$^{+++}$	-2.450**$^{+++}$
coefficient	(1.088)	(1.104)	(1.116)	(1.120)	(1.125)
(Gini	2.634**	2.294**	2.244**	2.161**	2.191**
coefficient)^2	(1.056)	(1.069)	(1.083)	(1.080)	(1.087)
Relative wage	0.037	0.056	0.075	0.079	0.062
	(0.161)	(0.161)	(0.161)	(0.158)	(0.163)
(Relative	-0.006	-0.008	-0.012	-0.013	-0.009
wage)^2	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)
National	0.594***	0.597***	0.586***	0.587***	0.614***
	(0.168)	(0.172)	(0.170)	(0.168)	(0.172)
Expansion	-0.181***	-0.055	-0.066	-0.059	-0.027
	(0.058)	(0.053)	(0.051)	(0.048)	(0.041)
Interaction	0.004	0.001	0.001	0.002	0.001
variable	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Constant	1.163***	1.019***	1.029***	1.018***	0.999***
	(0.389)	(0.392)	(0.396)	(0.394)	(0.393)
R^2	0.264	0.248	0.250	0.250	0.246
Observations	344	344	344	344	344

Dependent variable is ln(PPG). Models include year and team dummies, and robust standard errors are in parentheses. The interaction variable is the continuous interaction of the Gini coefficient with a team's years in existence. **Coefficient significant at 5% level, and

***coefficient significant at 1% level. $^{+++}$Linear and squared terms jointly significant at 1% level.

Only the coefficient associated with the one-year definition for an expansion team in Column (1) demonstrates high statistical significance (both while excluding and including the interaction variable). These results point in the same direction as the results of the testing in Table A1, allowing me to settle on defining expansion as only one year as a meaningful definition for the main results presented above in this paper.

Having established a meaningful definition of the expansion variable, I now move on to the separate but related topic of the wage dispersion-franchise age interaction variable. If the age of a franchise is important for how wage dispersion affects team performance, it could be that the relationship is continuous, however the results in the bottom half of Table A1 actually already confirm a lack of significance for this continuous interaction variable. For ease of comparison, I report these results in Column (1) of Table A3, highlighting the lack of statistical significance for this continuous interaction variable.

Table A3. Results of Model Estimations – Testing Interaction Variable

Variable	(1)	(2)
Gini coefficient	-2.906 (1.088)***$^{+++}$	-2.867 (0.993)***$^{+++}$
Gini coefficient squared	2.634 (1.056)**	2.622 (1.025)**
Relative wage	0.037 (0.161)	0.036 (0.162)
Relative wage squared	-0.006 (0.035)	-0.006 (0.036)
National	0.594 (0.168)***	0.588 (0.169)***
Expansion	-0.181 (0.058)***	-0.312 (0.180)*
Interaction variable	0.004 (0.176)	0.264 (0.147)*
Constant	1.163 (0.389)***	1.131 (0.301)***
R^2	0.264	0.265
Observations	344	344

Dependent variable is ln(PPG). Models include year and team dummies, and robust standard errors are in parentheses. In Column (1), the interaction variable is the continuous interaction of the Gini coefficient with a team's years in existence; in Column (2), the interaction variable is the interaction of the Gini coefficient with the expansion dummy variable. *Coefficient significant at 10% level, **coefficient significant at 5% level, and ***coefficient significant at 1% level. $^{+++}$Linear and squared terms jointly significant at 1% level.

Even given the lack of statistical significance for the continuous interaction variable, it could still be that an expansion team handles wage dispersion differently than non-expansion teams, ultimately resulting in different effects of wage dispersion on these two groups' team performance. The Column (2) estimation results in Table A3 employ an interaction variable capturing the interaction of the Gini coefficient with the one-year expansion dummy variable. Given the statistical significance of the Column (2) results, I include the dispersion-expansion measure as the appropriate interaction variable in the main results presented above.

Appendix B

Wage dispersion on a given MLS team reflects differences in individuals' on-field performance, however it is also possible that wage dispersion at least partially reflects individuals' marketability, likely particularly true with superstar signings. Therefore, I employ a simple measure of salary concentration amongst teams that allows for testing my initial results for robustness while excluding a given number of extreme cases. I calculate the individual salary share as $share = \frac{individual\ salary}{team\ wage\ bill}$, then use this statistic and three distinct thresholds to exclude outlier observations for the robustness checks.

Table B1. Results of Model Estimations – Checks for Robustness

Variable	(1)	(2)	(3)
Gini coefficient	-3.382 (1.034)***$^{+++}$	-3.171 (1.057)***$^{+++}$	-3.458 (1.053)***$^{+++}$
Gini coefficient squared	3.191 (1.069)***	2.961 (1.103)***	3.212 (1.107)***
Relative wage	-0.030 (0.162)	0.004 (0.164)	0.066 (0.167)
Relative wage squared	0.010 (0.036)	-0.002 (0.036)	-0.018 (0.036)
National	0.570 (0.171)***	0.571 (0.171)***	0.625 (0.180)***
Expansion	-0.350 (0.203)*	-0.337 (0.196)*	-0.341 (0.199)*
Interaction variable	0.303 (0.172)*	0.277 (0.160)*	0.289 (0.168)*
Constant	1.321 (0.311)***	1.244 (0.318)***	1.283 (0.319)***
R^2	0.283	0.290	0.294
Observations	339	328	314

Dependent variable is ln(PPG). Models include year and team dummies, and robust standard errors are in parentheses. The interaction variable is the interaction of the expansion dummy variable with the corresponding measure of wage dispersion. *Coefficient significant at 10% level, **coefficient significant at 5% level, and ***coefficient significant at 1% level. $^{++}$Linear and squared terms jointly significant 5% level, and $^{+++}$linear and squared terms jointly significant 1% level.

Table B1 displays the estimation results, excluding outlier observations by tiers of the $share$ measure. Column (1) results from an estimation excluding those observations where a team has a player with $share > 0.6$, resulting in the exclusion of five observations. Column (2) displays results where observations with a team player with $share > 0.5$ were excluded (sixteen observations), while Column (3) displays results where observations with a team player with $share > 0.4$ were excluded (thirty observations). I list the team, year, individual player, and salary share for the excluded observations in each tier, respectively, in Table B2. Not surprisingly, this list includes a handful of the players that have been arguably the most "marketable" in MLS across the league but also in particular teams' regional markets, including David Beckham, Kaká, and Cuauhtémoc Blanco, and more recently, Carlos Vela and Lionel Messi.

Overall, compared to initial results in Table 4, there is slight variation in the size of estimates but the direction and significance of the estimated coefficients is fairly consistent across the multiple robustness checks. Excluding outlier observations makes the largest impact on the size of the estimates for the wage dispersion variables, while the national players, expansion, and interaction variable estimates are also slightly affected. Of the excluded observations, only two correspond to teams in their first year of expansion – Orlando FC in 2015 and Seattle Sounders in 2009. While this check for robustness does not fully resolve the question of whether wage dispersion is associated with on-field performance, individual marketability, or both, these consistent results do indicate that they do not suffer from particularly high sensitivity to excluding the extreme cases of superstar signings measured by the $share$ statistic.

Table B2. Excluded Observations – Checks for Robustness

Team	Year	Player with max. salary	Salary Share
Salary Share > 0.6:			
Los Angeles Galaxy	2007	David Beckham	0.641
Los Angeles Galaxy	2008	David Beckham	0.687
Los Angeles Galaxy	2009	David Beckham	0.675
Orlando FC	2015	Kaká	0.640
Orlando FC	2016	Kaká	0.647
0.6 ≥ Salary Share > 0.5:			
Chicago Fire	2007	Cuauhtémoc Blanco	0.588
Chicago Fire	2008	Cuauhtémoc Blanco	0.599
Chicago Fire	2009	Cuauhtémoc Blanco	0.595
Los Angeles Galaxy	2010	David Beckham	0.581
Los Angeles Galaxy	2011	David Beckham	0.519
New England Revolution	2014	Jermaine Jones	0.556
New England Revolution	2015	Jermaine Jones	0.507
New York Red Bulls	2009	Juan Pablo Ángel	0.518
Orlando City SC	2017	Kaká	0.524
Seattle Sounders	2013	Clint Dempsey	0.554
Seattle Sounders	2014	Clint Dempsey	0.556
0.5 ≥ Salary Share > 0.4:			
Chicago Fire	2017	Bastian Schweinsteiger	0.490
Chicago Fire	2018	Bastian Schweinsteiger	0.468
Chicago Fire	2022	Xherdan Shaqiri	0.414
Chicago Fire	2023	Xherdan Shaqiri	0.446
DC United	2019	Wayne Rooney	0.408
FC Dallas	2012	Julian de Guzmán	0.410
Inter Miami FC	2023	Lionel Messi	0.445
Los Angeles FC	2019	Carlos Vela	0.409
Los Angeles FC	2020	Carlos Vela	0.417
Los Angeles Galaxy	2013	Robbie Keane	0.442
New York City FC	2018	David Villa	0.426
New York Red Bulls	2008	Juan Pablo Ángel	0.481
Seattle Sounders	2009	Freddie Ljungberg	0.429
Toronto FC	2022	Lorenzo Insigne	0.446