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Drivers' moves in Formula One Economics: A network analysis since 2000

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ABSTRACT

This paper explored the potentiality of social networks analysis to discuss the industrial organization of Formula One since the 2000 season. We tested three major hypotheses related to the centrality of championship teams, their selectiveness when observing drivers' moves, and the role of certain explicative attributes. There are oligopolistic elements in Formula One, with champions adopting high values of betweenness centrality, sending and receiving drivers from some other teams and opting to exchange drivers and resources from other teams with not-so-competitive scuderias. Formula One teams that win the Constructors' Championship tend to assume central roles in the network of drivers' moves. Despite their centrality, these winning teams are very selective regarding the origin of the drivers they want to contract. There are more chances of contractual ties between teams which are not significantly close in terms of ranks or budgets.

KEYWORDS

Motorsports; Transfers; Network Analysis; Industrial Organization

1. INTRODUCTION

Until now, most studies using a statistical approach to analyze F1-related topics focused on variables constructed upon the observation of F1's agents (e.g., teams, investors, drivers, fans/supporters). In this paper, we focus our attention on drivers' moves among Formula One teams since 2000. We observed how these moves created a dense network of relationships that can be studied as a reflex of the heterogeneous power detained by each "scuderia" (team) in the Formula One industry. Besides this opportunity, we discussed here how the observed network can be a powerful determinant of the dynamics observed in this motorsport. This is a pioneering research in the scientific fields of sports economics, sports management, social networks analysis, and F1 studies.

For an overall insight of these dimensions, we suggest the works of Pflugfelder (2009); Cabral (2012); Mourao (2017). However, the contribution of social networks analysis has been missing so far. As we demonstrate, social network analysis enriched common statistical procedures with a complimentary insight in which actors (i.e., F1 teams) have connections, and these connections interfere in the entire group's dynamics (Hanneman & Riddle, 2005; Giuffre, 2013). The study of these linkages allows us to characterize the network of Formula One teams in several dimensions only able to be highlighted by Social Networks Analysis (SNA). As it will be detailed in next sections, there are three major potentialities derived from this contribution. First, the study of relations clarifies in a better way the likely path of the players (in this case, F1 drivers and teams). As it is usually pointed for SNA, we have to carefully analyze the links between the players for designing their evolution. Second, understanding the own characteristics of the network (by recurring to measures like the centrality or connectiveness indicators) will provide insights able to identify the oligopolistic forces operating on stage (Gilbert et al, 2018). Finally, the study of SNA will allow us to identify the relevance of each team's place on the industry's structure which is essential for discussing the own sustainability of this sporting industry (Budzinski & Muller-Kock, 2017).

Confirming whether the top-ranked teams also have central places is relevant for assessing the structure of oligopoly in the network (Marriotti & Haider, 2017). Various works have proven how sports supported by oligopolistic structures have to consider additional challenges – the financial difficulties of low-ranked teams, the race to indebtedness by the most competitive teams/firms, and the flows of resources from the top-ranked teams to the low-ranked ones (Jenkins, 2002).

We explore social network analysis to test three major hypotheses: Champion teams preserve competitive drivers; champion teams are highly selective in terms of receiving drivers from other F1 teams; and dominant teams create hierarchical structures in which they move drivers to low-ranked teams more likely than moving to other same-ranked teams. The test of these three hypotheses will enhance us to reply to three major motivations: to characterize the centrality and the density of Formula One's networks, to discuss the dependence of different teams' roles and to observe the dynamic pattern of the relations/ties between F1 teams.

Let us clarify these hypotheses. We consider as 'champion teams' those F1 teams already having won a F1 Constructor Championship (considering the observed sample). Their list, for the observed seasons of 2000-2017, is composed by Ferrari (champions at 2000-2004 and 2007-2008), Renault (champions at 2005-2006), Brawn Mercedes (champions at 2009), Red Bull Renault (2010-2013), and Mercedes (2014-2017).

'Competitive driver' is a driver who has at least finished in the top-3 positions of a World Driver Championship of F1. Their list is easily available on official sources and so we skip it for avoiding an unnecessary extension of this paper. 'Dominant team' is a constructor already ranked in the top-3 of the World Championship of Constructors (being the remaining teams classified as 'low-ranked' ones in this work).

The remainder of this paper is structured as follows. Section 2 reviews the literature on sports economics, especially motorsports economics. It also illustrates the strengths of social network analysis to deepen certain methodological purposes for a more robust discussion regarding the industrial organization of this sport, which tends to be considered the most-expensive motorsport in the world. Section 3 provides an empirical section in which our three major hypotheses will be tested according to specific methodological domains of social networks analysis (centrality analysis, P1 models, and exponential random graph models). Section 4 discusses the implications of the results we achieved and concludes the paper.

2. LITERATURE REVIEW

2.1. Network Analysis and Professional Sports

2.1.1. Network analysis and interest in sports transfers

Previous works (Szymanski, 2013; Mourao, 2016) explained values and flows of transfers of clubs considering clubs' dimensions. Following Fialho et al. (2018), groups of individual actors/nodes are created within the network and by the network itself. Groups of players interfering in the transfers' universe are created within a globalized network, and it becomes essential to study those micro-organizations as well as the involved network.

Sports transfers are therefore the result of the action of complex communities. There are three main reasons for this occurring (Budzinski et al, 2021; Judde et al, 2013).

i) Each actor/node is simultaneously a rival/competitor and a collaborator of other agents. For instance, a dense network is usually associated with a community of similar people with significant cohesion. In sports – especially in sports transfers – a dense network may reveal a dynamic process in which rival actors may/must interact because they need to do so to achieve exclusive goals.

ii) The reality of sports transfers provides studies of network analysis with a promising field which has not been well-investigated so far.

iii) Sports transfers are important for sports sustainability (Mourao, 2016). Although it seems almost unbelievable, current research has not focused the potentialities of network analysis for sports sustainability in a robust way, having in mind that the industry's sustainability depends upon the entire network of agents operating in Formula One.

2.1.2. Hypotheses

Recalling the literature on network analysis, specifically Mariotti and Haider (2017), we can no longer neglect the advantages provided by network analysis for a deeper effort regarding identifying the position of each team regarding drivers' moves toward a higher chance of winning a championship. Additionally, and following Mourao (2017), we want to observe the selectivity of these paths, testing the claim that certain teams make the moving their drivers to other teams easier. Finally, we want to observe if certain teams' characteristics enhance the creation of ties with other teams in terms of drivers' moves (or if these characteristics make these ties more difficult). We are particularly thinking of budgets, points in constructors' championship or centrality positions (Cabral et al., 2012; Mourao, 2017). Therefore, we want to test three major hypotheses:

1. Hypothesis 1): Champion teams preserve champion/competitive drivers (Cohen & Kleiner, 2004; Tavani & Vasudevan, 2014), and so these teams do not have a high rotation of drivers.
2. Hypothesis 2): Champion teams are highly selective in terms of receiving drivers from other Formula One teams (Zimmermann, 2010; Lapre & Cravey, 2022).
3. Hypothesis 3: Dominant teams create hierarchical structures in which they move drivers to low-ranked teams easier than to other same-ranked teams to keep themselves (the Dominant teams) competitive (Gilbert et al., 2018; Storm et al, 2019).

3. Empirical Section

Three applications of social networks analysis in the world of Formula One for testing our three hypotheses:

3.1. Different centralities in a world of many centers

Considering official data from F1 records (Formula One, 2018), we collected all drivers' moves among F1 teams since 2000. We covered the first 18 seasons after the included 2000's one for three major reasons. First, several works (Mourao, 2017; Olsen, 2004) have proven these seasons characterized as the most expensive seasons in Formula One History; therefore, the study of these seasons will enlighten us about the income effect on these networks' dynamics. Second, these 18 seasons have observed the collapse of seven teams (Arrows, Caterham/Team Lotus, Jaguar, Prost Grand Prix, Super Agury and Toyota Racing) whose rate (collapsing teams per season) prove the difficulties of surviving in Formula One and the difficulties of maintaining sustained ties in this industry. Third, after 2000, authors like Mourao (2017) have found decreasing values for drivers' and teams' concentration of points (which can be read as a positive trend of competitive balance); therefore, although the financial difficulties faced by many teams, the competitive balance of Formula One has increased since 2000 which put additional strategic pressures for drivers' flows (Varotti et al, 2020).

We constructed Figure 1 which highlights the moves of F1 drivers among the observed 24 teams that raced during the period 2000 to 2017 (without the "Out/retirement" node).

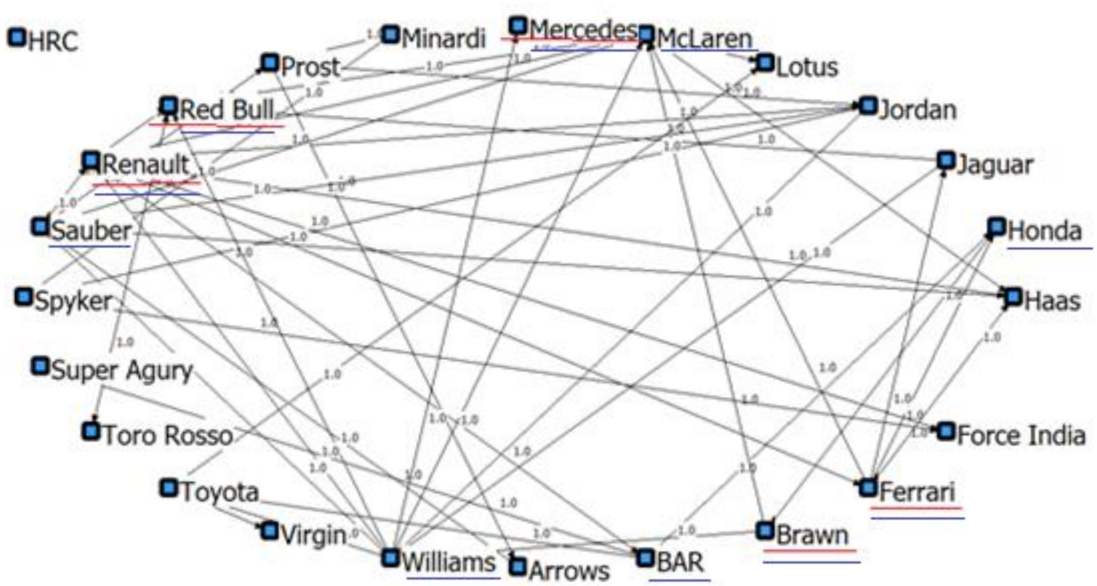

Figure 1. Number of drivers' moves between F1 teams (2000-2017), excluding situations out of competition. *Note: Underlined on red, Champion teams. Underlined on blue, Dominant teams.*

From Figure 1, we can check how most teams only exchanged one, or in rare cases, two drivers with a few other teams in the observed period. As a consequence, different indicators of social network analysis (which have the function for the traditional descriptive statistics in quantitative works) exhibit a heterogeneous distribution of the values attributed to these teams.

There are several indicators for assessing this descriptive purpose of a network. For an overall perspective of these measures, we suggest some worldwide disseminated references like Hanneman and Riddle (2005) or Giuffre (2013). In this paper, we will focus on the most widely used: “In degree”, “Out degree”, “In ARD”, “Out ARD”, “Out closeness”, “In closeness”, and “Betweeness”.

“Out degree” measures the number of ties initiated at each team and the “in degree” values the number of ties going to each team in the observed network. Following Valente et al. (2008), actors who have more ties have greater opportunities to establish ties and control flows. According to our Table 1, besides the “out” node, certain teams reveal particular moves: Minardi (13, out; 11, in), Sauber (12, out; 11, in), or Renault (10, out; 10, in). In our network, and following these values, this suggests these teams – Minardi, Sauber and Renault – are teams characterized by a high rotation of drivers between the seasons of 2000 to 2017. Even if we construct an alternative network without the “out” node (Figure 2), these teams keep high values for out degree or in degree. There is also the entrance of Ferrari in the group of teams with high values for the out degree when we exclude the out node, which can be explained by the significant number of drivers’ exits from Ferrari to other teams (and not properly to the universe outside F1 competition). OutARD refers to “Outgoing Average Reciprocal Distance of nodes,” and InARD refers to Incoming Average Reciprocal Distance of nodes. In this case, a higher score is associated with a team/actor more adjacent to the other teams/actors. Certain teams (Mercedes, Honda, or HRC) have a higher out closeness value; this reveals these teams are the closest teams of the observed set for sending a driver to another F1 team. This can also be interpreted as proof that these teams tend to promote the move of a F1 driver more directly to another node of the network.

Following Mourao (2021), we have additional definitions for closeness and betweenness: “Out Closeness” attributes a value to each node based on its ‘closeness’ to all other nodes within the network. This value corresponds to the shortest paths between all nodes reached by the flows starting in the highlighted node (in our case, in each team) and then assigns each node a score based on its sum of shortest paths.

“In Closeness”—again attributes a value to each node based on its ‘closeness’ to all other nodes within the network. However, this specific value corresponds to the shortest paths between all nodes reached by the flows going to the highlighted node (in our case, going to a specified team) and then assigns each node a score based on its sum of shortest paths.

"Betweenness Centrality"—measures the number of times a node—in our case, a F1—is located on the shortest path between other F1 teams. "Table 1 shows these indicators for the 178 moves among the 24 players.

Table 1. Indicators of social network analysis (F1 drivers' moves, 2000-2017)

	Out Degree	In Degree	Out ARD	In ARD	Out Close	In Close	Betweeness
Arrows	5.000 (1.000)	3.000 (1.000)	11.917 (7.733)	10.083 (5.267)	48.000 (80.000)	59.000 (108.00)	0.000 (0.000)
BAR	5.000 (4.000)	3.000 (1.000)	14.000 (10.917)	10.083 (6.500)	41.000 (63.000)	59.000 (95.000)	13.800 (37.000)
Brawn	2.000 (2.000)	2.000 (2.000)	10.333 (9.083)	6.333 (4.883)	57.000 (71.000)	85.000 (113.00)	**22.000 (21.000)**
Ferrari	4.000 (26.000)	4.000 (4.000)	12.833 (10.033)	11.333 (7.167)	44.000 (70.000)	55.000 (93.000)	**22.367 (32.333)**
Force India	1.000 (0.000)	3.000 (2.000)	12.833 (0.000)	11.333 (8.250)	49.000 (161.00)	58.000 (82.000)	0.000 (0.000)
Honda	2.000 (2.000)	2.000 (2.000)	8.333 (6.883)	77.000 (6.117)	**69.000 (88.000)**	**0.001 (102.00)**	18.000 (15.000)
HRC	0.000 (0.000)	2.000 (0.000)	10.083 (0.000)	115.00 (0.000)	**69.000 (161.00)**	**0.001 (161.00)**	0.000 (0.000)
Jaguar	**7.000 (2.000)**	**7.000 (1.000)**	12.417 (8.867)	10.083 (5.400)	47.000 (73.000)	59.000 (105.00)	1.000 (7.400)
Jordan	**11.000 (5.000)**	**9.000 (4.000)**	13.917 (11.750)	11.083 (8.083)	44.000 (59.000)	57.000 (89.000)	3.667 (53.400)
Lotus	0.000 (0.000)	2.000 (2.000)	9.000 (0.000)	115.00 (7.833)	**65.000 (161.00)**	**0.000 (85.000)**	0.000 (0.000)
McLaren	**6.000 (4.000)**	**6.000 (6.000)**	13.833 (10.333)	12.000 (9.667)	42.000 (67.000)	53.000 (83.000)	**30.050 (42.400)**
Mercedes	0.000 (0.000)	2.000 (2.000)	0.000 (0.000)	10.833 (5.867)	**115.000 (161.00)**	**54.000 (100.00)**	0.000 (0.000)
Minardi	**13.000 (2.000)**	**11.000 (0.000)**	12.417 (8.000)	9.583 (0.000)	47.000 (84.000)	60.000 (161.00)	0.000 (0.000)
Out	**65.000**	**61.000**	21.333	17.833	27.000	42.000	**296.267**
Prost	6.000 (4.000)	4.000 (3.000)	12.917 (9.283)	11.083 (7.250)	46.000 (73.000)	57.000 (95.000)	2.500 (32.000)
Red Bull	3.000 (6.000)	5.000 (5.000)	11.917 (9.167)	11.833 (8.417)	48.000 (70.000)	54.000 (89.000)	2.500 (38.417)
Renault	**10.000 (8.000)**	**10.000 (11.000)**	14.833 (13.167)	12.333 (10.667)	40.000 (54.000)	53.000 (81.000)	12.933 (144.350)
Sauber	**12.000 (6.000)**	**12.000 (5.000)**	134.333 (11.5000)	12.333 (9.500)	41.000 (61.000)	53.000 (84.000)	9.800 (56.267)
Spyker	3.000 (1.000)	3.000 (2.000)	11.917 (1.000)	10.583 (6.700)	48.000 (155.00)	58.000 (96.000)	0.833 (1.833)
Super Agury	3.000 (0.000)	3.000 (1.000)	11.417 (0.000)	10.083 (5.400)	49.000 (161.00)	59.000 (104.00)	0.000 (0.000)
Toro Rosso	4.000 (2.000)	6.000 (2.000)	11.917 (6.633)	10.083 (5.617)	48.000 (90.000)	59.000 (103.00)	0.000 (0.000)
Toyota	7.000 (2.000)	7.000 (2.000)	12.583 (0.000)	10.833 (5.683)	46.000 (161.00)	56.000 (102.00)	8.667 (0.000)
Virgin	0.000 (0.000)	2.000 (1.000)	10.583 (0.000)	115.00 (5.683)	56.000 (161.00)	0.000 (102.00)	0.000 (0.000)
Williams	**9.000 (7.000)**	**9.000 (3.000)**	14.583 (12.417)	11.500 (7.750)	42.000 (57.000)	54.000 (91.000)	**26.617 (63.556)**

Note: The Haas team entered F1 in 2016 and so it was decided to omit this team in this set of observations. (Between parentheses, there appear the scores related to the network excluding the "Out" node).

Now, we explore two models (P1 and Exponential Random Graph Models/ERGM) that will allow us to continue to test the remaining hypotheses and provide us a deeper understanding of the forces behind the constitution of the commented networks of F1 teams. These methods will contribute to explaining the connectivity between the F1 teams under study based on the characteristics of the network's structure (Holland & Leinhardt, 1981).

3.2 Attractive teams, central teams and the probability of making a transfer

As argued, an F1 team can either receive drivers from other nodes or can send drivers to the latter. These connections can be reciprocal if the two F1 teams, at the same period, receive and send drivers from one another or if the two teams can be disconnected (i.e., if neither receives drivers from the other). These patterns of established relationships tend to present statistical regularities, which can be disclosed by a probabilistic model (p1).

Following Uddin & Hossain (2013), we can classify all dyads of F1 teams (i, j) as mutual (xij = xji = 1), asymmetric (xij not equal to xji), or null (xij = xji = 0). The probabilities of each type of dyad are modelled as a function of three sets of parameters: expansiveness of each team (i.e., capacity of majorly 'exporting' drivers), popularity of each team (i.e., capacity of mainly attracting F1 drivers), and reciprocity (capacity of simultaneously attracting and exporting drivers). The probabilities of mutual, asymmetric and null dyads, denoted mij, aij, and nij, respectively, are modelled as follows:

$$mij = \lambda ij exp(\rho + 2\theta + \alpha i + \alpha j + \beta i + \beta j) \quad \text{(Equation 2)}$$

$$aij = \lambda ij exp(\theta + \alpha i + \beta j) \quad \text{(Equation 3)}$$

$$nij = \lambda ij \quad \text{(Equation 4)}$$

In Equations 2-4, the α parameters are interpreted as "expansiveness" measures for each node (in our case, for each team). The β parameters are interpreted as "attractiveness" measures. The ρ parameter is related to a general measure of the tendency towards "reciprocity" in the network. The θ parameter is a function of the density of the network, reflecting the total number of observed arcs (an arc is defined as a directed path in a network). Finally, the λ parameters are normalizing constants used to guarantee that the modelled probabilities add to 1 for any given dyad. Additional references can be Hanneman & Riddle (2005); Giuffre (2013)

Following Holland & Leinhardt (1981), positive values for each parameter provide statistical evidence of how the studied effects favor establishing relationships between Formula One teams. A positive θ indicates that if the density of the net increased (i.e., as the amount of connections between teams grows), it will be expected that any particular team may establish a greater number of connections with other sectors. In contrast, when ɵ is negative, the interpretation of Holland & Leinhardt (1981) suggests that the number of connections in the net does not help explain the density of connections between a team and the remaining scuderias. In practical terms, this implies that, independently of the density, existing ties tend to be explained by certain latent trends of selectivity assumed by F1 teams. Additionally, a positive ρ implies that any team is likely to establish reciprocal connections with other teams. Table 2 shows these estimates for the periods 2000-2017.

Table 2. P1 estimates for F1 teams

G-Square DF -------- -------- 278.72 [df= 646] (251.54) [df=385] Theta(ɵ) = -2.7013 (-2.356) Rho(ρ) = 1.9839 (1.600)	Alpha (α) (Expansiveness/ Ability to 'Export' Drivers)	Beta (β) (Attractiveness/ Ability to 'Import' Drivers)
Arrows	-0.649 (-0.978)	-0.715 (-0.882)
BAR	0.983 (0.713)	-1.157 (-1.233)
Brawn	-0.445 (-0.180)	-2.115 (-1.018)
Ferrari	0.870 (0.625)	-0.385 (-0.388)
Haas	0.325 (-0.497)	0.841 (0.767)
Force India	-2.262 [no data]	0.193 (0.106)
Honda	-2.089 (-1.116)	-0.507 (-0.071)
HRC	[no data] (no data)	0.109 (no data)
Jaguar	0.096 (-0.180)	-0.891 (-1.018)
Jordan	1.112 (0.889)	0.068 (0.094)
Lotus	[no data] (no data)	0.109 (no data)
McLaren	0.550 (0.395)	1.008 (0.984)
Mercedes	-2.089 (no data)	-0.507 (0.106)
Minardi	0.248 (-0.048)	-2.280 (no data)
Out	3.937	4.026
Prost	0.337 (0.131)	0.287 (0.253)
Red Bull	-0.325 (-0.497)	0.841 (0.767)
Renault	1.336 (1.195)	1.389 (1.421)
Sauber	0.916 (0.748)	0.910 (0.914)
Spyker	-0.826 (-1.116)	0.035 (-0.071)
Super Agury	-2.089 (no data)	-0.507 (0.106)

Note: Between parentheses, estimated values without OUT.

The negative value found for the ɵ -parameter is interpreted as follows: the trend of this network is to not have random flows of drivers among the teams. This means the existing arcs are defined by exogenous dimensions. However, the positive value for the ρ suggests that when there is a move from drivers from one team to another it is also expected there will be moves of drivers from the firstly recipient team to the originally sending one.

From Table 2, we observe how the estimated parameters are different across the F1 teams. We identify F1 teams which have positive estimates for the parameter of "expansiveness," suggesting a higher capacity of exporting drivers. If we consider the related parameter for "attractiveness," i.e., the capacity of receiving drivers, we can graph these estimates in Figure 2. Teams characterized by significant and positive parameters are Sauber, Renault, and McLaren, which follows Table 1 or works like Kesteren & Bergkamp (2022) which used other methods. Therefore, we can consider these teams as significantly dynamic in the observed network, highly exposed to the global flows (Olsen, 2004). In the reverse quadrant (negative-negative), we have the most "timorous" teams: Toro Rosso, Brawn, and Arrows. It is relevant to notice these teams have been used along the observed seasons as associated teams of other scuderias like Red Bull, Brown, and Renault. The other quadrants also deserve comment. The quadrant of positive estimates for attractiveness and negative values for expansiveness is composed of teams like Red Bull and Haas, which do not report a high number of driver entrances but exhibit a high value of exits. The quadrant of negative estimates for attractiveness and positive values for expansiveness is composed of teams like Ferrari and BAR, known for sending a good number of drivers to other teams and for having a limited number of different drivers signing contracts for them (Calvo & Cadaval, 2021).

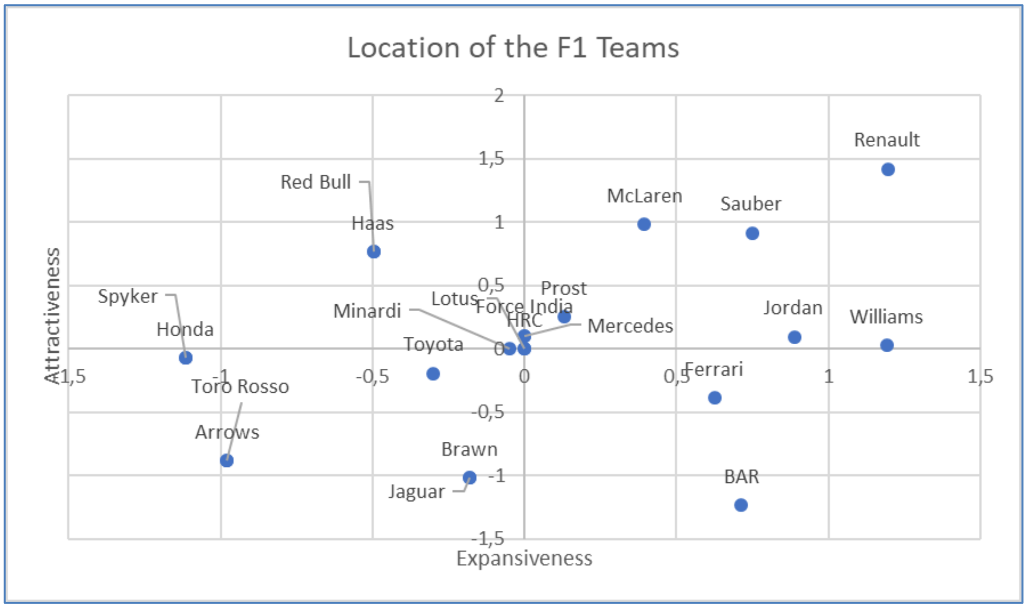

Figure 2. Distribution of F1 teams in terms of estimated expansiveness and attractiveness parameters

Additional figures (e.g., dendrograms) can be exhibited to clarify the different groups of F1 teams considering the estimates for the P1 parameters. These dendrograms, converging with Figure 2, are available under request. P1 methodology also allows the computation of estimated probabilities of a dyad between each pair of F1 teams. The estimated probabilities (available under request) reveal the most-likely dyads: Renault/Williams, Renault/Jordan, and Renault/Sauber. These values converge with the simultaneous presence of positive values for expansiveness or attractiveness of some of the mentioned teams such as Renault and Sauber (Calvo & Cadaval, 2021; Budzinski & Feddersen, 2019).

Following these observations, we concluded F1 drivers' moves among F1 teams are not random. Therefore, next section will clarify which dimensions can explain these moves.

3.3. The attraction between extremes or the discrete charm of the differences

As Morris (2013) denotes, "people may come and go, the links form and dissolve but the structural pattern remains." Thus, it is relevant to study the probability of observing a graph (i.e., a set of relationships) y on a fixed set of nodes. In our case, we keep the motivation to explain the existence of the observed structure of drivers' moves because of dimensions like the existence of arcs, the simultaneous presence of bi-directed moves (i.e., drivers coming from a team and going to another team and the reverse) or even the effect of certain exogenous variables such as the points of each team, its budget value or the centrality scores.

Following Holland & Leinhardt (1981) and their original models, we use Exponential Random Graph Models (ERGM).

As the previous authors showed, there are properties of ERGM which must be noticed, as these types of models "can easily accommodate other relations, attributes, and structural estimates as predictors of a given network" (Snijders et al., 2006). Additionally, and still quoting Snijders et al. (2006), ERGM can differentiate "the senders of relations, the receiver of relations, or that actors with the greatest differences in valued attributes are likely to have relations."

Following the notation of Shumate and Palazzolo (2010), we can enunciate the ERGM model as follows:

$$P(X = x) = \frac{\exp\{\theta' z(x)\}}{k(\theta)} \qquad \text{(Equation 5)}$$

According to Equation 5, we are modeling the probability of a given network P(x) depending on the estimation of a vector of model parameters ɵ. z(x) refers to a vector of network statistics, and k is a normalizing function. The role of this normalizing function is to guarantee a certain probability distribution across the random networks.

For the estimation of Equation 5, we have to use maximum pseudolikelihood estimations. This method fits a logistic regression for the vector of network statistics. Therefore, we will work with the following maximum pseudolikelihood estimation:

$$PL(\theta) = \prod_{i \neq j} \prod_{m=1}^{r} P(X_{ijm} = 1 | X_{ijm}^{C})^{X_{ijm}} P(X_{ijm} = 0 | X_{ijm}^{C})^{1-X_{ijm}} \qquad \text{(Equation 6)}$$

Following Shumate and Palazzolo (2010), the maximum pseudolikelihood estimation for each parameter is computed as a product of the log-odds ratio of two probabilities: the probability for each observed tie, P(X=1) and the probability of not observing that tie in the network, P(X=0). Additional features – such as use of pseudolikelihood ratio statistics, discussion of the independence assumptions, and robustness in small samples – are discussed by authors including Shumate and Palazzolo (2010) or Robins et al. (1999).

Following the literature (Cimarosti, 1997; Pflugfelder, 2009; Potkanowicz & Mendel, 2013; Mourao, 2017), we have first collected the following attributes (for the seasons 2000-2017):

- Average number points of the team
- Median rank of the team in WCC
- Median budget (in 1990 US dollars' prices)
- Accumulated number of wins
- Accumulated number of retirements
- Out-Degree score
- In-Degree score
- Betweenness centrality score

The reasons for this choice follow the established literature on F1 economics. A team's competitiveness can be measured by the track of its number of points along the seasons as well as the profile of its rank. For having a homogeneous pattern, we considered the reward system to be the system of rewards used between 1962 and 1990 (nine points for the winner, six for runner-up, four for third, three for fourth, two for fifth, and one for sixth). We used several attributes to capture an enlarged perspective, so we collected dimensions like race wins and race retirements (Cimarosti, 1997; Mourao, 2017; Budzinksi and Muller-Kock, 2017). The financial aspect is of crucial relevance in this analysis, so we collected values for the budget identified for each F1 team along the observed seasons. Finally, and given the significance of the centrality scores in the tests of the first hypothesis, we considered some of the indicators as of special importance to be analyzed here. We therefore observed the Out-Degree, In-Degree and betweenness centrality scores of each team.

The sources for these variables are own computations of official values for each team's points, ranks, victories, and withdrawals. For the budget attribute, we referred to Forbes (several years) and Mourao (2017). For out-degree score, in-degree score and betweenness centrality score, we referred to Table 1 in this paper. The attribute model can consider several dimensions of the collected attributes – sum, difference, product, matching, or mismatch of the values/categories observed for the players' characteristics. Table 3 shows the descriptive statistics of these attributes.

Table 3. Descriptive Statistics of the F1 teams' attributes (2000-2017)

	Avg #Points	**Median rank**	**Median Budget**	**Acc Wins**	**Acc Retirem**	**Out-Deg**	**In-Deg**	**Betweeness**
Mean	47.7	11.3	158.4	27.0	144.2	6.9	6.8	10.0
Std Dev	117.6	4.4	127.1	60.1	174.4	6.5	5.9	11.6

Max	541.0	18.0	433.0	219.0	541.0	28.0	27.0	32.0
Min	0.0	2.0	9.0	0.0	0.0	0.0	2.0	0.0

Following Musau (2011), the match of values is used to test homophily among the network's participants, and the mismatch of the values is used to test the likelihood of ties among different individuals. As Jenkins (2002); Mourao (2017); Enzenberger & Dimitriou (2018) observed, Formula One's relationships (e.g., among drivers, teams, suppliers, investors) are proper of oligopolist markets. Therefore, authors like Benchekroun et al. (2018) claim that resource flows among oligopolists are less frequent (or characterized by a low significant value) than between an oligopolist and other (following) firms or companies. In the F1 world, this means we can expect a reduced number of drivers' moves between top-ranked teams than between a highly competitive team and not-so-competitive teams. Therefore, in the ERGM attribute model, we are going to consider the mismatch of the considered attributes. Table 4 exhibits the estimates and the acceptance rates for each model.

Table 4. ERGM estimates for F1 drivers' moves (2000-2017)

Parameters	ML Estimate	Std Error
Model 1: Arc Baseline		
Arc	-2.59579*	0.19335
[Acceptance rate: 0.59]		
Model 2: Structural Parameters		
Arc	-3.33817*	0.24579
Reciprocity	1.84000*	0.46889
2-out-star	0.17932*	0.05978
[Acceptance rate: 0.62]		
Model 3: Attributes		
Arc	-3.344803*	0.63227
Team_points' mismatch	0.578751*	0.94344
Team rank's mismatch	-0.267442*	0.04722
Budget's mismatch	-0.988361*	0.26678
Wins' mismatch	0.335634*	0.04451
Retires' mismatch	-1.005402*	0.14755
OutDegree's mismatch	-0.439127*	0.01150
InDegree's mismatch	1.630940*	0.31724

Betweeness' mismatch	0.825288*	0.07091
[Acceptance rate: 0.63]		
Model 4: Combined model		
Arc	-3.243646*	0.63870
Reciprocity	1.237245*	0.61779
2-out-star	0.209612*	0.05105
Team_points' mismatch	0.728377*	0.08659
Team rank's mismatch	-0.288986*	0.02903
Budget's mismatch	-0.858027*	0.25526
Wins' mismatch	0.213241*	0.09458
Retires' mismatch	-1.218107*	0.12974
OutDegree's mismatch	-0.377676*	0.05621
InDegree's mismatch	1.644663*	0.19853
Betweeness' mismatch	0.627830*	0.02512
[Acceptance rate: 0.69]		

Following Shumate & Palazzolo (2010), higher acceptance rates tend to be associated to models with better statistical qualities. Therefore, we observe that the combined model (Model 4) is the most complete for inference.

This model includes the possibility of the attributes suggested by the literature to explain the properties of the network. As we have noticed, and following Shumate & Palazzolo (2010), besides the relevance of getting convergence statistics below 10% for the maximum-likelihood estimates, also related to the relationship between estimated value and estimated standard error (which must be greater than 2.0 for significant estimates), we must also observe the values obtained for the goodness-of-fit indices. Following the literature (detailed by Robins et al., 1999), and regarding the goodness-of-fit indices for the models (fourth column in Table 3), it is important to note some details. Convergence statistic values lower than 1.0 are indicators of a good fit for the estimated parameters in each model Additionally, values between 1.0 and 2.0 also indicate satisfactory fits for the parameters which have not been considered for estimation in the model. For instance, in Table 3, we estimated the arc parameter (ML estimate: -2.596; standard error 0.193; convergence statistic lower than 10%; goodness-of-fit t <0.01), and we did not estimate any of the remaining network parameters selected for discussion: reciprocity, SD indegree distribution, skewness indegree distribution, SD out-degree distribution, and skewness out-degree distribution. Considering these network parameters of

Model 1 in Table 3, we can conclude that only the reciprocity parameter has not been plausibly modeled by the structural parameters of Model 1.

This model 4 provides convergence statistics which are good for the ML estimates and satisfactory values for the goodness-of-fit of this model's indices, even for the estimated structural parameters. Therefore, we can provide a more complete perspective with Model 4. In this model, we observe that ties between F1 teams are not random (suggested by the estimated negative sign for the ML estimate related to arc). We also find that there are more ties between teams with reciprocal moves than with unilateral moves of drivers (Budzinski & Stohr, 2019; Schreyer & Torgler, 2016). We can also state the positive contribution for the composition of the observed network of central teams that "export" drivers to at least two other F1 teams. We can further assert that drivers tend to move between teams that are not of the same competitive rank (e.g., it is more likely that a driver moves from a bottom-ranked team to a top-ranked team than moving to another bottom-ranked team). Independently of the used variable, this direction remains. Conversely, moves are less likely between teams of the same championship or same budget, also reinforcing the competitive environment characterizing these moves.

4. CONCLSUIONS

This research has exploited the strengths of social network analysis for a deeper insight into the complex world of Formula One drivers' moves among teams since 2000. Some of the major conclusions can be synthesized by the following:

- Formula One teams that win the Constructors' Championship tend to assume central roles in the network of drivers' moves.
- Despite their centrality, these winning teams are very selective regarding the origin of the drivers they want to contract.
- There are more chances of contractual ties between teams which are not significantly close in terms of ranks or budgets.

As can be checked in the literature, this work is an original contribution for the scientific fields of Sports Economics, Industrial Economics and Social Networks Analysis. It is an original contribution for three major reasons. First, it has been the first work combining the strengths of Social Networks Analysis with data of transfers of F1 drivers. Second, also taking advantage of Social Networks Analysis, this work detailed the hierarchical structure of oligopolies operating in F1 world. Finally, it identified the difficulties of competitive drivers moving between competitive teams, which can launch several criticisms on the ultimate competitiveness of F1 industry.

Our conclusions recognize that this evidence can explain the invisible structure of “hierarchical” relationships characterized by Formula One teams in the observed period (but which can easily be confirmed for the period since 1950). Competitive drivers tend to stabilize in competitive teams established by highly selective processes of relationship with other F1 teams. This strategy is not only responsible for the current structure of concentration of F1 resources, competitiveness and prizes’ collection; it also has significant implications in terms of future perspectives.

The first implication regards the division of F1 teams in various maturing groups for professional drivers – since low-ranked teams are conceived as internships for entrants to the most historical and champion teams, observed as the ultimate step in F1 careers because of prizes, wages and potential competitiveness for the most-skilled drivers. The second implication states that depending upon certain exogenous factors related to the dependence of certain teams to their own suppliers, the competitive balance of F1 can degenerate into a more clarified oligopoly in which a maximum of three teams control the entire network participating in the competition or, if conditions take a different profile, a larger number of teams can appear as significantly competitive for disputing the Constructors’ Championship.

Our results are the first to discuss the structure of the network in the Formula One industry and how this network interferes with the distribution of titles, points and budgets. We are aware of some derived challenges, especially from the limitations we are able to recognize at this effort. We are majorly thinking about the restrictive period here sampled, about the generalization assumptions made for the ‘Out’ node and about the chosen exogenous dimensions included in the ERGM. The first challenge regards the possibility of extending this analysis to the entire network, considering as initial observation the first modern championship (1950). The second challenge comes from the possibility of disaggregating the out node in the centrality analysis; in this case, we can consider junior series, status of test drivers, or retirement positions. The third opportunity relates to the ability of ERGM including other characteristics of teams which we did not include in this effort; we are referring to dimensions such as the nationality of each team’s head-office, the coinciding nationality of each driver, or each driver’s years of experience in Formula One. We also recognize the opportunity of a fourth line of research – the one related to the possibility of extending this methodology for other Formula One actors, like Team Directors or Engineers.

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The authors declare no conflict of interest.

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