1. Introduction

This document is an executive summary of Inter Milan's performance in the 2017/18 season. We will outline the main findings for the past season and make recommendations required for a successful campaign in 2018/19. More extensive details on methodology and background can be found in the technical appendices.

Due to weak economy, it is imperative to qualify for the Champions League next season despite the constraints set by Financial Fair Play. Spending on players in the close season must be careful and well founded.

2. Previous Season Performance

Offensively we performed well, but we are highly dependent on the creative output from both Perisic and Candreva as well as Icardi's aerial ability up front in addition to set pieces. We have observed an overperformance vs expectations on headers and set pieces which will most likely not be replicated next season, and we should therefore add more creative options to reduce this risk. Note that loan players Cancelo and Rafinha also made significant contributions during the second half of the season which needs to be replaced as the loan deals are not prolonged.

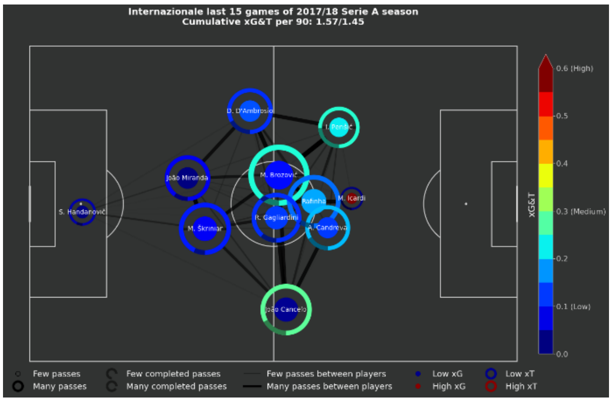

Figure 1: Offensive contributions from most frequently used players from the last 15 games of Serie A

Defensively we have found that our opponents often targeted on our weak left side, where they tended to go wide and around the left back, probably due to D'Ambrosio playing on his weaker side. We have identified several targets that we are confident will help us concede less goals than in 2017/18. The primary target is Atletico Madrid's Filipe Luis, valued at €8.0m. Younger understudies are also

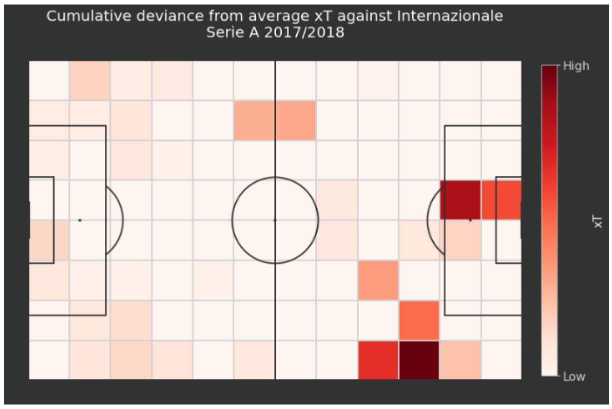

Figure 2: Key areas target by opposition teams 2017/18

Looking at the season game-by-game, we identify a mid-season slump of eight win-less games between gameweek 16 and 24. With two excruciating Coppa Italia games added to the league games in this period, the two most obvious underlying causes are player fatigue and bedding-in issues as Cancelo was loaned to play at right back, while Nagatomo was released and D'Ambrosio moved over from right back to left back.

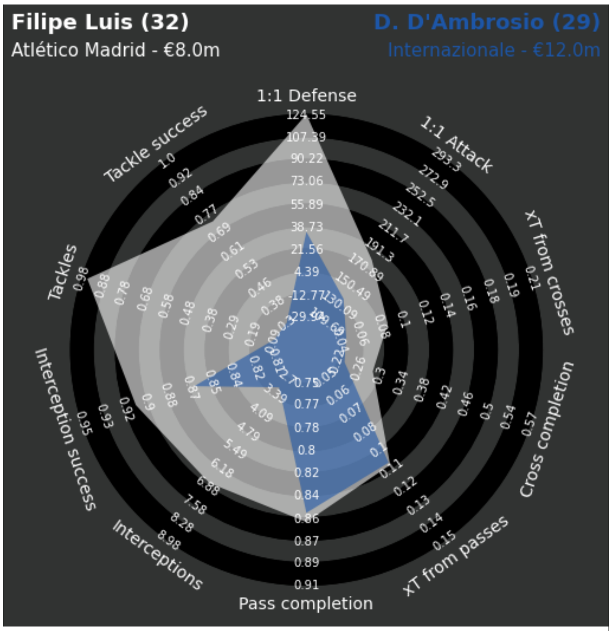

Figure 3: Our proposed solution to the defensive issues highlighted in Figure 2.

The last 15 games show a more stable defense as well as an encouraging trend in attacking output, but as mentioned earlier much of this output can be attributed to loan players that have already left and replacements must be acquired both to avoid drop in performance and to help alleviate additional player load due to the Champions League games. It is well known that performances tend to drop off after mid-week CL games, and we need a broader squad with options to rotate to avoid this if we are to retain a top four placement and CL qualification.

3. Upcoming Season Predictions

To assess how we are likely to perform in the upcoming season, we have simulated five different scenarios. We have also simulated the previous season to assess how merited our 4th place was based on underlying metrics.

- Base Case assumes that no teams change – all teams start the season as strong as they finished
- Scenario A assumes all rivals invest in squad while Inter does not
- Scenario B assumes all teams (including Inter) invest in squad
- Scenario C assumes that Inter invests more aggressively than competitors
- Scenario D assumes that Inter invests to strengthen according to our player recommendations

Table 1: Simulations of previous and upcoming season

2017/2018 Season Simulation				
Team	**Pts**	**P(pos)**	**1st**	**CL**
Juventus	**85**		**67%**	**99%**
Napoli	78		22%	91%
Inter	70		2%	61%
Roma	70		3%	57%
Lazio	69		3%	55%
Atalanta	62		0%	17%

2018/2019 Base Case				
Team	**Pts**	**P(pos)**	**1st**	**CL**
Juventus	**83**		**50%**	**94%**
Napoli	77		20%	80%
Roma	77		17%	78%
Inter	73		6%	54%
Atalanta	70		4%	40%
Lazio	69		3%	38%

2018/2019 Scenario A				
Team	**Pts**	**P(pos)**	**1st**	**CL**
Juventus	**83**		**49%**	**95%**
Napoli	78		20%	82%
Roma	77		19%	79%
Inter	71		5%	52%
Atalanta	70		4%	42%
Lazio	69		3%	35%

2018/2019 Scenario B				
Team	**Pts**	**P(pos)**	**1st**	**CL**
Juventus	**83**		**50%**	**95%**
Napoli	77		19%	80%
Roma	77		17%	78%
Inter	73		6%	51%
Atalanta	70		4%	44%
Lazio	69		3%	37%

2018/2019 Scenario C				
Team	**Pts**	**P(pos)**	**1st**	**CL**
Juventus	**83**		**49%**	**94%**
Roma	78		19%	80%
Napoli	77		18%	79%
Inter	71		7%	54%
Atalanta	70		3%	39%
Lazio	69		4%	39%

2018/2019 Scenario D				
Team	**Pts**	**P(pos)**	**1st**	**CL**
Juventus	**83**		**48%**	**94%**
Napoli	77		16%	76%
Roma	77		15%	74%
Inter	76		16%	76%
Lazio	69		2%	33%
Atalanta	69		3%	35%

As seen from the simulation summaries in the table above, a target player acquisition strategy is imperative if we want to ensure a top four finish, with estimated probability of qualification increasing by almost 50% compared to more traditional strategies.

4. Player Acquisition and Return on Investment

We have identified eight players that we believe will help us achieve our target of a top four finish. Four of these are defensive options that will both help alleviate the weakness on our left side as well as provide adequate rotation options. Two are central midfielders who will add creativity through the middle to reduce dependency on our wingers for creating chances, and two are rotation options for Perisic and Candreva. Total cost for all players is estimated at €44m, which is around the low estimate for CL prize money.

Our RoI analysis concludes that the expected return in available cash by acquiring these players for the next season is approximately 172% of the investment, and we trust that the board will agree that we should move forward on these acquisitions as soon as possible.

Technical Appendix

A. Expected Goals (xG) Model

The expected Goals (xG) model used in this exercise is based on the open source VAEP based implementation from socceraction[1]. The model is based on a gradient boosted tree model (XGBoost, Extreme Gradient Boosting) from the sklean library, trained on all the data from all the big five leagues in the WyScout 2017/18 dataset.

The implementation was benchmarked against both a naïve baseline model (the mean of the shot outcomes) and a more traditional logistic regression model, outperforming both alternatives. (The naïve baseline model had an ROC AUC of 0.5, a Brier score of 0.107 and a log-loss of 0.372, while the logistic regression model had an ROC AUC of 0.8, Brier score of 0.085 and a log-loss of 0.315. The XGBoost model had an ROC AUC of 0.818, Brier score of 0.095 and a log-loss of 0.406.)

The model takes into account not only the location a chance was taken from, but also if it was a set piece, the body part used, the team the chance fell to, the score at the time the chance came about as well as a user determined number of previous actions leading up to the shot. In this exercise we have used two (n=2) look-back events in our xG model. A chance from a given location coming directly after regaining possession far into the opponents final third will thus have a greater xG value than the same shot coming after circulating the ball within your own team, as a chance from a break usually means that the opposition's defence is unbalanced and more open.

While xG by now is a well-known metric for assessing performance, it is important to note that the events measured by xG and xA (expected assists) models typically represent less than 1% of the on-ball-actions in a football match. As these models give purely outcome-based metric and as such does not take underlying pitch dominance into account, they are not sufficient to explain an entire season's performance for a team.

B. Expected Threat (xT) Model

The Expected Threat (xT) model used in this exercise is based on the framework developed by Karun Singh[2]. In contrast to xG, xT is a purely location-based, limited game state model that captures non-shot related game domination that will be ignored by outcome-based models. Behind the scenes it uses a possession-based Markov model to value ball-progressing actions.

xT values are easy to interpret and is not easily skewed by outliers, giving more robust player ratings – especially for small sample sizes. The specific implementation used is based on the open source xT model implementation from socceraction[3], using only open play events. The expected threat is calculated on a 12x8 grid covering the entire pitch and formulated as in the equation below:

$$xT_{x,y} = (s_{x,y} \times g_{x,y}) + (m_{x,y} \times \sum_{z=1}^{12} \sum_{w=1}^{8} T_{(x,y)\rightarrow(z,w)} xT_{z,w})$$

This equation is solved iteratively for each cell until convergence.

[1] See https://github.com/ML-KULeuven/socceraction/blob/master/public-notebooks/EXTRA-build-expected-goals-model.ipynb for details on the implementation used
[2] See https://karun.in/blog/expected-threat.html for details
[3] See https://github.com/ML-KULeuven/socceraction/blob/master/public-notebooks/EXTRA-run-xT.ipynb for detail on the implementation used

C. Combination of Expected Goals and Expected Threat Models

Because neither xG nor xT alone is sufficient to explain a football match, we have used a weighted value of xG and xT dubbed xG&T to simulate the previous season. Rather than simulating the following season right away, we opted to simulate 2017/18 season in order analyze how fair Inter's ranking was at the end of the season. To measure fairness, we simulated the season with a model where goals are dependent variables and xG&T is the independent variable, controlled by "team" and "opponent" binaries. For each game, team binary will be equal to 1 for the team that scores the goals,whilst opponent binary will be one for the team that those goals being scored against.

We know that xG is a very strong predictor of goals. In order to add some "fairness" to xG, we decided to weight it with Karun Singh's xT, in such a way that the weighted value skews towards xT when the team played a heavily possession game in a given match, while if the team managed to reach high shot ratio (team shots divided by the total shots taken in the game), then the value skews towards xG. To realize the idea, we calculated possession rate and shot ratio for each team and then used these to calculate xG&T. The equation is:

$Team: Set\ of\ teams\ in\ Serie\ A$
$Game: Set\ of\ games\ in\ Serie\ A$

$$\boldsymbol{xG\&T_{ijk}} = \frac{\boldsymbol{Shotratio_{ikj}}}{(\boldsymbol{Shotratio_{ikj}} + \boldsymbol{Possession_{ikj}})} * \boldsymbol{xG} + \frac{\boldsymbol{Possession_{ikj}}}{(\boldsymbol{Shotratio_{ikj}} + \boldsymbol{Possession_{ikj}})} * \boldsymbol{xT}$$
$$i \in Team, k \in Team, j \in Game, i \neq k\ (index\ k\ stands\ for\ the\ opponent\ team)$$

There are several weighting techniques, out of those, we opted to use weighted arithmetic mean of xG and xT in this case, as we want the weighted value to be the average of xG and xT in such cases where shot ratio is equal to the possession rate. Using other techniques, such as weighted harmonic mean would skew the value towards xT, which is systematically lower and less explanatory than xG. In other words, by using weighted arithmetic mean, we aim to get the best out of both models.

D. Simulation of previous season (2017/2018)

As briefly mentioned in Section C, we simulated the previous season with the following model:

$Team: Set\ of\ teams\ in\ Serie\ A$
$Game: Set\ of\ games\ in\ Serie\ A\ played\ in\ 17/18\ season$
$Goals: Number\ of\ goals\ scored\ by\ each\ team\ in\ each\ game$
$xG\_xT\_weighted: xG\&T\ created\ by\ each\ team\ in\ each\ game\ (Formula\ is\ described\ in\ Section\ C)$
$team: team\ binary. team = 1\ for\ the\ team\ who\ scores\ the\ goal\ in\ each\ observation$
$opponent: opponent\ binary. opponent$
$= 1\ for\ the\ opponent\ the\ goal\ of\ the\ team\ is\ scored\ against\ in\ each\ observation$
$\lambda: Expected\ value\ of\ goals\ scored\ by\ each\ team\ in\ each\ game\ (E[Goals])$

Poisson Regression model:

$$\log(\boldsymbol{\lambda_{ikj}}) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 xG\_xT\_weighted_{ikj}} + \boldsymbol{\beta_2 team_{ikj}} + \boldsymbol{\beta_3 opponent_{kij}}\ \ i \in Team, k \in Team, j \in Game,$$
$$i \neq k\ (index\ k\ stands\ for\ the\ opponent\ team)$$

It should be noted that the probability of observing $goals_{ikj}$ is Poisson distributed, that is:

$$PMF(goals_{ikj} | xG\_xT\_weighted_{ikj}) = \frac{e^{-\lambda_{ikj}} * \lambda_{ikj}^{goals_{ikj}}}{goals_{ikj}!}, i \in Team, k \in Team, j \in Game,$$
$$i \neq k\ (index\ k\ stands\ for\ the\ opponent\ team)$$

Unlike the well-known Dixon-Coles model, we did not add home advantage to ours as the xG&T values already contain this information, given that it is highly and positively correlated with home advantage. Therefore, our model can be evaluated as a modified version of Dixon-Coles. We fit our model into the data and found out that it fitted well enough to run a "fair" simulation of 2017/2018 season. The summary of the model can be seen in Figure 4.

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  goals   No. Observations:                  760
Model:                            GLM   Df Residuals:                      720
Model Family:                 Poisson   Df Model:                           39
Link Function:                    log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -956.73
Date:                Sun, 08 Nov 2020   Deviance:                       595.46
Time:                        12:02:16   Pearson chi2:                     493.
No. Iterations:                     5
Covariance Type:            nonrobust
==================================================================================================
                                coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------------
Intercept                    -0.8449      0.223     -3.796      0.000      -1.281      -0.409
team[T.Benevento]            -0.0333      0.222     -0.150      0.881      -0.468       0.402
team[T.Bologna]               0.1776      0.211      0.843      0.399      -0.235       0.590
team[T.Cagliari]             -0.1272      0.221     -0.575      0.565      -0.561       0.306
team[T.Chievo]                0.0304      0.216      0.141      0.888      -0.393       0.453
team[T.Crotone]               0.1339      0.210      0.638      0.523      -0.277       0.545
team[T.Fiorentina]            0.0623      0.191      0.327      0.744      -0.312       0.436
team[T.Genoa]                -0.1360      0.221     -0.614      0.539      -0.570       0.298
team[T.Hellas Verona]        -0.0486      0.229     -0.212      0.832      -0.498       0.401
team[T.Internazionale]        0.1229      0.182      0.677      0.499      -0.233       0.479
team[T.Juventus]              0.4948      0.172      2.885      0.004       0.159       0.831
team[T.Lazio]                 0.4141      0.170      2.430      0.015       0.080       0.748
team[T.Milan]                 0.1311      0.189      0.693      0.488      -0.239       0.502
team[T.Napoli]                0.2371      0.176      1.350      0.177      -0.107       0.581
team[T.Roma]                 -0.0239      0.185     -0.129      0.897      -0.387       0.339
team[T.SPAL]                  0.1706      0.212      0.805      0.421      -0.245       0.586
team[T.Sampdoria]             0.2323      0.190      1.224      0.221      -0.140       0.604
team[T.Sassuolo]             -0.2336      0.231     -1.012      0.312      -0.686       0.219
team[T.Torino]                0.2506      0.192      1.307      0.191      -0.125       0.627
team[T.Udinese]               0.1660      0.197      0.841      0.400      -0.221       0.553
opponent[T.Benevento]         0.0881      0.201      0.437      0.662      -0.307       0.483
opponent[T.Bologna]          -0.0101      0.213     -0.048      0.962      -0.428       0.408
opponent[T.Cagliari]          0.0247      0.208      0.119      0.905      -0.383       0.432
opponent[T.Chievo]           -0.0765      0.211     -0.362      0.717      -0.490       0.337
opponent[T.Crotone]          -0.0225      0.207     -0.109      0.913      -0.428       0.383
opponent[T.Fiorentina]       -0.0220      0.219     -0.100      0.920      -0.451       0.407
opponent[T.Genoa]            -0.1304      0.222     -0.587      0.557      -0.566       0.305
opponent[T.Hellas Verona]    -0.0697      0.205     -0.340      0.734      -0.471       0.332
opponent[T.Internazionale]   -0.2762      0.243     -1.136      0.256      -0.753       0.200
opponent[T.Juventus]         -0.3543      0.260     -1.363      0.173      -0.864       0.155
opponent[T.Lazio]             0.0790      0.216      0.366      0.714      -0.344       0.502
opponent[T.Milan]             0.0153      0.223      0.069      0.945      -0.422       0.452
opponent[T.Napoli]           -0.1499      0.246     -0.609      0.542      -0.632       0.332
opponent[T.Roma]             -0.3740      0.248     -1.508      0.132      -0.860       0.112
opponent[T.SPAL]              0.0099      0.209      0.047      0.962      -0.401       0.420
opponent[T.Sampdoria]        -0.0003      0.209     -0.002      0.999      -0.410       0.410
opponent[T.Sassuolo]         -0.1902      0.214     -0.888      0.375      -0.610       0.230
opponent[T.Torino]           -0.0903      0.219     -0.412      0.680      -0.520       0.339
opponent[T.Udinese]           0.1888      0.205      0.920      0.358      -0.214       0.591
xG_xT_weighted                0.7736      0.055     14.147      0.000       0.666       0.881
==================================================================================================
```

Figure 4: Summary of xG&T model fit

The impact of xG&T on goals is statistically very significant and the model has a fair log-likelihood. We therefore opted to base a part of our 2017/2018 season analysis on the simulation run by the above model.

E. Simulations of upcoming season (2018/2019)

For the upcoming season simulations, we have used a slightly different approach. Instead of relying on the xG&T model, we are using the 2017/18 end-of-season offensive and defensive ratings from FiveThirtyEight[4] as the base case. We are here assuming that the SPI metrics of the promoted teams in the 18/19 season can be represented by the SPI metrics of the relegated teams in the 17/18 season. After running several models, we concluded that using offensive rating of the team and defensive rating of the opponent is a good starting point. The summary of the above-mentioned model can be seen in Figure 5.

[4] See https://fivethirtyeight.com/methodology/how-our-club-soccer-predictions-work/ for details

As we see in the p-values in Figure 5, both ratings have statistically significant in terms of explaining the number of goals scored by each team in each game. We could not use these two ratings by itself, given that we need to run several different simulations corresponding to different possible scenarios. We therefore decided to use a single variable derived from the weighted harmonic mean of offensive ratings of each team and defensive ratings of each opponent in each game. During weighting process, we used the SPI ratings of each team and opponent from the FiveThirtyEight website. The formula of the above-mentioned variable can be seen in the below:

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  goals   No. Observations:                  760
Model:                            GLM   Df Residuals:                      757
Model Family:                 Poisson   Df Model:                            2
Link Function:                    log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -1060.8
Date:                Sun, 01 Nov 2020   Deviance:                       803.65
Time:                        11:58:07   Pearson chi2:                     690.
No. Iterations:                     5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -2.2054      0.190    -11.628      0.000      -2.577      -1.834
Off_18         0.7508      0.076      9.899      0.000       0.602       0.899
Def_18         1.1273      0.121      9.327      0.000       0.890       1.364
==============================================================================
```

Figure 5: Summary of 2018/19 base case model

$Team$: $Set\ of\ teams\ in\ Serie\ A$
$Game$: $Set\ of\ games\ in\ Serie\ A\ played\ in\ 17/18\ season$

The weighted harmonic mean of the offensive (of the team) and the defensive (of the opponent) ratings ($weighted\_off\_def$) is:

$$\boldsymbol{weighted\_off\_def_{ijk}} = \frac{\frac{\boldsymbol{SPI_{ij}}}{\boldsymbol{SPI_{kj}}} + \frac{\boldsymbol{SPI_{kj}}}{\boldsymbol{SPI_{ij}}}}{\frac{\boldsymbol{SPI_{ij}}}{\boldsymbol{SPI_{kj}}}/\boldsymbol{Off_{ij}} + \frac{\boldsymbol{SPI_{kj}}}{\boldsymbol{SPI_{ij}}}/\boldsymbol{Def_{kj}}}$$

$$i \in Team, k \in Team, j \in Game, i \neq k\ (index\ k\ stands\ for\ the\ opponent\ team)$$

In this way, we will be able to recalculate SPI ratings of each team and opponent to reflect the scenarios we want to simulate, and the weighted harmonic mean will change accordingly. Our assumption here is that the changes in for instance squad value (without any knowledge of a specific players added to the squad) will have an impact on the club's offensive and defensive ratings. We realize this impact by increasing the SPI values instead of the metrics themselves, and then use the weighted harmonic average that we presented above for each observation. Moreover, we added the home advantage into our model, as unlike in xG&T (which is different for every game as they reflect actual events), offensive and defensive ratings do not contain home advantage information (values do not change per game, there is one single offensive and one single defensive rating for each team, and therefore opponent.). Our final base case simulation model for 2018/19 season is realized by a Poisson Regression model as follows:

$$\log(\lambda_{ij}) = \beta_0 + \beta_1 weighted\_off\_def_{ij} + \beta_2 home_{ij} \quad i \in Team,\ j \in Game$$

$Team$: $Set\ of\ teams\ in\ Serie\ A$
$Game$: $Set\ of\ games\ in\ Serie\ A\ played\ in\ 17/1\ 8\ season$
$Goals$: $Number\ of\ goals\ scored\ by\ each\ team\ in\ each\ game$
$weighted\_off\_def$: $weighted\ harmonic\ mean\ of\ offensive\ (team) and\ defensive\ (opponent)\ ratings$
$home$: $home\ advantage\ binary.home = 1\ if\ team\ plays\ home, home = 0\ otherwise$
λ: $Expected\ value\ of\ goals\ scored\ by\ each\ team\ in\ eah\ game\ (E[Goals])$

It should be noted that the probability of observing $Goals_{ij}$ is Poisson distributed, that is:

$$PMF(Goals_{ij} | weighted\_off\_def_{ij}) = \frac{e^{-\lambda_{ij}} * \lambda_{ij}^{Goals_{ij}}}{Goals_{ij}!}, i \in Team, j \in Game$$

The summary of the model can be seen in Figure 6, and we concluded that the model was good enough to run our base case scenario. The base is that everything remains unchanged from the end of the 2017/18 season and the start of the 2018/19 season.

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  goals   No. Observations:                  760
Model:                            GLM   Df Residuals:                      757
Model Family:                 Poisson   Df Model:                            2
Link Function:                    log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -1061.0
Date:                Fri, 06 Nov 2020   Deviance:                       804.06
Time:                        11:09:53   Pearson chi2:                     697.
No. Iterations:                     5
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept           -1.3754      0.130    -10.559      0.000      -1.631      -1.120
weighted_off_def     1.2071      0.088     13.683      0.000       1.034       1.380
home                 0.1755      0.063      2.787      0.005       0.052       0.299
====================================================================================
```

Figure 6: Summary if SPI based prediction model.

After running the simulation for the base case, we also tested four different scenarios for the upcoming season, each with a different impact on the SPI and/or the offensive/defensive rankings and re-ran the simulations accordingly. The assumption here is that the SPI values increase as a function of spending, but that the players acquired are not especially well scouted. This is supported by research by amongst others Paul Tomkins and Graeme Riley indicate that as much as 60% of transfers fail to make an impact for the average club.

- **Scenario A:** Inter pursues a very cautious strategy in terms of increasing the squad’s value, while rivals (Juventus, Napoli, Milan, Atalanta, Lazio, Roma) aggressively invest in new transfers, increasing their values by roughly 6 percentage points more than the league average. In this case, we assume Serie A grows by 16% in current EUR terms from May 2018 to September 2018 (Club values, and therefore Serie A’s value is gathered from www.transfermarkt.com). A short note should also be added about the growth rate of Serie A, which is the fact that we assumed a growth rate of 16% for Serie A bases on the exponential growing trend in the market value of football in general, while Serie A grew by around 8% within the same period in 2017.
- **Scenario B**: Inter pursue a similar strategy as the rivals in terms of increasing the squad's value compared to its rivals. We here assume similar growth in squad value for the top of the league (rivals and Inter), while a lower growth for mid-table and lower-end teams. It is assumed that Serie A grows by 16%.
- **Scenario C**: Inter pursue an aggressive strategy in terms of increasing the squad's value noticeably higher than the average growth, while its rivals increase their squad value around 10 percentage points less than Inter. It is assumed that Serie A grows by 14%.
- **Scenario D:** Inter pursue a similar strategy in terms of increasing the squad's value compared to its rivals, but wisely manages its transfer strategy with the addition carefully scouted players to help alleviate key weaknesses identified in the team.

For each scenario, we recalculated SPI ratings of the clubs by basing on one single assumption:
If the difference in a club’s value relative to mean from May 2018 to September 2018 changes by 0.1, the SPI rating of the corresponding club changes by 0.5. How we calculated the differences in clubs’ values relative to mean from May 2018 to September 2018 can be seen in the below:

$$T: Set\ of\ times. \{0,1\}, 0 = May\ 2018, while\ 1 = September\ 2018$$
$$N: Set\ of\ Clubs\ in\ Serie\ A$$

$$The\ difference\ in\ club's\ value\ relative\ to\ mean = \left(\frac{Clubvalue_{nt=0}}{\frac{\sum_{n=1}^{N} Clubvalue_{t=0}}{|N|}}\right) - \left(\frac{Clubvalue_{nt=1}}{\frac{\sum_{n=1}^{N} Clubvalue_{t=1}}{|N|}}\right) \quad t \in T, n \in N$$

We denote $The\ difference\ in\ club's\ value\ relative\ to\ mean$ as $Difference\_in\_value$. Therefore, recalculated SPI for each club under any given scenario is:

$$Recalculated\ SPI_n = Base\ SPI_n * (5 * Difference\_in\_value_n)$$

Recalculating SPI ratings by taking club's values relative to the mean value was inspired by the approach of FiveThirtyEight. However, FiveThirtyEight's approach is likely different from ours, as their formulation is not provided in their website. It can be shown that a club's SPI value is not only dependent on its own financial decisions, but also by the outcome of the other club's financial actions, as we use relativity to the mean as a benchmark. We therefore concluded that this approach is realistic enough to run simulations based on different financial scenarios. It is important to note that for Scenario D we also adjusted the offensive and defensive metrics for Inter based on the assumed impact from the targeted players.

It is also important to note that all simulations are run 'cold', i.e. the SPI rankings are not dynamically updated during the simulation runs.

F. Key Weaknesses and Risks Identified from 2017/18

We have made a significant effort to identify key weaknesses and risks in our performance from the previous season, both offensively and defensively. From Figure 7 (right) we see that we are performing well defensively around our own 16-yard box, mainly restricting our opponents to low value chances. We perform better than the opposition offensively (left), but we are also taking too many low value chances. We recommend coaching the players to take up better shooting positions in order to avoid wasting possession and opening ourselves up for counter attacks.

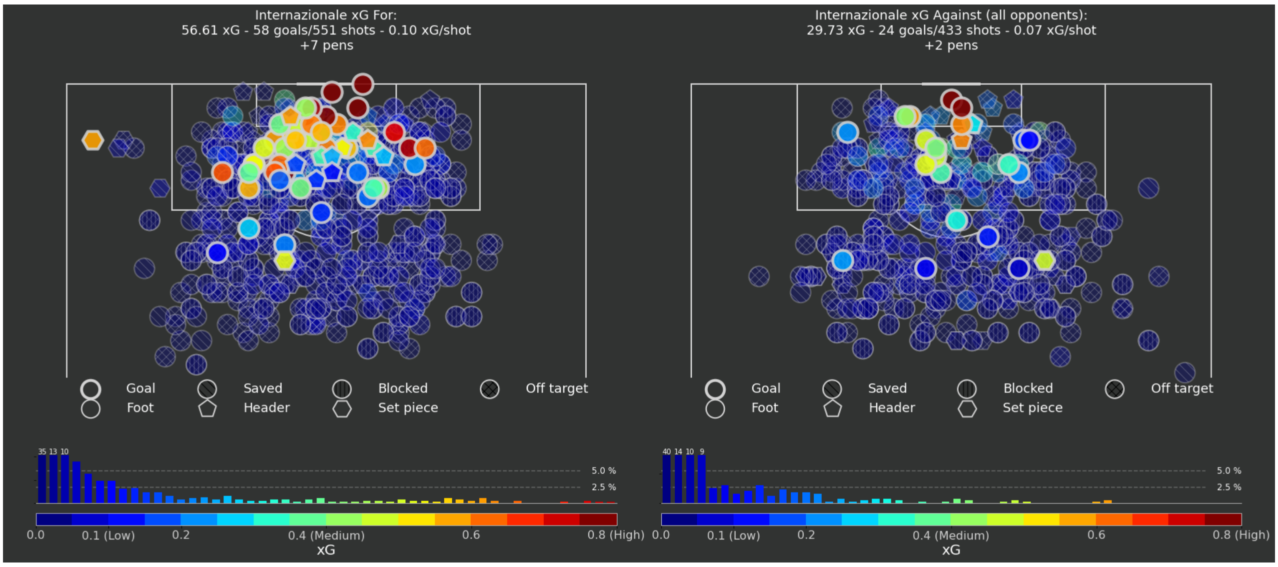

Figure 7: xG for (left) and against (right) from 2017/2018 excluding penalties.

As shown in Figure 8, we also need to be aware that overperformed vs expectations on goals from headers and set pieces both offensively and defensively, to the order of a potential six extra games in our disfavor if this proves to be unsustainable and regress towards to mean. This then needs to be rectified by adding creativity and goals to the squad that are not present at the time of writing.

Furthermore, as shown in Figure 9, we had an eight-game mid-season winless slump that could easily have cost us Champions League qualification. This slump coincided with two Coppa Italia games that both went to extra time, and we believe that the slump was partly caused by player fatigue. We propose that we boast the squad with viable rotation options for the upcoming season to avoid this occurring again. We believe that unless we do this, the mid-season slump will be worse this season due to the additional player load caused by the Champions League.

As mentioned in the executive summary and shown again here in Figure 10 (left), we rely heavily on the output from our wingers, with Perisic and Candreva the main sources of assists for Icardi. In the second half of

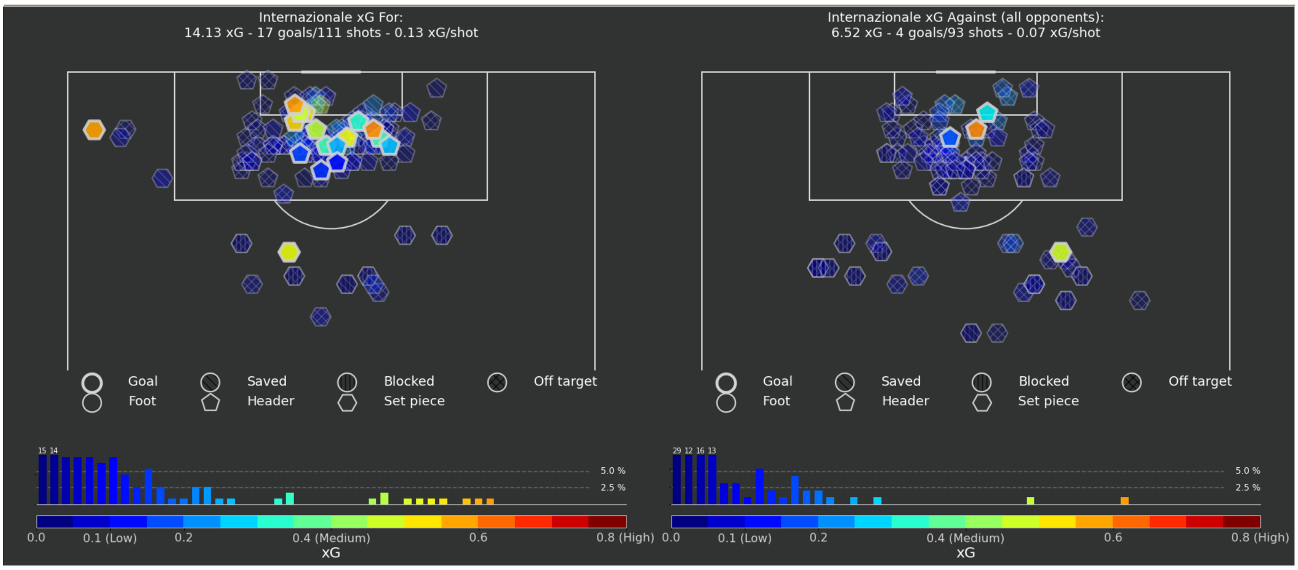

Figure 8: xG for (left) and agains (right) for 2017/18, headers and set pieces only.

the season, Cancelo and Rafhina also contributed well offensively, but both these loan players are now returning to their parent clubs and their output needs to be replaced.

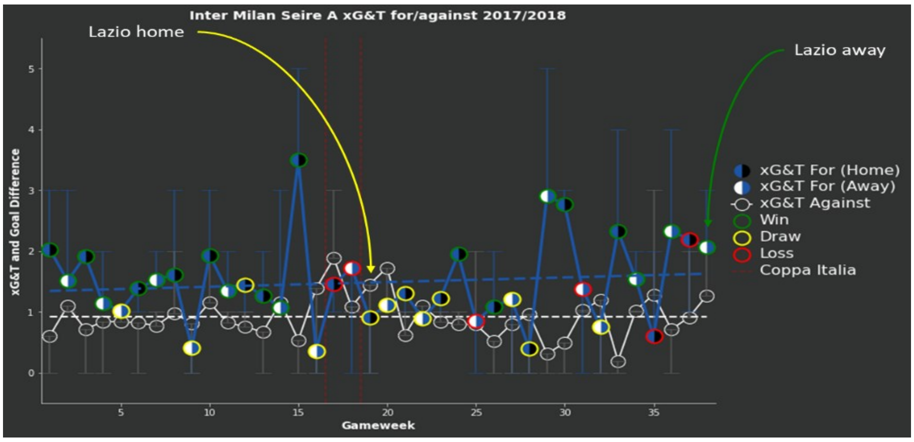

Figure 9: Inter's performance throughout the season.

We also desperately need to shore up our left hand side defensively, as this is a weakness that was systematically targeted by our opponents during the previous season, as shown in Figure 10 (right). This plot shows how teams specifically deviated from their normal attacking patterns when playing against us, creating a lot of threat from the space occupied by our left backs. This could be because D'Ambrosio is right footed, and it may therefore be easier to move around him on the outside than for a naturally left-footed left back.

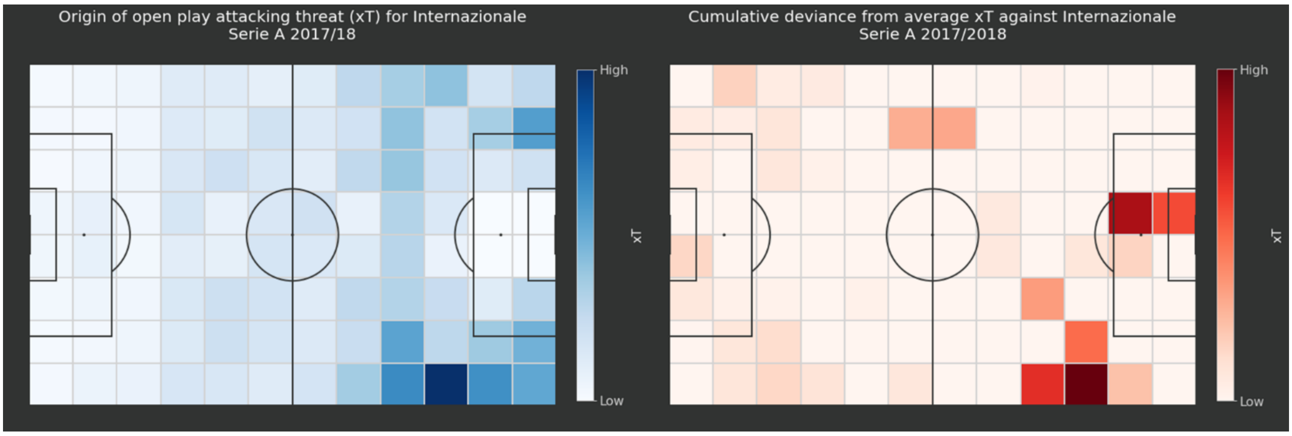

Figure 10: Main sources of attack for (left) and against (right) during the 2017/18 season.

G. Player Acquisition and Return-on-Investment Analysis

In collaboration with the player evaluation and player fitness groups, we have identified eight key players that we believe will help us retain a top four finish in the upcoming season. We have identified four defensive options, where two are first team options and two are young and cheap prospects with a potential high ceiling and sell-on value.

For the first team options, we have calculated their expected contribution to our offensive SPI metrics as the delta between historical contributions in xG and xT per 90 between the player to be replaced and the new player. If the player to be placed contributed to 0.1 xG and 0.05 xT offensively, then this is added to the SPI offensive score. In similar fashion, we have quantified the expected improvement of our defence by looking at their relative contribution to the xT prevented (xTp) against the previous season. The xTp against is calculated by looking at the defensive actions of a team in their own third. We find the areas where the team wins the ball back, calculating the xT from that position and add it to the team's xTp metric.

The rationale here is that actions fail mainly due to pressure from nearby players and should thus reflect the ability of a defender to prevent threat in his zone. Teams with low values of both tend to be those that win the ball back far away from goal more often than not, thus limiting the opposition teams from high quality chances. Vice versa teams with high values of both tend to be those relying on last ditch efforts, and while they might be able to limit teams from shots by blocking a high percentage of them and thus being rated well on xG conceded, their weaknesses get highlighted with xTp. No between-league adjustments have been made at this point.

Another key metric when identifying defensive options was their abilities as defenders in 1:1 situations, both in defense and attack. For this we have used the ELO ratings from the player evaluation group. A high score for 1:1 defense indicates that the player is hard to beat in 1:1 situations, while a high score for 1:1 attack indicate a high-quality dribbler.

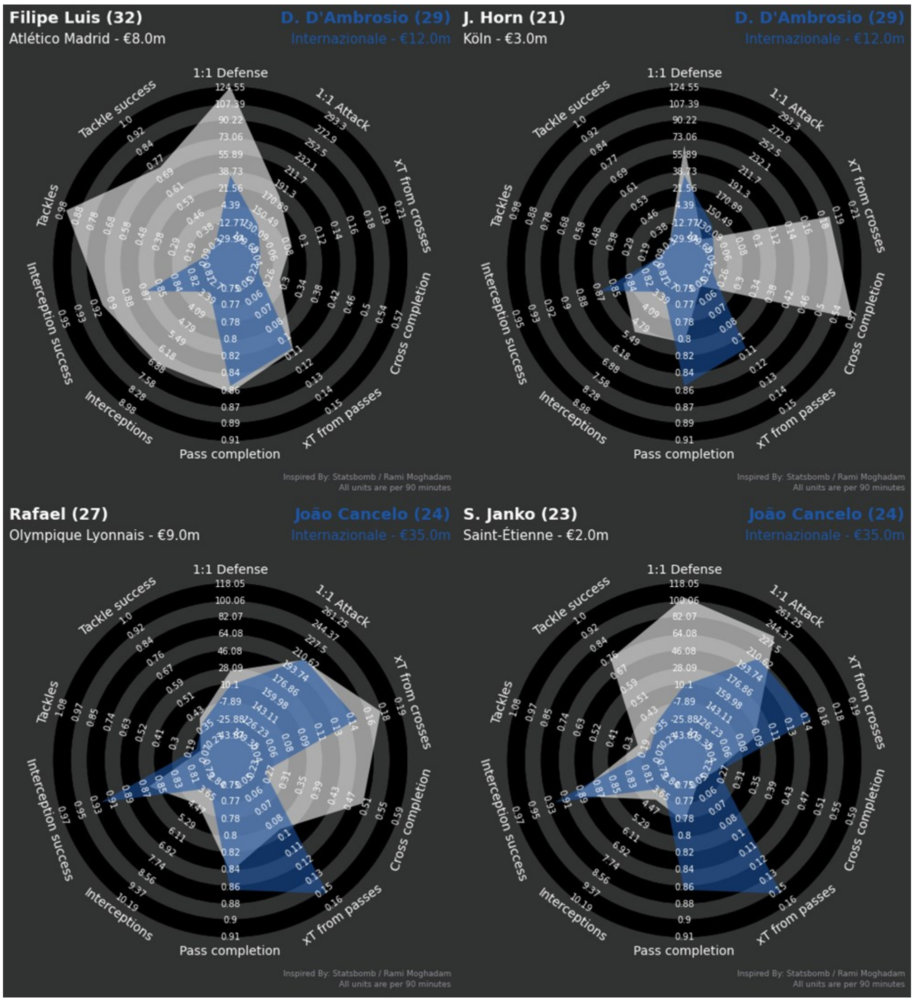

Figure 11: Key defensive options identified

When identifying the players shown in the radars in Figure 11 and Figure 12, we have binned the players from the big five leagues into their respective positions and filtered on players performing in the top 95th percentile for the criteria selected. Players are then picked based on price, age and ability. For the defensive players we believe Filipe Luis from Atletico Madrid to be a key short-time solution to our defensive issues, while Jannes Horn from Köln is identified as a prospect for the future and rotating option on the left hand side.

On the right side, we believe that Rafael of Olympique Lyonnais is capable of replicating Cancelo's contributions, while Janko of Saint-Étienne is potentially a better player defensively for the more difficult games.

The estimated reduction in our defensive SPI metric from these players is 0.105, based on their assumed share of the xT against (xTA) for their respective teams in 2017/18, as shown in Table 2. The expected contribution is then calculated by finding the share of xTA for the player and assuming that a similar output would be replicated in the Inter defence.

Table 2: Expected Threat Prevented by zone for teams with targeted players

Team	xTA by LB/90	xTA by LCB/90	xTA by RCB/90	xTA by RB/90	xTA/90 Total
Internazionale	0.32	0.05	0.05	0.33	0.70
Atlético Madrid	0.34	0.07	0.01	0.45	0.87
Köln	0.53	0.13	0.13	0.55	1.34
Olympique Lyonnaise	0.44	0.07	0.05	0.34	0.90
Saint-Étienne	0.45	0.11	0.08	0.42	1.06

For instance, Filipe Luis contributed to 39% of the xTA for Atlético Madrid, while the LB position at Inter contributed to 46% of the xTA at Inter. Dropping Filipe Luis into the Inter defense is then expected to reduction the xTA by (0.7*45%)-(0.7*39%) = 0.042. For Rafael we see that the reduction is expected to be (0.7*47%)-(0.7*38%) = 0.063. This is then taken as a direct proxy for the improvement in the defensive numbers.

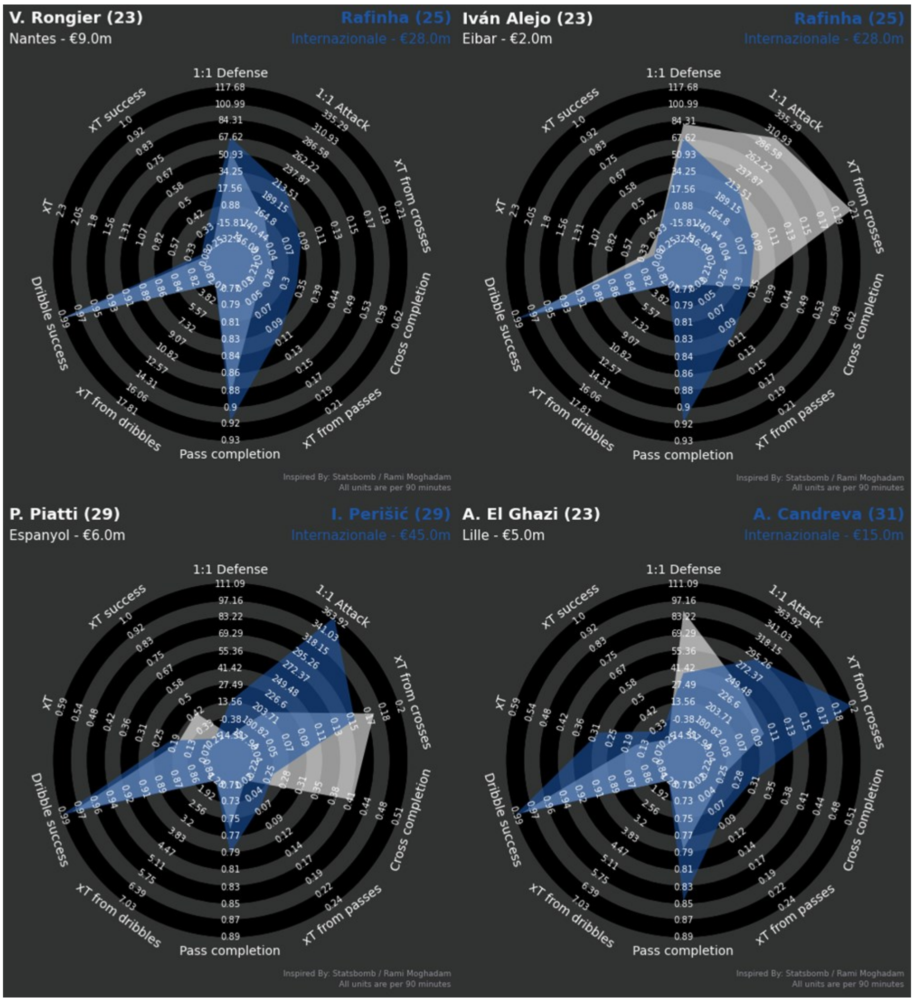

Figure 12: Key offensive options identified.

Offensively we have focused on players that can reproduce the output from Rafhina and add creativity through the middle of the pitch as well as looking for good crossers to feed Icardi.

We have identified Rongier of Nantes as a like-for-like replacement for Rafhina with Alejo of Eibar as the rotation option. As backups to Perisic and Candreva, we have identified Piatti of Espanyol and El Ghazi from Lille as affordable options. Assumed prices are sourced from transfermarkt.com. The improvement in attacking SPI metrics is here derived directly from the additional expected xT due to improved crossing ability and improvement in creativity through the middle, estimated to add 0.05 to the offensive metric.

These eight players should be available for around €44m, which is approximately the same amount as we expect to receive in prize money from the Champions League. It should be noted that Inter's spending power is hampered due to Financial Fair Play regulations, and that expensive signings will not be likely. To ensure that we will get value from the players suggested, we do a quick expected revenue analysis for the upcoming year. The net return is conservatively taken as the minimum expected revenue from the Champions League the upcoming season, which amounts to €33m starting fee, plus €2.7m per win and €0.9 per draw.

The investment cost for a player in this exercise is full acquisition cost divided by the length of his contract (5 years) plus the assumed annual salary, which is here assumed to be similar to the acquisition cost. The motivation is two-fold, one is to see the impact for this year, the other is to keep the investment analysis in line with book-keeping practices, where the cost of the player will be amortized over the length of the initial contract.

However, we must take into account that we do not have a 100% chance of qualifying for the Champions League next season given we acquire these players. Our simulations indicate that the chances of qualifying are around 76% when acquiring these players. The risked revenue is therefore €40m * 76% = €30.4m.

The risked return on the investment is therefore:

$$RoI = \frac{€40m * 76\%}{€88m/5} = 172.27\%$$

As such, our clear recommendation to the board is to sign off on the acquisition of the targeted players so we can ensure sustained success in the upcoming years.