LOCAL ECONOMY EFFECT OF SPORTS TEAMS: SYNTHETIC CONTROL APPROACH

by Jun Yeong Lee

Minerva School at KGI

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# Abstract

This article analyzes how sports affect city economy because it generates essential insights for both policymakers and investors. It investigates how the acquisition of Manchester City Football Club in 2008 and improvement in its performance affected the real GDP per capita in Manchester using the synthetic control method. Results support the previous findings, and the real GDP per capita of the actual Manchester did not deviate substantially from its synthetic counterpart. In other words, the Manchester City Football Club's purchase and its performance enhancement did not significantly affect Manchester's real GDP per capita. The downstream impacts of a local sports team, however, could still be economically significant compared to the initial investment amount.

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# List of Abbreviations

| | |
|---|---|
| COVID-19 | Coronavirus Disease 2019 |
| F.C. | Football Club |
| GDP | Gross Domestic Product |
| MSE | Mean Square Error |
| NASDAQ | National Association of Securities Dealers Automated Quotations |
| OECD | Organization for Economic Co-Operation and Development |
| PPP | Purchasing Power Parity |
| SCM | Synthetic Control Method |
| UK | United Kingdom |
| USD | United States Dollar |

# 1. Background

As the nature of the workforce continues to shift, companies and organizations increasingly need leaders who can utilize data to make informed decisions (Minerva School at KGI, 2021). In return, academic institutions are scrambling to put together data-science programs (Provost & Fawcett, 2013), and policymakers place tremendous faith in the power of data to transform practice (Spillane, 2012). Mandinach et al. present a framework for data-driven decision making where decision-makers can utilize the data through an iterative feedback process (2006). Data-driven decision making is a complex process, and Figure 1 can provide guidance. The current paper uses computer programming and a statistical method to apply meanings to the data, connect the information and finally make a data-driven decision.

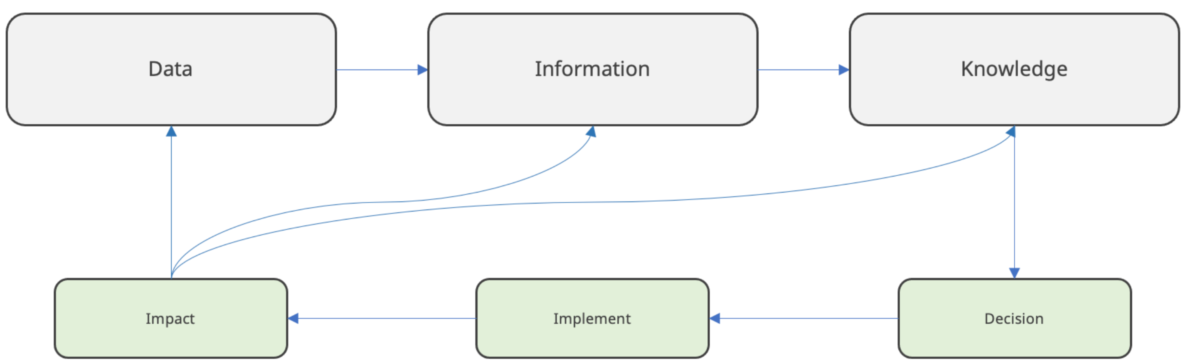


**Figure 1.** Framework for Data-Driven Decision Making. Decision-makers utilize the data through an iterative feedback process (Mandinach et al., 2006). The current paper uses computer programming and a statistical method to apply meanings to the data, connect the information and finally make a data-driven decision.

Sports have been closely tied to human society. It has been one of the most valuable tools to relieve stress and have some fun, and politicians used to exploit bread and circuses to distract citizens from policymaking (Duffy & Ashley, 2012). For instance, gladiator fights and Colosseum in ancient Rome made people satisfied with current affairs. In recent years, sports still turned out to have many positive aspects on the local community. Football was introduced by colonial administrators, industrialists, and missionaries as part of their civilizing mission (Chipande, 2016). Immigrants in the United States develop a sense of belonging through sports (Santos Gómez, 2014). Sports facilities and various sporting events also contribute to urban transformation (Koch, 2018). Likewise, sports and the city interact in many other ways that scholars have arguably only scratched the surface. The current study aims to reveal some interactions and concentrates explicitly on the local economy. More specifically, it addresses the effect of a local sports team on the local economy.

It is crucial to understand how sports affect the city economy because it then generates essential insights for both policymakers and investors, especially now with many major football teams in Europe going bankrupt due to COVID-19. If sports teams can provide direct economic benefits, politicians can utilize them as a policy option (Sage, 1993). Knowledge of sports franchise will provide a piece of evidence on the budget allocation and policymaking. On the other hand, for business owners and investors, sports teams can be an alternative investment strategy that generates long-term profit. Although the investors would wish to know the return-on-investment ratio, a causal inference between sports franchise and economic benefits can be an excellent start to answer the question, 'Should a long-term profit-seeker invest in a local sports team?' This article will start answering the question by assembling a narrative within the academic literature on sports franchise and developing a synthetic control model to investigate the relationship between sports and the local economy. Then, it will define an effect estimation strategy and finally analyze the result of the model.

# 2. Literature Review

Sports have been closely associated with human society, and many scholars have attempted to study the effect on various areas. A narrative within the academic literature on sports franchise helps identify limitations of the previous research and introduce a potential alternative to test.

Munyo claimed that the Uruguayan national football team games reduced aggregate crime rates (2014). He found that total offences were decreased by 13 per cent during highly relevant games. An important football match would keep potential offenders off the streets. However, this phenomenon is partially compensated by an increase in the aftermath of the game due to violent interactions.

Furthermore, recent studies confirmed the role of sports as a generator of tourist expenditure. Using the UK International Passenger Survey and unconditional quantile regressions, Rudkin and Sharma revealed that benefits from footballing events spread beyond the stadium into the wider community (2020). Football attendance significantly affects tourist expenditures even without ticket prices. While formalizing the direct link between the expenditures and footballing events can be questionable as participants do not answer where they spend, the vital link between successful sports franchises and economic benefits broadly backs up the notion that expenditure is linked to matchday experience (Davis & End, 2010).

Sports can also play a crucial role in trading behaviour. Statistically significant evidence of localized trading was found in NASDAQ stocks that stock trading volume dropped for firms in blizzard-struck cities compared to firms located in other cities (Loughran & Schultz, 2004). This behaviour is an example of sentiment trading, and sports fandom can also influence the shares of local firms. Akhigbe et al. examined the relationship between the National Basketball Association playoff games and trading of firms headquartered in the geographic area of the participating teams, concluding a significant increase in volume before the game (2017). Investment decisions are firmly ruled over by our emotion (Barberis & Thaler, 2002). Wins of local sports teams are associated with positive stock price returns for localized businesses.

Taken collectively, it may seem evident that sports have various positive aspects, and there are multiple reasons for policymakers to encourage an expansion. However, when Islam studied the effect of the National Football League expansion on employment growth, no significant treatment effect was found using a synthetic control method (2019). The expansion of the National Football League allowed three cities to enter the league. However, the time path of employment growth in the three treated cities did not significantly deviate from their synthetic counterparts. This result supports the counterarguments, casting doubt on a new sports franchise's ability to spur economic growth (Coates, 2015).

Those who are against the economic benefits of sports question the existing empirical models. For example, Coates and Humphreys point out that the average year to year change in per capita income should be looked at as a proportion, not an absolute value (1997). Cities with major sports teams are likely to have a higher standard of living, to begin with, and are in a better position for absolute growth. Moreover, city development is a highly complex system with countless confounding variables (Figure 2). Sports franchises can be a result of other events. Excessive cash inflow for a city can stimulate people to invest, and a sports team is a great investment alternative. In it, the cause of sports franchises is also a cause of economic growth, rather than sports teams helping the city grow.

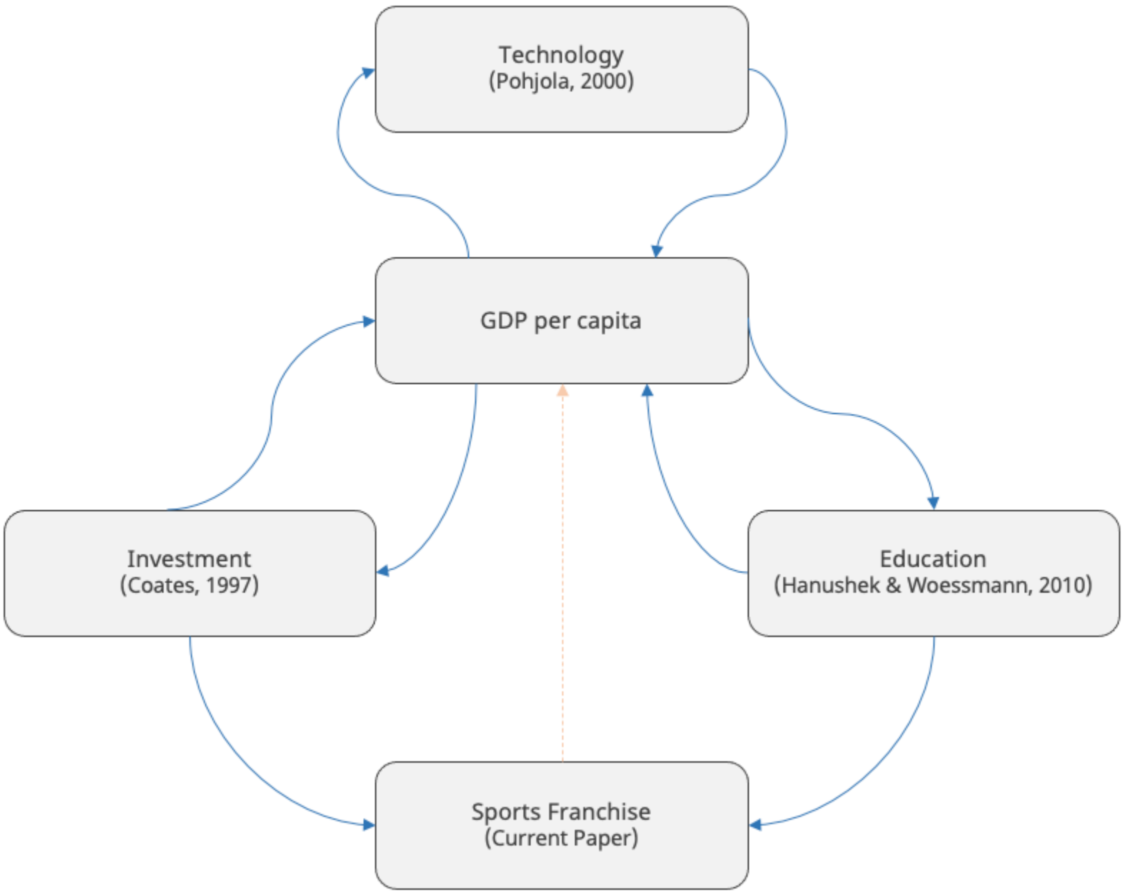


**Figure 2.** GDP per Capita Feedback Loop. Investigating the causal effect of a sports franchise on GDP per capita can be difficult due to the iterative nature of the loop. For instance, with investment and education affecting both GDP per capita and sports franchise simultaneously, existing empirical models has limitations to draw a casual inference between sports franchise and GDP per capita.

In that sense, Islam's synthetic control model well-controlled potential biases and generated a somewhat counterintuitive result of no treatment effect. The author chose employment growth as the outcome variable with population growth and real per capita income growth as the predictor variables. In other words, population growth and real per capita income growth are used to determine weights and form a synthetic control unit, measuring the treatment effect in employment growth. The study repeated the analysis three times with three different locations. For all treated cities, Jacksonville, Tennessee, and

Carolina, construction of the new stadiums was the treatment, and the treatment effects were measured afterwards. Again, the treatment effects of the local sports franchises in all three treated cities were not significant based on the placebo tests. The conclusion simply stated that sports franchises do not contribute to employment growth in the communities in which they are located.

Nevertheless, there are still some gaps. Despite the fact that employment growth is typically correlated with output growth, it was not always the case (Garibaldi et al., 2002). Sweden or Japan had negative employment growth between 1980 and 2000, but higher than the average GDP growth. The time path of employment growth is only a tiny fraction of city developments and cannot be relied on solely. Also, the synthetic unit was formed by only comparing income growth and population growth. While those two predictor variables are generally accepted for economic status, other significant variables, such as level of education and Purchasing Power Parity (PPP) index, can add more values to the model.

The fact that the three treated regions from the original paper did not outperform the other cities during the treatment period cannot be neglected. The Jacksonville Jaguars had four wins and twelve losses in 1995, the following season with the new stadium. The Tennessee Titans had eight wins and eight losses in 1997, and the Carolina Panthers had seven wins and nine losses. Entering the league and constructing a new stadium as a part of the expansion is exciting but may not be enough treatment for economic benefits. If the local economic growth is a result of the high performance of the local teams, both sides' arguments and conclusions can be explained. The tourist expenditure in community and trading volumes for localized businesses increased because the local team won and performed well in the league. Yet, no treatment effect was observed on the employment growth because the representing teams tended to lose, and fans were frustrated.

# 3. Problem Statement

To fill the gaps in variables and controls, the current study replicates Islam's analysis (original paper) and clarify the question. To better estimate the treatment effect in GDP per capita, the model would be controlled for population growth, employment rate, and educational attainment. Unlike the Jacksonville Jaguars, Tennessee Titans, and Carolina Panthers from the original paper, a champion team will be selected to address the effect. A significant difference between the actual city and the synthetic city will support the hypothesis that a sports franchise positively impacts the local economy when it is performing well. Otherwise, if no significant effect in GDP per capita is observed, it supports the opposite argument that sports franchise either does not affect the local economy at all or just a mediator variable caused by other events along with the predictor variables. Either way, the result of this paper can generate essential insights for both policymakers and business owners. If sports teams can provide direct economic benefits, politicians can utilize them as a policy option and business owners as an alternative investment strategy (Sage, 1993).

# 4. Method

Synthetic control method (Abadie, A., Diamond, A., & Hainmueller, J., 2010; Abadie, A., & Gardeazabal, J., 2003) provides a systematic way to choose comparison units in comparative case studies (Abadie, A., Diamond, A., & Hainmueller, J., 2015), and it has a significant advantage when studying the effect of interventions that are implemented at an aggregate level affecting a small number of large units, such as city, on some aggregate outcome of interest (Abadie, 2013). Multiple areas have been exploiting the method, including government policy (Kreif et al., 2016), trade liberalization and child mortality (Olper, A., Curzi, D., & Swinnen, J., 2018), and concealed carry laws (Gius, M., 2019). Current study develops a synthetic control model to investigate the effect of a sports team on the local economy.

The synthetic model follows a form of quasi-experimental design, where it does not rely on random assignment. Abadie et al. analyzed the economic cost of the 1990 German reunification (2010). It is not feasible to select a group of people to experience reunification while the others are controlled. Post-reunification Germany could be compared to pre-reunification Germany, but multiple confounding variables can contribute to the gap. Alternatively, another country sharing similar economic attributes to pre-reunification Germany could be selected, but it can be challenging to find one with the exact same condition. Instead, Abadie et al. construct a synthetic Germany using a combination of countries around the world, minimizing the gap in pre-reunification attributes.

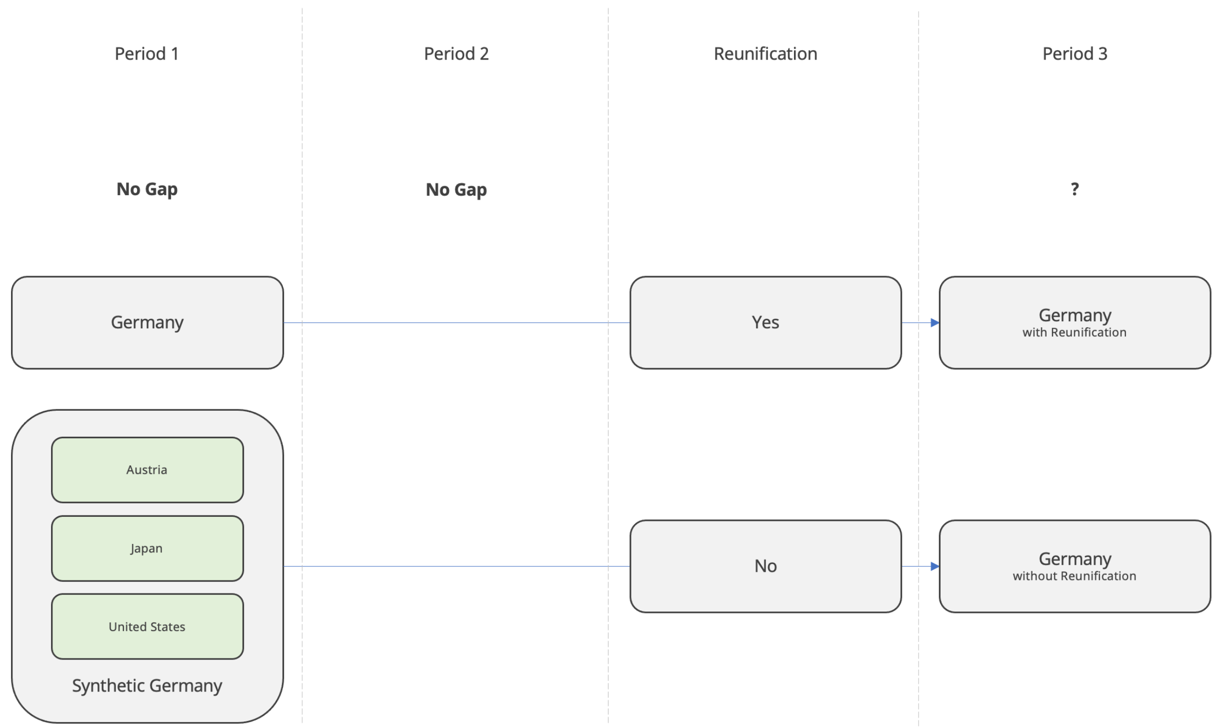


**Figure 3.** Synthetic Control Model Conceptual Diagram 1. The constructed synthetic unit shows what would have happened if the actual unit did not receive the treatment.

A critical assumption here is that synthetic Germany captures what would have happened if Germany was not unified. By observing no gap during pre-reunification, the model assumes the combination of countries successfully mimics Germany, and the post-reunification synthetic Germany can be used for the comparison. Hence, the selection of comparison units is a crucial step to this approach. Using a weighted average of predictor variables, the synthetic unit should mimic the treated unit during pre-treatment. It can, however, diverge during the post-treatment since there was no treatment applied. If the synthetic counterpart is not sufficiently simulating the treated unit, then the difference between the two units would be observed during the pre-treatment. The below research design section elaborates the model in detail.

Manchester City Football Club, founded in 1880, gained promotion to the Premier League in 2002 but remained in the middle ranks until 2008 (Manchester City FC., 2020). It is when Abu Dhabi United Group decided to purchase the club for 200 million pounds, supporting a tremendous amount of funds for facilities, staffs, and players (Kerr, 2008). The club came to fruition four years after the investment, winning the League Championship for the first time in 44 years. The acquisition being treatment, the current study creates a synthetic Manchester, which shows the same level of pre-treatment GDP per capita and compares the post-treatment gap. Figure 4 further elaborates how current analysis applies the synthetic control method to estimate treatment effect of Manchester City Football Club on Manchester's local economy. If having a successful team helps the local economy, then the actual Manchester's GDP per capita will lie above the synthetic Manchester post-treatment, supporting the hypothesis of positive effect.

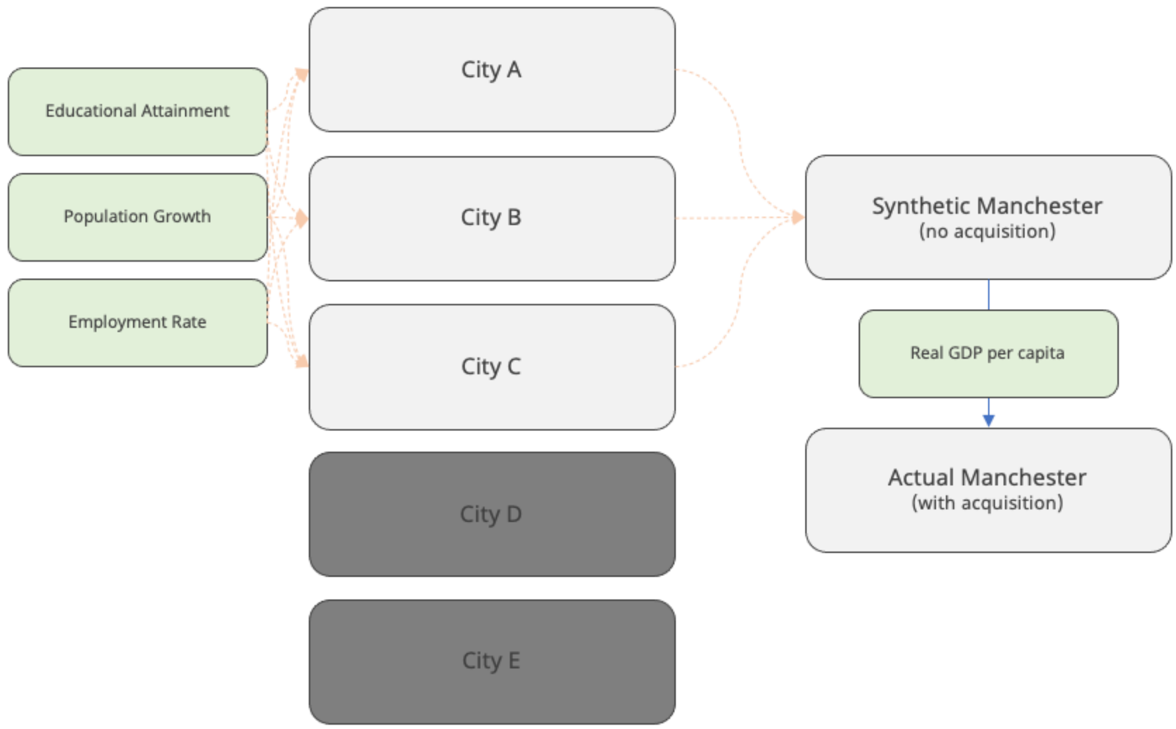


**Figure 4.** Synthetic Control Model Conceptual Diagram 2. Synthetic Manchester shows what would have happened if Manchester did not experience the acquisition of the local team, which allows measurement of the treatment effect.

## *4.1 Research Design*

Manchester being the treated unit, the donor pool consists of 38 cities across the United Kingdom, from Aberdeen to Wirral. In other words, in a sample of $J + 1$ cities, indexed by $j$, $j = 1$ is the Manchester and $j = 2$ to $j = J + 1$ are the other 38 cities from the United Kingdom. This set of 38 untreated units is used to create a synthetic "untreated" Manchester to estimate the treatment effect of the takeover. The time periods, $t = 1, \dots, T$, contain pre-intervention periods of $1, \dots, T_0$ and post-intervention periods of $(T_0 + 1), \dots, T$. The data have been collected from 2001 to 2018, and the acquisition took place in 2008. Therefore, $T_0$ is 2008 in the current analysis. If synthetic Manchester is sufficiently constructed and mimicking the actual Manchester, the time path of the outcome variable, $Y$, should be relatively close between the two units from 2001 to 2007. Moreover, significant divergence in $Y$ should be observed from 2008 to 2018, if a sports franchise does affect the local economy.

The model defines two outcomes. $Y_{jt}^{I}$ and $Y_{jt}^{N}$ denote the outcome that would be observed for unit $j$ at time $t$, with and without the treatment. For instance, the goal can be to define and estimate the effect of the acquisition on GDP per capita in the post-treatment periods, $\alpha_{1t} = Y_{1t}^{I} - Y_{1t}^{N}$ for periods $(T_0 + 1), \dots, T$. Here, $Y_{jt}^{I}$ can be found in the data collected, but $Y_{jt}^{N}$ needs to be estimated. To construct the synthetic control unit and estimate $Y_{jt}^{N}$, a vector of weights, $W = w_2, \dots, w_{(J+1)}$ , needs to be defined. Each $W$ represents a particular weighted average of control units and therefore has to be nonnegative and sum to 1. Abadie and Gardeazabal (2003) and Abadie et al. (2010) propose to choose the weights $W^*$ such that the resulting synthetic control unit best approximates the unit exposed to the intervention in the pre-treatment period and minimizes the following:

$$V_1\left(X_{11} - w_2X_{12} - \cdots - w_jX_{1j}\right)^2 + \cdots + V_k\left(X_{k1} - w_2X_{k2} - \cdots - w_jX_{kj}\right)^2$$

where $V_k$ is the weight given to each predictor variable. For example, if the employment rate is particularly more important than the population growth in predicting GDP per capita, $V_{employment\ rate}$ will have a higher weight than $V_{population\ growth}$.

For this study, the outcome $Y$ variable is real GDP per capita, and predictor $X$ variables are population growth, employment rate, and secondary educational attainment. The most frequently used, reliable measurement of economic growth is the inflation-adjusted, real gross domestic product (GDP). However, the GDP can vary due to the size of the city, not the standard of living. For instance, Greater Manchester had a total GDP of 130 billion US dollars in 2015, while Oxford only had a total of 25 million US dollars. Nevertheless, GDP per capita, the city's gross domestic product divided by its population, for Oxford was 6000 US dollars higher than for Manchester. To accurately measure the local economy, real GDP per capita is used to estimate the treatment effect of the sports franchise.

The outcome $Y$ variable can be added to the predictor $X$ variables as it perhaps best represents the actual Manchester when constructing a synthetic Manchester. However, Kaul et al. warn to never use all pre-intervention outcomes as economic predictors (2016). If the outcome variable itself becomes another predictor variable, it can have a weight, $V_{GDP\ per\ capita}$, close to 1, resulting in all other predictors assigned zero $V_k$. This behaviour can be even more problematic if the GDP per capita is biased by some other factors. To avoid such issues, the model excludes the GDP per capita from the predicting variables.

Abadie et al. (2010) used GDP per capita, percentage of secondary school attained in the total population aged 25 and older (schooling), industry share of value-added (industry), inflation, export plus imports as a percentage of GDP (trade openness), and the ratio of real domestic investment to real GDP (investment rate). This choice of variables is an excellent place to start for a standard measure of economic growth. However, scholars have been raising concerns that GDP per capita fails to reflect a few important aspects of well-being. It had a sizeable difference with other key indicators such as life expectancy and education (Easterlin, 2000; United Nations, 1952). Also, London has led the United Kingdom's economic growth since the 1990s, followed by an increasing degree holder percentage of the population. Whether the economic growth attracted highly educated people to move in or the higher education affected the economic growth, it can be said that the educational attainment is positively correlated with the economy, being a good indicator. Furthermore, the United Kingdom stated that full-time education is compulsory for all children under the age of 16. Especially in England, the requirement extended to the age of 18 since 1997. Because of this, the current study looked at the educational attainment for the population between 25 to 64 years old. The pupil population has close to 100 per cent educational attainment rate, and therefore, it is difficult to differentiate the result by the city distinctly. By looking at the rest of the population, it could highlight the gap in education among the cities, adding extra values to the synthetic model. Similar to Abadie et al. (2010), secondary educational attainment was collected since a university degree is considered optional, and secondary education better represents the overall education level.

Challenges to the city level analysis included data availability. The inflation rate and PPP index were not much different in the city level comparison. Instead, the current synthetic analysis uses the real GDP per capita, which is already adjusted for the inflation and PPP index. In a similar vein, industry share, trade openness, and investment ratio data were not able to be found. These indicators are available instead in a country level summary, so they are excluded for model simplification. Population growth from the original paper continues to be used as a predictor variable. The classical theory of population growth holds that a rise in income tends to increase birth rates and decrease death rates (Coale & Hoover, 2015). It is another proper measurement of the local economy. The employment rate, the output variable from the original paper, is also used to construct synthetic Manchester.

Because the model explicitly analyzes the treatment effect for a better performing team, excluding the league champions of the Premier League during the period was also considered. Nevertheless, no constraint on the donor pool selection was applied due to two reasons. First, Abu Dhabi United Group acquisition was a "once in a lifetime" deal, and it meant more than just winning the trophy. Since the takeover, Manchester City purchased dozens of world-class players, supporters count increased significantly, and the club kept the momentum until now. There is no other team winning the league in consecutive years, so the exclusion is absolutely unnecessary. Second, Manchester is the second-largest city in the United Kingdom, following the capital London. The league champions happened to be all based on either London or Manchester for the last 20 years except for 2016, Leicester. It can become extremely complicated to construct a synthetic Manchester without having London. For those reasons, the synthetic counterpart was constructed using all cities available in the data.

## *4.2 Data Collection*

Real GDP per capita, population growth, and employment rate are collected from the OECD regional database, developed by the OECD Centre for Entrepreneurship, SMEs, Regions and Cities (CFE). In it, city-level annual indicators are available from 2001 to 2018, which allows a brief analysis of those parameters. Real GDP per capita is measured in USD and generally shows an upward trend. The average real GDP per capita in 2001 was $33,159.44. Throughout the timeframe, the average increases by 20 per cent, hitting $39.784.87 in 2018. While the annual growth typically shows approximately 2 per cent, it is interesting to observe the average real GDP per capita shrank in 2008 and 2009 by 1 and 3 per cent.

This was when the United Kingdom experienced an economic recession, with the Royal Bank of Scotland posting a 28 billion pounds loss. It becomes problematic to construct a synthetic Manchester if Manchester behaves in a unique way during the recession. For example, Stoke-on-Trent showed a 1.5 per cent growth in 2008, followed by a 5.5 per cent decrease in 2009. Considering 2008 is when the intervention was applied, the validity of the data must be carefully reviewed. Thankfully, Manchester also experienced the national trend of a decrease in real GDP per capita. National real GDP per capita decreased by 1.0 per cent in 2008 and 3.6 per cent in 2009, while Manchester's real GDP per capita in 2008 and 2009 decreased by 3.2 per cent and 2.8 per cent respectively.

Population growth is measured by a proportion of the total population index, having 2001 as 100. In other words, Bournemouth had a 100.50 growth index of the total population in 2002, meaning it grew 0.5 per cent compared to the year before. On the other hand, Dundee City shows a 99.50 growth index in 2002, meaning it shrank by 0.5 per cent. It also shows an upward trend, including the years in the recession. On average, the population of the United Kingdom grew by 11.02 per cent for the last 17 years.

The employment rate is calculated by the employment for the population ages between 15 and 64 years old over the entire population ages between 15 and 64 years old. This is the only variable that did not show an upward trend. The level of employment rate in 2001, 70.61, is indifferent to the level of employment rate in 2018, 70.47. However, the differences among the cities are significant enough to form a synthetic unit with it. For instance, Middlesbrough's employment rate in 2004 is 60.50, which is 21.2 per cent lower than Aberdeen.

Schooling indicates the educational attainment, collected by the Centre for Entrepreneurship, SMEs, Regions and Cities (CFE), in coordination with the Directorate for Education and Skills (EDU). It represents the percentage of the population aged between 25 to 64 years old that completed secondary education. For instance, the average schooling of the United Kingdom in 2018 is 38.69, meaning approximately 38.69 per cent of the population aged between 25 to 64 years old achieved secondary education. Despite the compulsory education for all children under the age of 16 since 1997, elders play a crucial role in reducing the percentage down below 50.

The biggest challenge of the schooling data is that it is at the regional, county level, unlike real GDP per capita, population growth, and employment rate. However, instead of converting schooling data into the city level, the current analysis mapped each city from the three variables to its corresponding region and further mapped to its county if available. More specifically, Aberdeen was mapped to Scotland, Blackburn with Darwen to Lancashire, Bournemouth to Dorset and Somerset, Brighton and Hove to Surrey East and West Sussex, Bristol to Gloucestershire Wiltshire and Bristol/Bath Area, Cambridge to East of England, Cardiff to Wales, Cheshire West and Chester to Cheshire, Colchester to Essex, Coventry to West Midlands, Derby to East Midlands, Dundee City to Scotland, Edinburgh to Scotland, Exeter to Devon, Glasgow to Scotland, Kingston upon Hull to East Yorkshire and Northern Lincolnshire, Leeds to West Yorkshire, Leicester to East Midlands, Liverpool to Merseyside, London to Greater London, Manchester to Greater Manchester, Medway to Kent, Middlesbrough to North Yorkshire, Milton Keynes to Berkshire Buckinghamshire and Oxfordshire, Newcastle upon Tyne to Northumberland and Tyne and Wear, Northampton to East Midlands, Norwich to East of England, Nottingham to East Midlands, Oxford to Berkshire Buckinghamshire and Oxfordshire, Plymouth to Devon, Portsmouth to Hampshire and Isle of Wight, Preston to Lancashire, Sheffield to South Yorkshire, Southampton to Hampshire and Isle of Wight, Stoke-on-Trent to Shropshire and Staffordshire, Sunderland to Northumberland and Tyne and Wear, Swansea to Wales, West Midlands urban area to West Midlands, and Wirral to Merseyside.

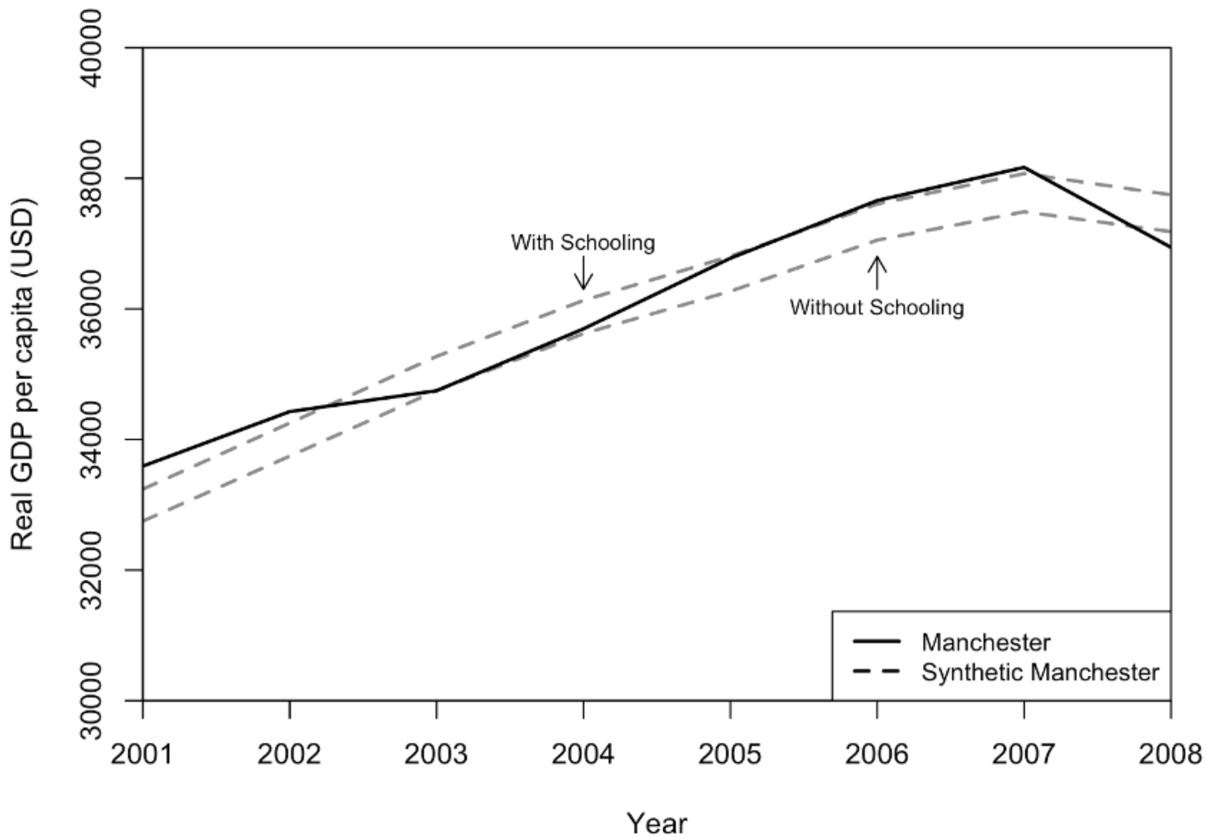


**Figure 5.** Synthetic Manchester with and without Schooling Data. Synthetic Manchester better replicates the actual Manchester with schooling data during the pre-treatment period (the vertical dotted line represents the acquisition).

The validity of the schooling data is still questionable. Since the data can be strongly biased while being converted and mapped, the value of the data needs to be confirmed before being used. Figure 5 shows synthetic Manchester with and without the schooling data during the pre-treatment period. It can be seen that the model slightly better replicates the actual Manchester with the schooling data. Despite the immaterial change, this figure justifies the use of schooling data as it increases validity of the analysis.


**Figure 6.** Correlograms for All Variables. Schooling is negatively correlated with the rest of the variables, but they are not significant except GDP per capita ($\alpha = 0.05$). Insignificant correlations are crossed out.

However, it is counterintuitive to observe that schooling is negatively correlated with year, real GDP per capita, population growth, and employment rate (Figure 6). Educational attainment is known to be a standard measurement of economic growth, but it is associated with lower real GDP per capita. It can be explained by that London, on average, shows 33.0 per cent of the population aged between 25 to 64 years old achieving secondary education. This number is 7 per cent lower than the United Kingdom average and the worst of all cities. Gibbons and Silva commented that this is not because urban environments disadvantage pupils, but because the most disadvantaged pupils with low average educational attainments attend the most urbanized schools (2008).

# 5. Result and Discussion

So far, the current paper assembled a narrative within the academic literature on sports franchise and developed a synthetic control model to answer the big question, 'Should a long-term profit-seeker invest in a local sports team?' This section shows the process of developing the estimation strategy to investigate the local economic effect of a sports team and the result of the model, followed by a validity test.

Manchester City Football Club started to perform very well right after the acquisition. In 2009, the City ended the season with eighteen wins, thirteen draws, and seven losses. It was a significant improvement compared to fifteen wins, five draws, and eighteen losses in 2008, justifying the treatment year. Furthermore, the best record the City had ever had in the premier league prior to the acquisition was 8$^{th}$ in 2004. Therefore, any observed economic impact can reasonably be linked to the acquisition and its performance, allowing for causal inference. Using population growth, employment rate, and schooling data, up until the treatment year, the current model constructed a synthetic Manchester that has not gone through the acquisition. Any differences in real GDP per capita between the actual Manchester and the synthetic Manchester can be interpreted as treatment effects of the takeover. To identify the significance of the gaps, the current study also performed placebo testing both in time and place.

## *5.1 Synthetic Model*

A synthetic Manchester, a combination of untreated units, was constructed with weights chosen to reproduce the best value of predicting variables in Manchester. More specifically, the $V_k$weights chosen by the cross-validation showed that the most relevant, crucial predicting variables are educational attainment (0.93), the employment rate (0.07) and population growth (0). It is interesting to observe 0 weight on population growth. Especially knowing that population growth is one of the critical indicators of economic growth, it is critical to understand why the synthetic model did not use population growth to construct a synthetic unit at all.

| Predictor Variable | Manchester | Synthetic Manchester | Sample Mean |
|---|---|---|---|
| Population Growth | 101.21 | 101.23 | 101.46 |
| Employment Rate | 69.39 | 69.41 | 71.26 |
| Schooling | 40.79 | 40.79 | 40.93 |

**Table 1.** Predictor Balances before Acquisition. Manchester is not too far from the sample mean, and synthetic Manchester reasonably replicates the balances.

The predictor balance among Manchester, synthetic Manchester, and sample mean can explain this phenomenon. Population growth showed steady upward trends for most of the cities in the United Kingdom throughout the experiment period. The mean Manchester's population growth during the pre-treatment period was 101.21, which is almost identical to the sample mean of 101.46. As it is strongly correlated to the time and was able to be matched without assigning any weight, population growth was excluded from the model when constructing the synthetic Manchester. The other predictor variables for the actual and the synthetic counterpart, along with the sample mean, can also be found in Table 1. Employment rate and schooling did not show distinct differences from the sample mean neither.

Table 2 indicates the weights of each city in the synthetic version of Manchester. The synthetic Manchester is a weighted average of all cities from the dataset except Exeter and Plymouth. For instance, Kingston upon Hull was given 9.50 per cent weight by the synthetic method, while Bournemouth only received 1.10 per cent. These well-spread weights can hedge the risk of confounding variables, but it comes at a cost. If there were hidden events in one of the cities that critically affected our variables, it would affect the validity of the model. Having a variety of cities in donor pool reduces such incidents because the model then most likely assigns lesser weights on a single city. However, large donor pools also raise overfitting concerns. With a number of resources to construct the synthetic counterpart, the model could create a synthetic unit that perfectly reproduces the predicting variables during the pre-treatment period but not realistic and mimics what would indeed happen without the treatment. Although the current model tries to avoid overfitting by cross-validation technique and removing population growth from the predicting variable, it should still be noted that the model's donor pool contains 33 cities from the United Kingdom.

| City | Weight | City | Weight |
|---|---|---|---|
| Aberdeen | 2.10% | Medway | 2.00% |
| Blackburn with Darwen | 2.60% | Middlesbrough | 6.40% |
| Bournemouth | 1.10% | Milton Keynes | 2.20% |
| Brighton and Hove | 2.10% | Newcastle upon Tyne | 3.00% |
| Bristol | 2.40% | Northampton | 1.80% |
| Cambridge | 1.50% | Norwich | 1.70% |
| Cardiff | 3.90% | Nottingham | 2.80% |
| Colchester | 2.10% | Oxford | 2.40% |
| Coventry | 2.90% | Plymouth | 0.00% |
| Derby | 2.20% | Portsmouth | 2.00% |
| Dundee City | 3.60% | Preston | 1.60% |
| Edinburgh | 2.70% | Sheffield | 3.00% |
| Exeter | 0.00% | Southampton | 2.20% |
| Glasgow | 4.00% | Stoke-on-Trent | 2.80% |
| Kingston upon Hull | 9.50% | Sunderland | 5.80% |
| Leeds | 2.90% | Swansea | 3.90% |
| Leicester | 2.30% | West Midlands urban area | 4.00% |
| London | 4.20% | | |

**Table 2.** Weights for Synthetic Manchester. Synthetic Manchester is composed by the weighted average of the above 33 cities in the United Kingdom.

Figure 7 reveals the trend in real GDP per capita for Manchester and synthetic Manchester. The dotted vertical line indicates the acquisition, which took place in 2008. The synthetic counterpart reasonably replicates Manchester's real GDP per capita during the pre-treatment period. The most enormous gap between the actual and synthetic Manchester prior to the acquisition is less than 1,000 US dollars or 3 per cent. If there is a treatment effect of a local sports team on the local economy, a significant deviation should be observed between synthetic Manchester and the actual Manchester. If the gap is minimal and intricate to conclude a significant difference, the initial hypothesis will be rejected.

In fact, the synthetic GDP per capita is very close to the actual GDP per capita between 2008 and 2010, lies above in 2011, is almost identical between 2012 and 2015, then falls below between 2016 and 2018. It is clear from the figure that no local economy effect can be claimed from the performance of a local team. The acquisition of the Manchester City Football Club and the improvement of its performance after the takeover did not lift the real GDP per capita of Manchester.

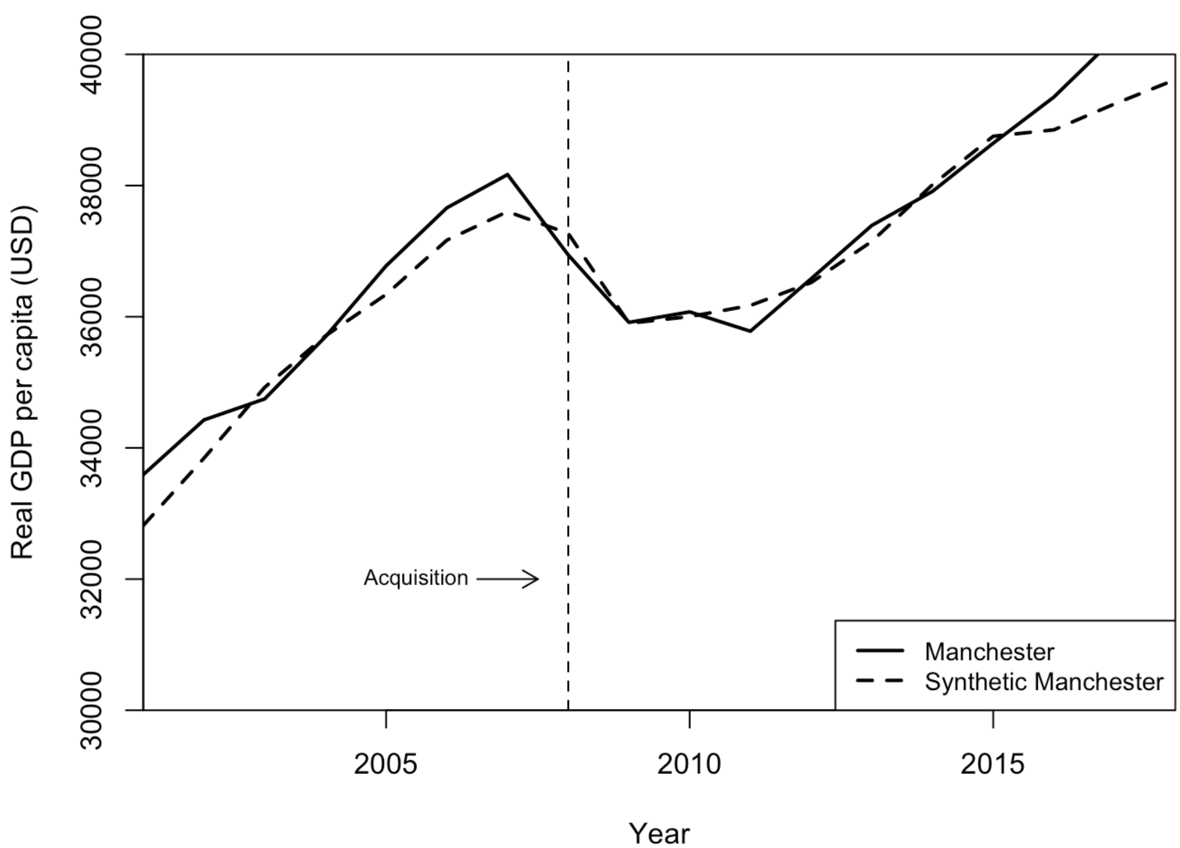


**Figure 7.** Trends in Real GDP per Capita between Manchester and Synthetic Manchester. No local economy effect can be claimed from the performance of a local team.

Figure 8 highlights the gap in real GDP per capita, making the treatment effect even more visible. The difference in real GDP per capita between 2008 and 2015 is smaller than the gap during the pre-treatment period. Again, there is no discernible trend to insist that the Manchester City Football Club brought positive impacts on the local economy. On the other hand, even though it is the opposite of what was initially expected, further clarification can be helpful for the gap between 2016 and 2018. It is possible that the treatment effect of the City's acquisition occurred after eight years without any short-run impact (2008-2015). This question can be answered by addressing the significance of the treatment effect.

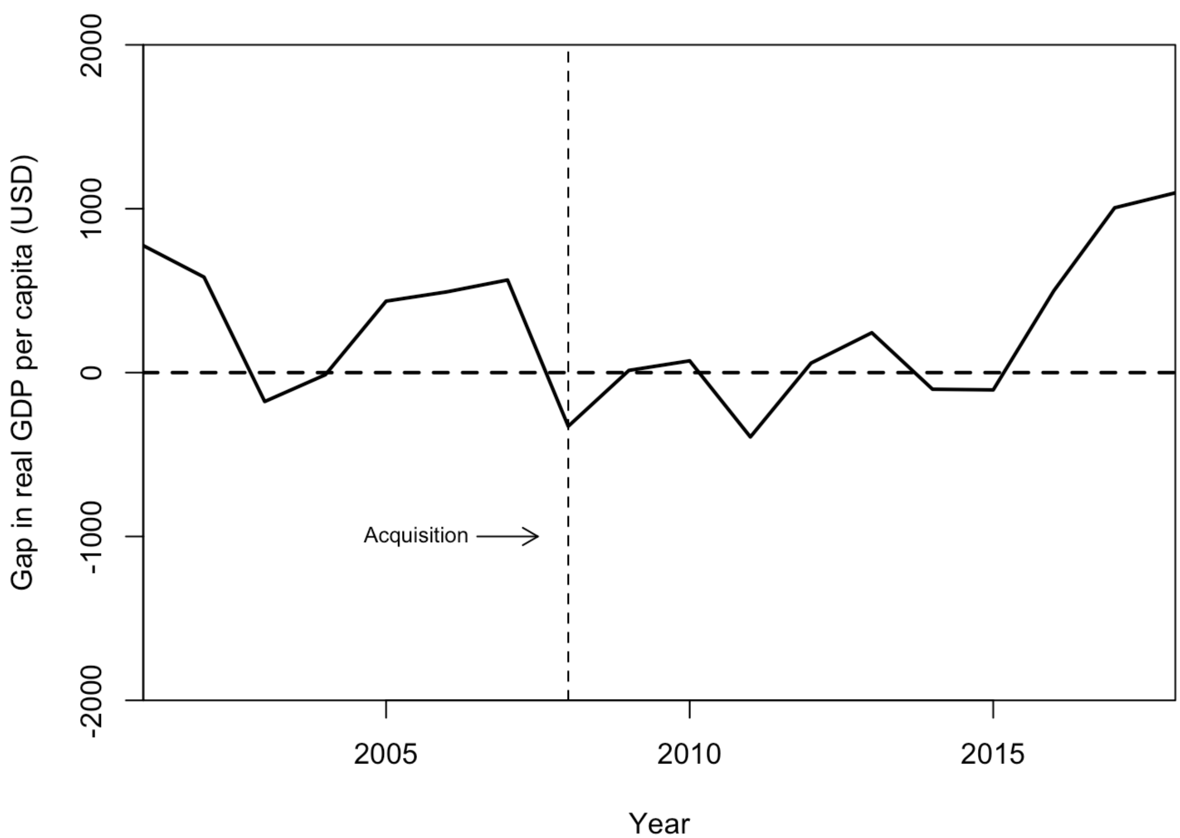


**Figure 8.** Real GDP per Capita Gap between Manchester and Synthetic Manchester. Again, there is no discernible trend to insist that the Manchester City Football Club brought positive impacts on the local economy.

## *5.2 Placebo Testing*

Significance tests were conducted in the form of placebo tests. In other words, to evaluate the credibility of the study result, placebo tests were performed. For each donor city, a synthetic counterpart was created using the same model design. The model uses population growth, employment rate, and educational attainment as predicting variables, and real GDP per capita for the output variable. The synthetic counterpart was constructed based on these predicting variables during the pre-treatment period of 2001 to 2007. Then, the difference in real GDP per capita between the synesthetic and the actual donor city was measured to evaluate the treatment effect, as if there was treatment applied. However, since the donor pool did not go through the acquisition, real GDP per capita for the synthetic donor city should not deviate from real GDP per capita for the actual donor city. If the majority of the donor cities show smaller gaps in the post-treatment period, the treatment effect can be claimed as significant. On the other hand, if the gap from Manchester does not deviate from the other donor cities, it can be said that there is no treatment effect.

Figure 9 visualizes the gap in real GDP per capita for Manchester and the other donor cities from its counterparts. It excluded cities with five times higher mean square error (MSE) than Manchester during the pre-treatment period to improve the validity of the result. If the synthetic approach experiences extremely high MSE during the pre-treatment period, it is challenging to insist that the post-treatment period captures sufficient treatment effect. Therefore, the placebo test, assuming each city in the donor pool received treatment in 2008, excluded Aberdeen, Brighton and Hove, Colchester, Dundee City, Edinburgh, Leicester, London, Medway, Middlesbrough, Milton Keynes, Northampton, Norwich, Oxford, Plymouth, Portsmouth, Sheffield, Stoke-on-Trent, and Swansea. Although the model almost lost half of the cities for the placebo test, eighteen cities are more than enough to measure the significance.

The difference in real GDP per capita between the synthetic Manchester and the actual Manchester hardly lies above 0. It has been confirmed from the earlier analysis. Nevertheless, it is fascinating to observe that the gaps in real GDP per capita for the majority of the control cities fall under the Manchester's. In fact, in 2014, the only cities with higher real GDP per capita in synthetic counterparts are Cambridge, Coventry, and Sunderland. Despite the fact that the synthetic Manchester showed $101 less real GDP per capita than the actual Manchester, it is still above 85 per cent of the donor cities the model had for the placebo test. Fifteen per cent is certainly not enough to conclude the treatment effect. However, it is essential to understand why the result shows some level of significance.

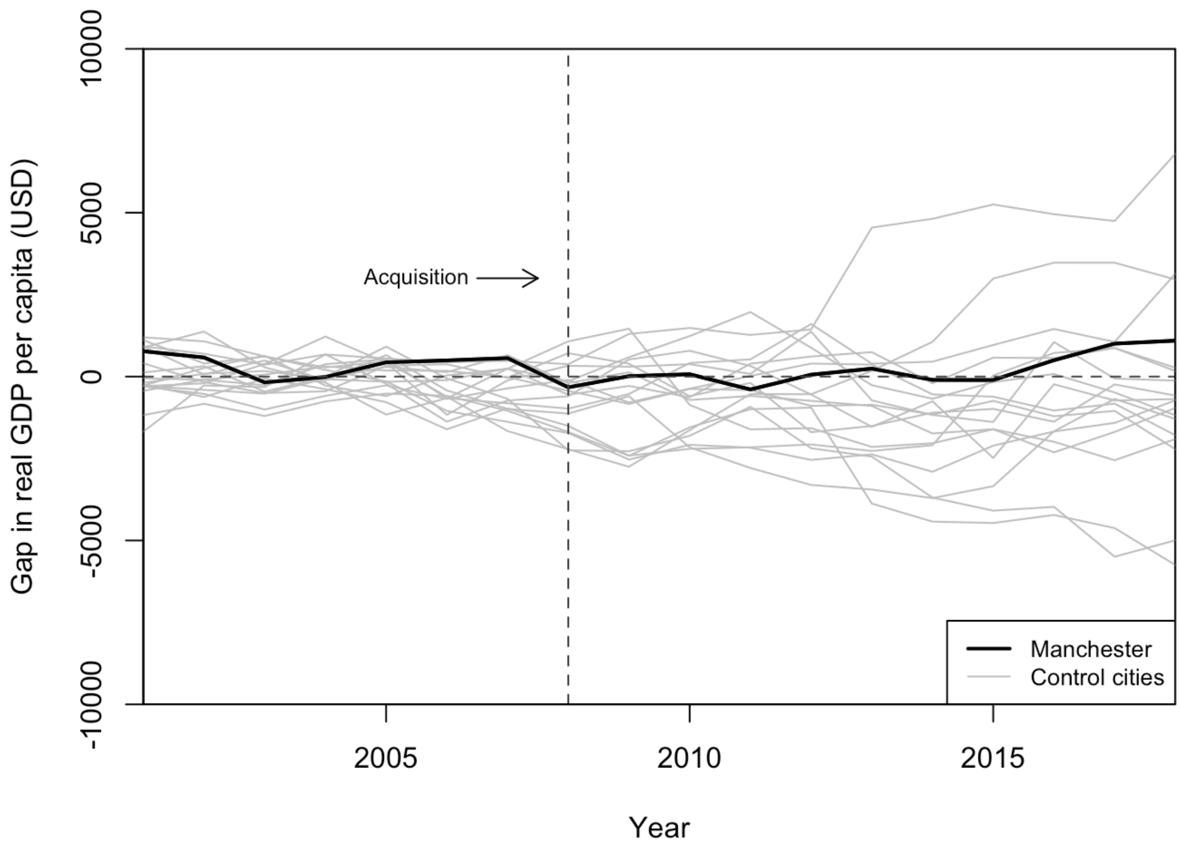


**Figure 9.** Placebo Test Assuming Each City in the Donor Pool Received Treatment in 2008. Interestingly, 85 per cent of the donor cities lie below the Manchester line.

One explanation is the economic recession the United Kingdom experienced. The Royal Bank of Scotland posted a 28 billion pounds loss. It caused a tremendous nationwide impact on the economy, and every city suffered from it. If the recession affected the entire nation, it makes sense to observe no gap in real GDP per capita between synthetic Manchester and the actual Manchester, even if there was a real treatment effect. It is possible that the treatment effect offset the downfall from the model's projection, creating a relatively horizontal line in Figure 9.

Another alternative is the Brexit referendum on 23rd June 2016. The United Kingdom held a referendum on whether or not to leave the European Union, and 52 per cent of voters voted to exit. The Brexit decision reduces investment by businesses and, therefore, can cost GDP. Although it was an act to soften cash outflow to the other European Union countries and expected to protect national income, Financial Times reported that the Brexit referendum resulted in a reduction of income by between 0.6 per cent and 1.2 per cent (Giles, 2017). Further research can be done either to identify the impact of the recession and the Brexit referendum or to conduct another synthetic control method on a local sports team but with different environments.

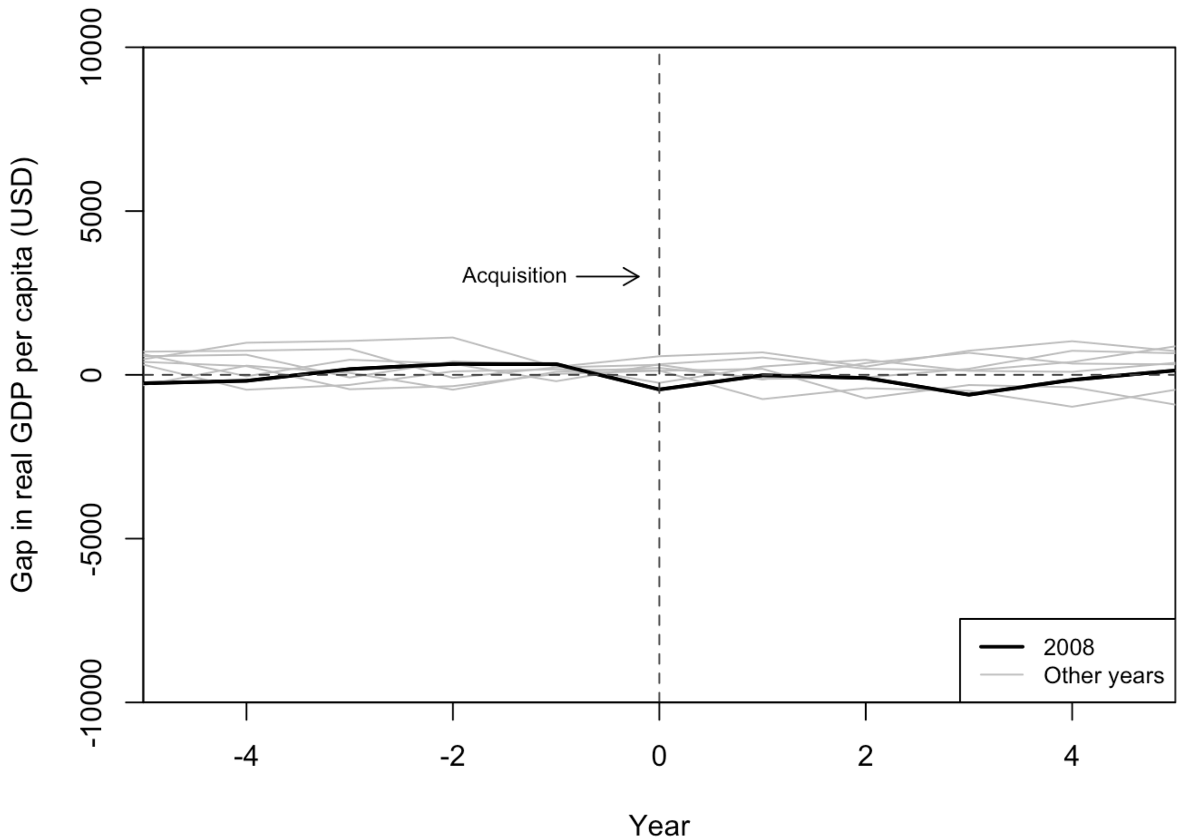


**Figure 10.** Placebo Test Assuming Treatment Year of 2006 to 2013 for Manchester. There is no significant treatment effect for 2008.

Figure 10 represents the gap in real GDP per capita for the treatment year of 2006 to 2013 for Manchester. Using the exact same design again, the placebo test assuming different treatment year reveals the significance of the treatment effect by rerunning the model with a hypothetical treatment. It also tried to exclude years with five times higher mean square error than 2008 during the pre-treatment period, but no data were removed from the model as it showed stable pre-treatment MSE. Year 0, the vertical dotted line, indicates treatment year, and the data were used from $T_0 - 5$ to $T_0 + 5$ for each iteration. Because the initial sample included from the year 2001 to 2018, only 2006 to 2013 were used for the placebo test as it holds sufficient pre-treatment and post-treatment data. Similar to the placebo test in place, if the majority of the non-treatment years show smaller gaps in the post-treatment period, the treatment effect can be claimed as significant. On the other hand, if the gap from the treatment year of 2008 does not deviate from the other years, it can be said that there is no treatment effect.

All different years in the placebo test relatively showed horizontal lines. In it, it is difficult to observe any deviation between 2008 and the other years, indicating no treatment effect. Putting it differently, setting up 2008 as the treatment year is no different from setting up 2006 or 2013 as the treatment year. The acquisition of the Manchester City Football Club only happened in 2008. The result of the placebo test in time suggests that 2008 for Manchester was 'business as usual', and the takeover did not affect its economy at all.

One limitation of this placebo test is that it only collected five years of post-treatment period. If the treatment of a local sports team has no short-run effect but only a long-run effect, it will not be able to be observed in the current placebo test in time. The actual Manchester with the treatment year of 2008 showed more considerable improvement in real GDP per capita, compared to the synthetic Manchester, starting 2016. This cannot be explained by the current placebo test, and it adds more weights to the concern regarding the Brexit referendum. Also, the treatment effect of the local sports team's performance could happen gradually over time as it gains fans. Commitment to a team does not occur after one good season. It may require a reasonable amount of time for fans to believe that the club is worth supporting. For instance, assuming fans on average needs five years to become supporters, 2006, 2008, and 2013 are not distinct enough to measure the significance.

# 6. Conclusion

Real GDP per capita for Manchester with a recent local sports team acquisition was studied using the synthetic control method. Constructing a synthetic Manchester with other cities in the United Kingdom, it was shown that the Manchester City Football Club's purchase and its performance did not significantly affect Manchester's real GDP per capita. In other words, the outcome variable of the actual Manchester did not deviate substantially from its synthetic counterpart. Placebo tests in place and time supported the result as well, with one outstanding question in Manchester performing better than 85 per cent of the other donor cities. It could be because of the economic recession the United Kingdom experienced, but nothing can be concluded without further analysis.

In conclusion, there is no evidence that a local sports team affects the local economy. This inference is consistent with Islam (2019) and Coates (2015). With much information pointing in the same direction, the answer to the question, 'Should a long-term profit-seeker invest in a local sports team?' should be no. However, statistical insignificance does not mean economic insignificance. The downstream impacts of a local sports team could still be economically significant compared to the initial investment amount. The final decision for both policymakers and investors should be ‘consider’.

The framework for data-driven decision making suggested a feedback, iterative loop among data, information, knowledge, decision, implementation, and impact. Therefore, just like any other scientific theories, the conclusion should not be final nor unchangeable. The UK economic recession might have affected the real GDP per capita and hidden a sports franchise's treatment effect. Further research can be done in different countries without economic recession. It will reveal whether Manchester performing better than most other cities was by chance or by the acquisition. Perhaps, the economic impacts from sports franchise appear slowly over the very long term. Another analysis can be done for different teams, with longer post-treatment period. It will clarify the effect period, which would especially be valuable for long term investors. The output variable, real GDP per capita, could be replaced by log real GDP per capita. It will increase robustness of the result. More studies and evidence can flip the decision. This study simply provided another information.

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# Appendix

## *Appendix A: Tables and figures*

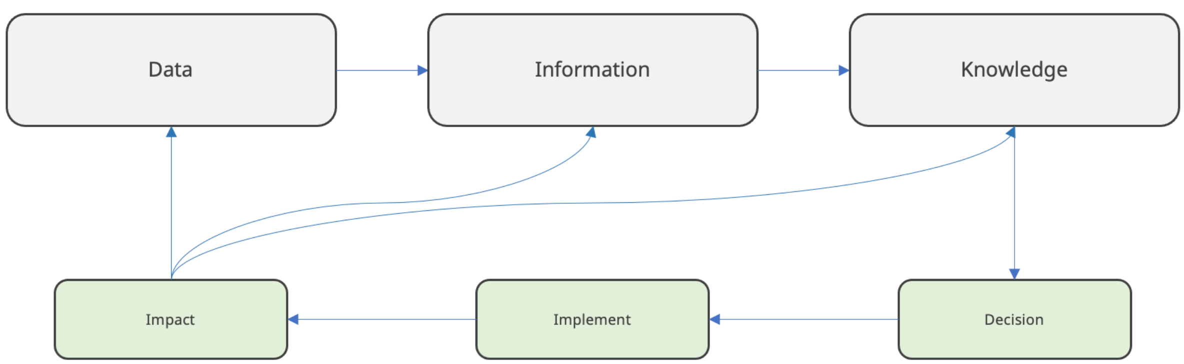


**Figure 1.** Framework for Data-Driven Decision Making. Decision-makers utilize the data through an iterative feedback process (Mandinach et al., 2006). The current paper uses computer programming and a statistical method to apply meanings to the data, connect the information and finally make a data-driven decision.

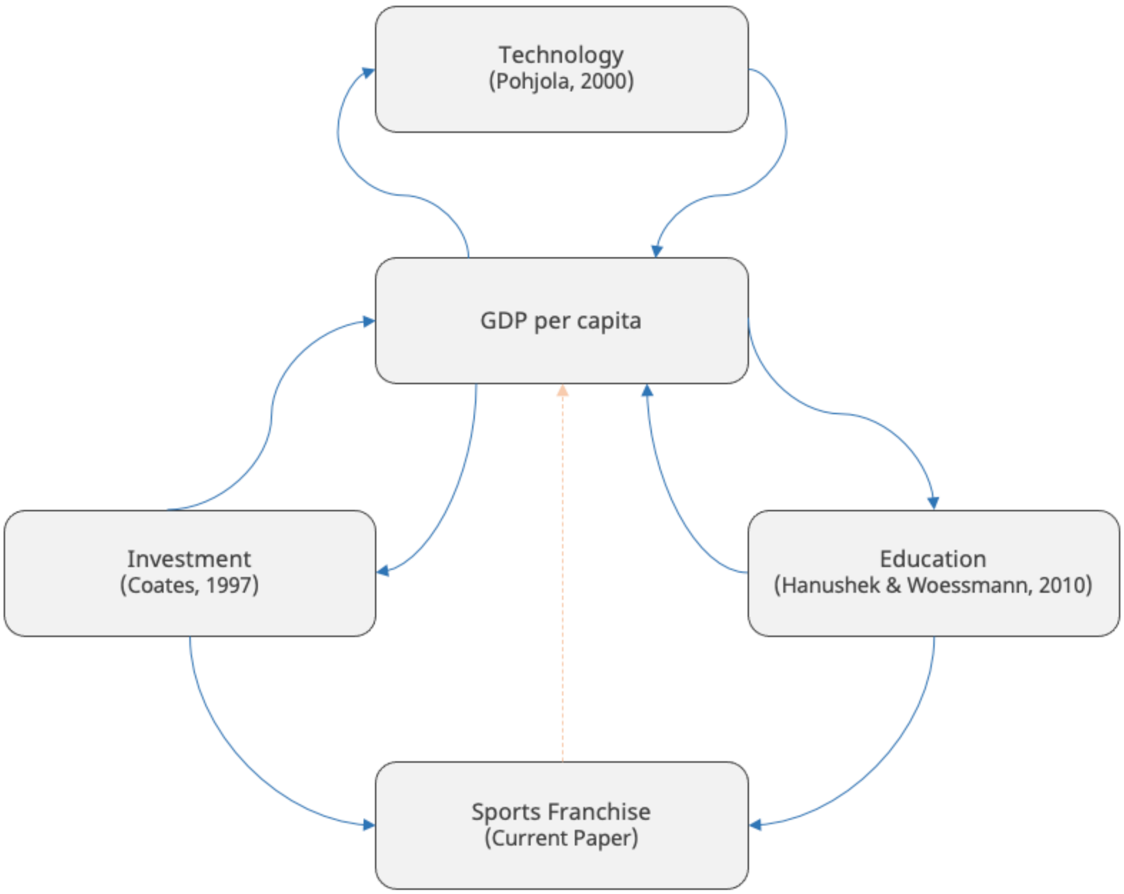


**Figure 2.** GDP per Capita Feedback Loop. Investigating the causal effect of a sports franchise on GDP per capita can be difficult due to the iterative nature of the loop. For instance, with investment and education affecting both GDP per capita and sports franchise simultaneously, existing empirical models has limitations to draw a casual inference between sports franchise and GDP per capita.

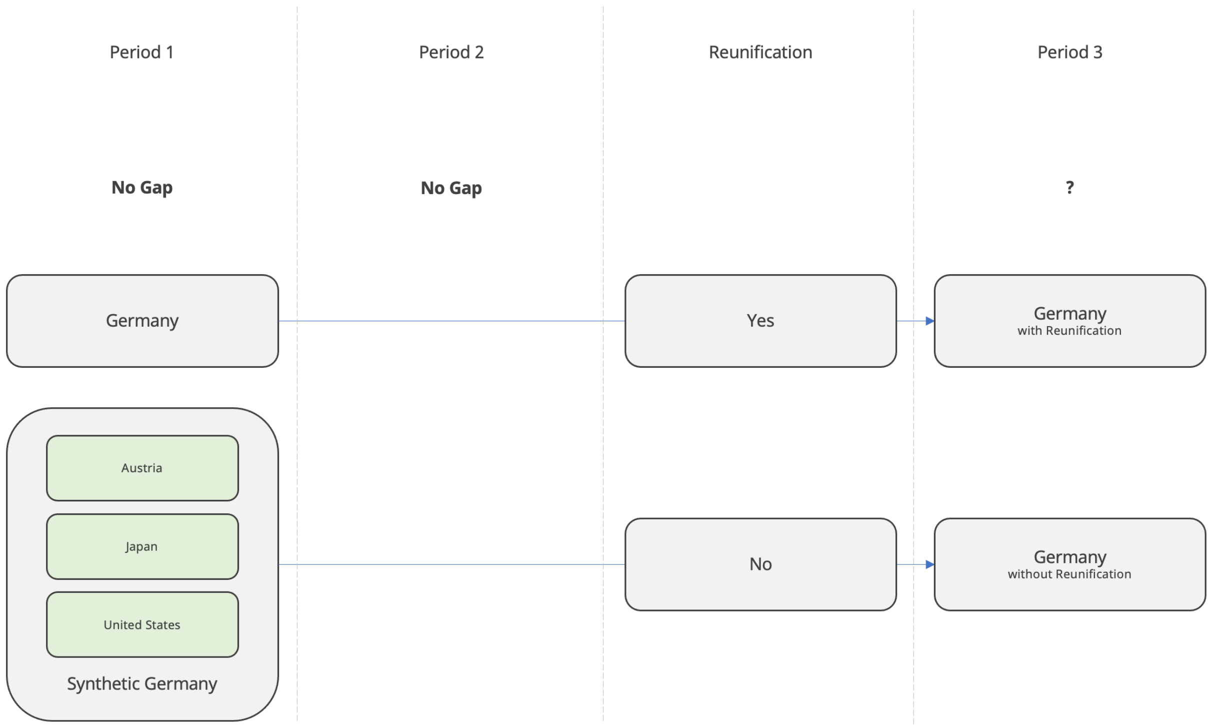


**Figure 3.** Synthetic Control Model Conceptual Diagram 1. The constructed synthetic unit shows what would have happened if the actual unit did not receive the treatment.

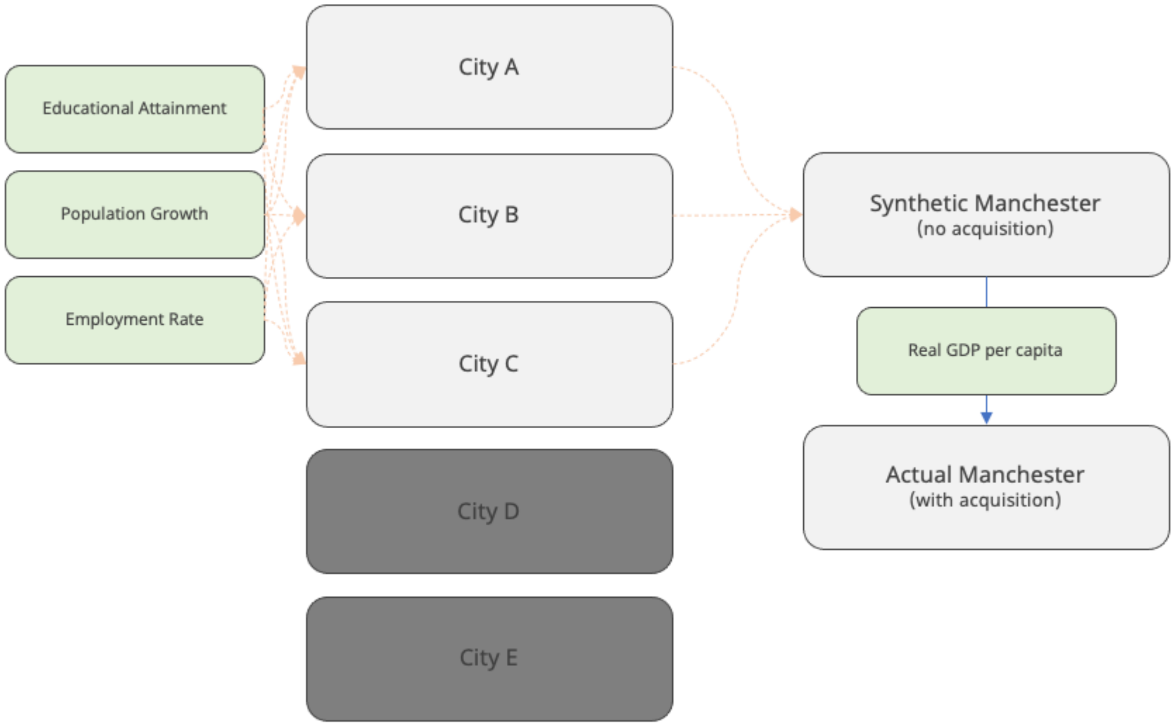


**Figure 4.** Synthetic Control Model Conceptual Diagram 2. Synthetic Manchester shows what would have happened if Manchester did not experience the acquisition of the local team, which allows measurement of the treatment effect.

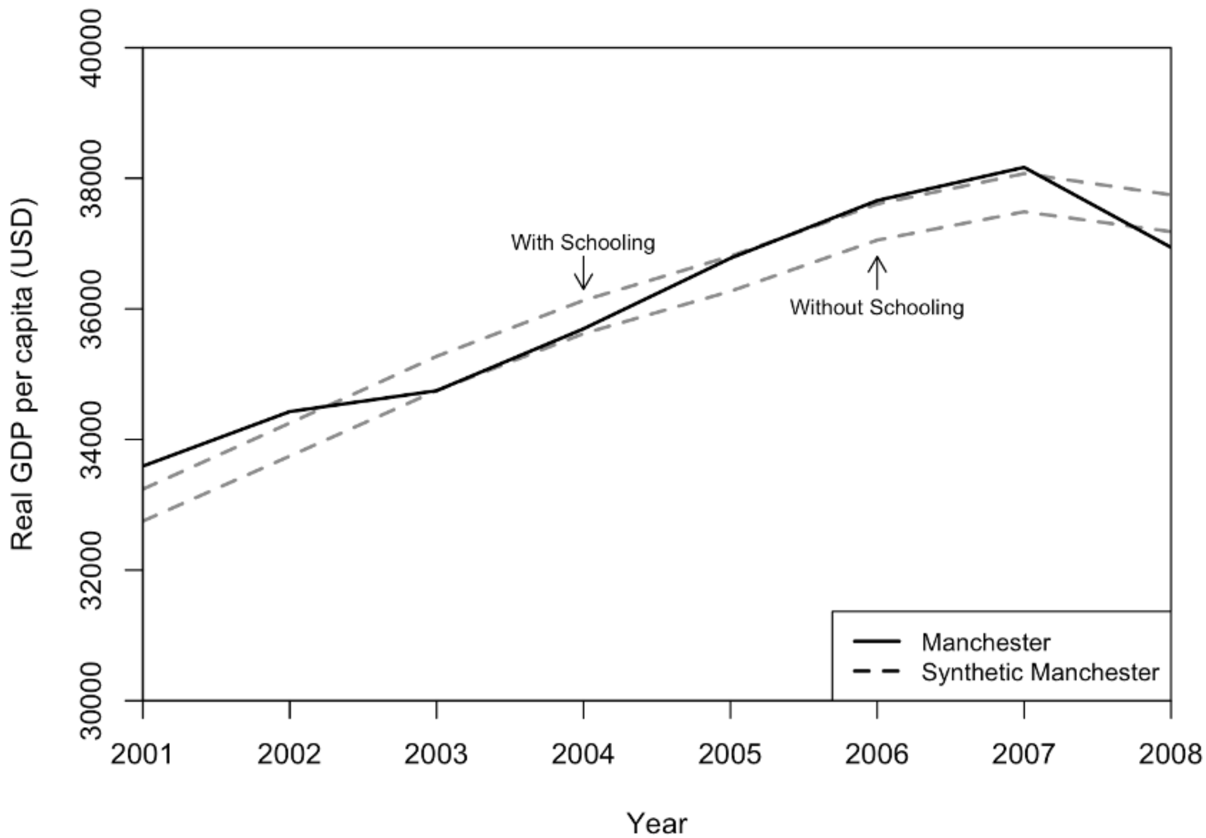


**Figure 5.** Synthetic Manchester with and without Schooling Data. Synthetic Manchester better replicates the actual Manchester with schooling data during the pre-treatment period (the vertical dotted line represents the acquisition).


**Figure 6.** Correlograms for All Variables. Schooling is negatively correlated with the rest of the variables, but they are not significant except GDP per capita ($\alpha = 0.05$). Insignificant correlations are crossed out.

| Predictor Variable | Manchester | Synthetic Manchester | Sample Mean |
|---|---|---|---|
| Population Growth | 101.21 | 101.23 | 101.46 |
| Employment Rate | 69.39 | 69.41 | 71.26 |
| Schooling | 40.79 | 40.79 | 40.93 |

**Table 1.** Predictor Balances before Acquisition. Manchester is not too far from the sample mean, and synthetic Manchester reasonably replicates the balances.

| City | Weight | City | Weight |
|---|---|---|---|
| Aberdeen | 2.10% | Medway | 2.00% |
| Blackburn with Darwen | 2.60% | Middlesbrough | 6.40% |
| Bournemouth | 1.10% | Milton Keynes | 2.20% |
| Brighton and Hove | 2.10% | Newcastle upon Tyne | 3.00% |
| Bristol | 2.40% | Northampton | 1.80% |
| Cambridge | 1.50% | Norwich | 1.70% |
| Cardiff | 3.90% | Nottingham | 2.80% |
| Colchester | 2.10% | Oxford | 2.40% |
| Coventry | 2.90% | Plymouth | 0.00% |
| Derby | 2.20% | Portsmouth | 2.00% |
| Dundee City | 3.60% | Preston | 1.60% |
| Edinburgh | 2.70% | Sheffield | 3.00% |
| Exeter | 0.00% | Southampton | 2.20% |
| Glasgow | 4.00% | Stoke-on-Trent | 2.80% |
| Kingston upon Hull | 9.50% | Sunderland | 5.80% |
| Leeds | 2.90% | Swansea | 3.90% |
| Leicester | 2.30% | West Midlands urban area | 4.00% |
| London | 4.20% | | |

**Table 2.** Weights for Synthetic Manchester. Synthetic Manchester is composed by the weighted average of the above 33 cities in the United Kingdom.

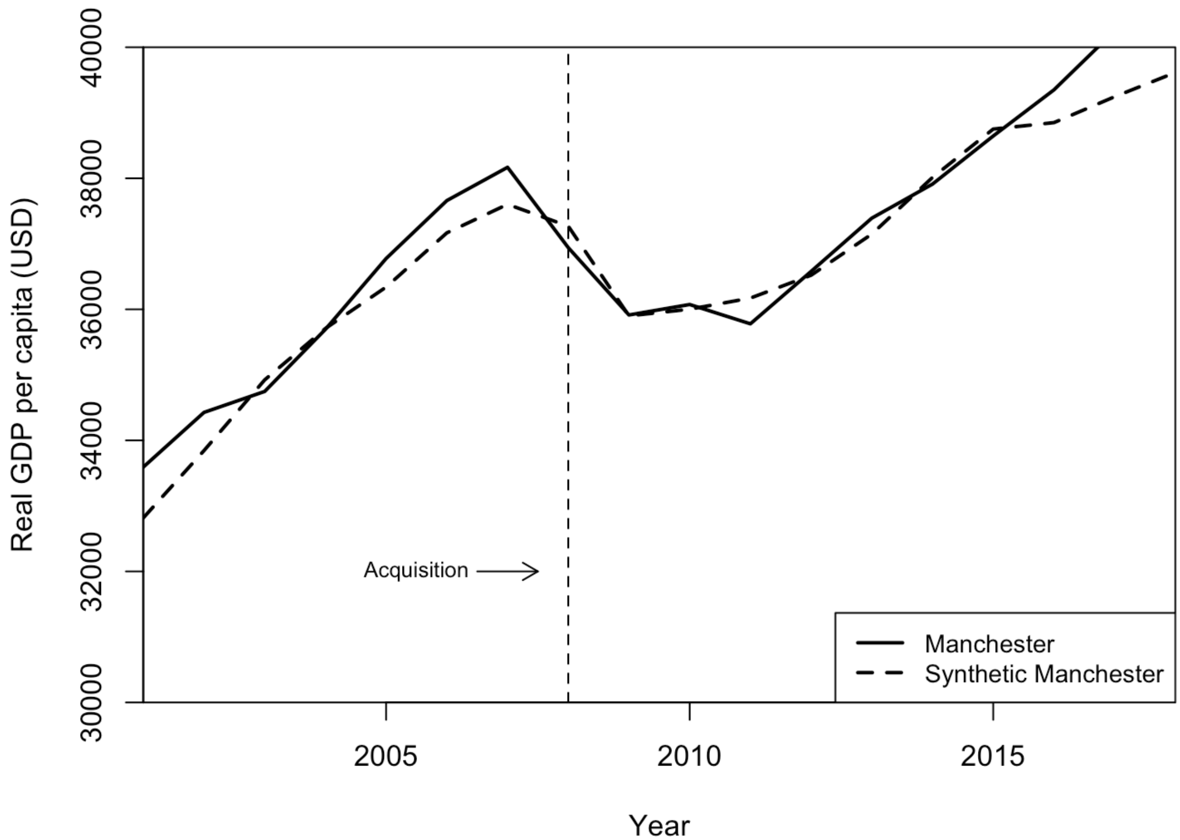


**Figure 7.** Trends in Real GDP per Capita between Manchester and Synthetic Manchester. No local economy effect can be claimed from the performance of a local team.

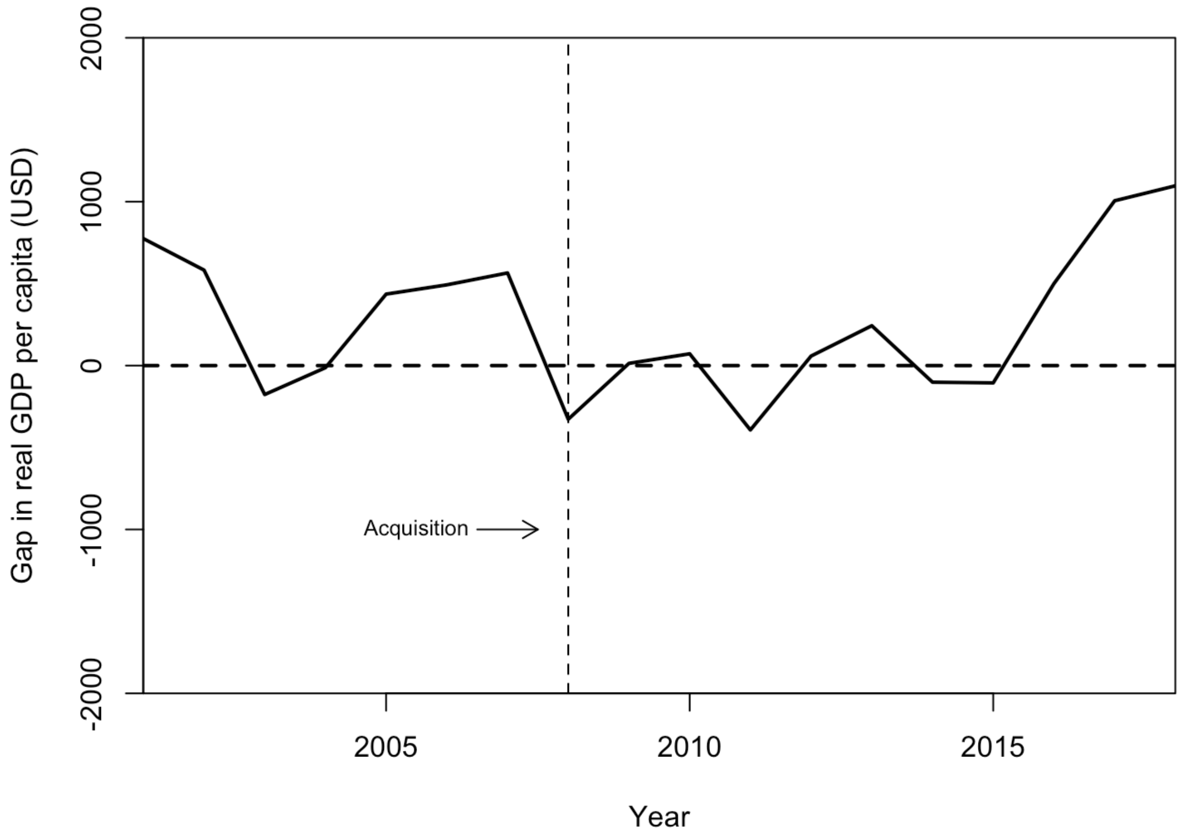


**Figure 8.** Real GDP per Capita Gap between Manchester and Synthetic Manchester. Again, there is no discernible trend to insist that the Manchester City Football Club brought positive impacts on the local economy.

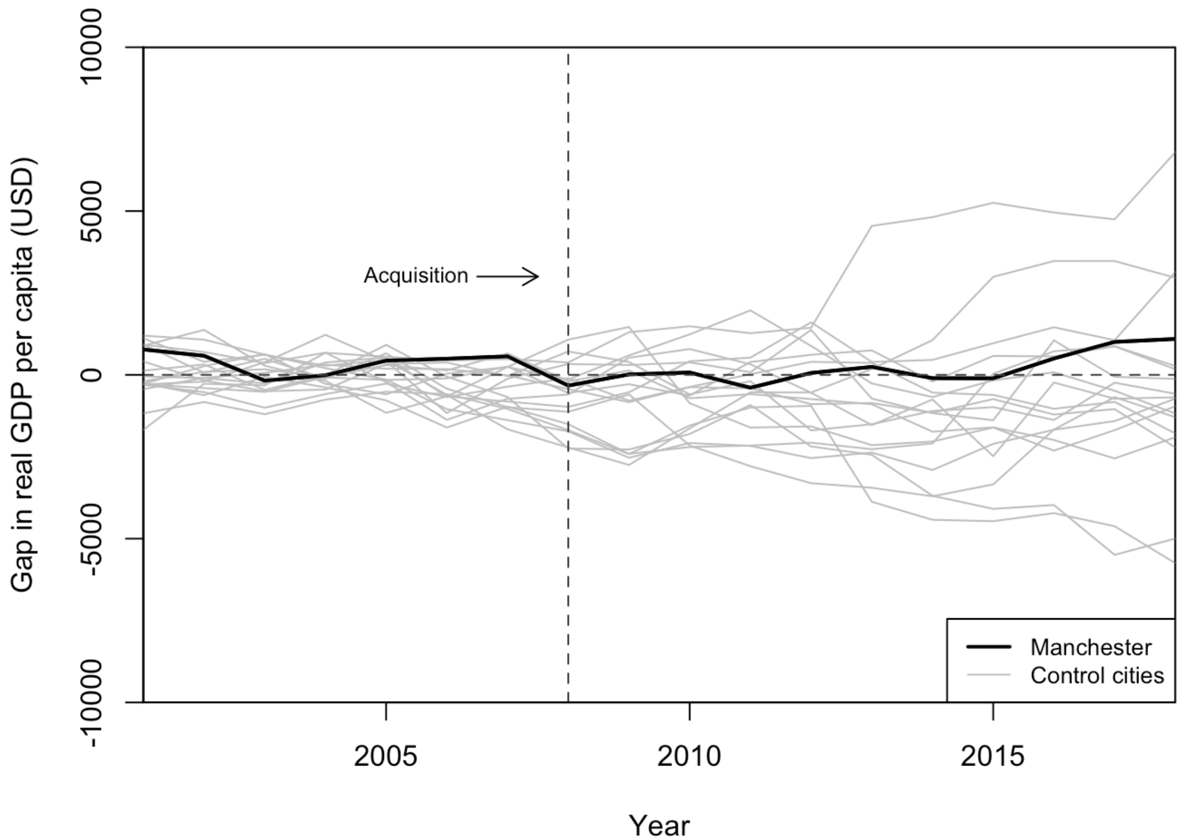


**Figure 9.** Placebo Test Assuming Each City in the Donor Pool Received Treatment in 2008.

Interestingly, 85 per cent of the donor cities lie below the Manchester line.

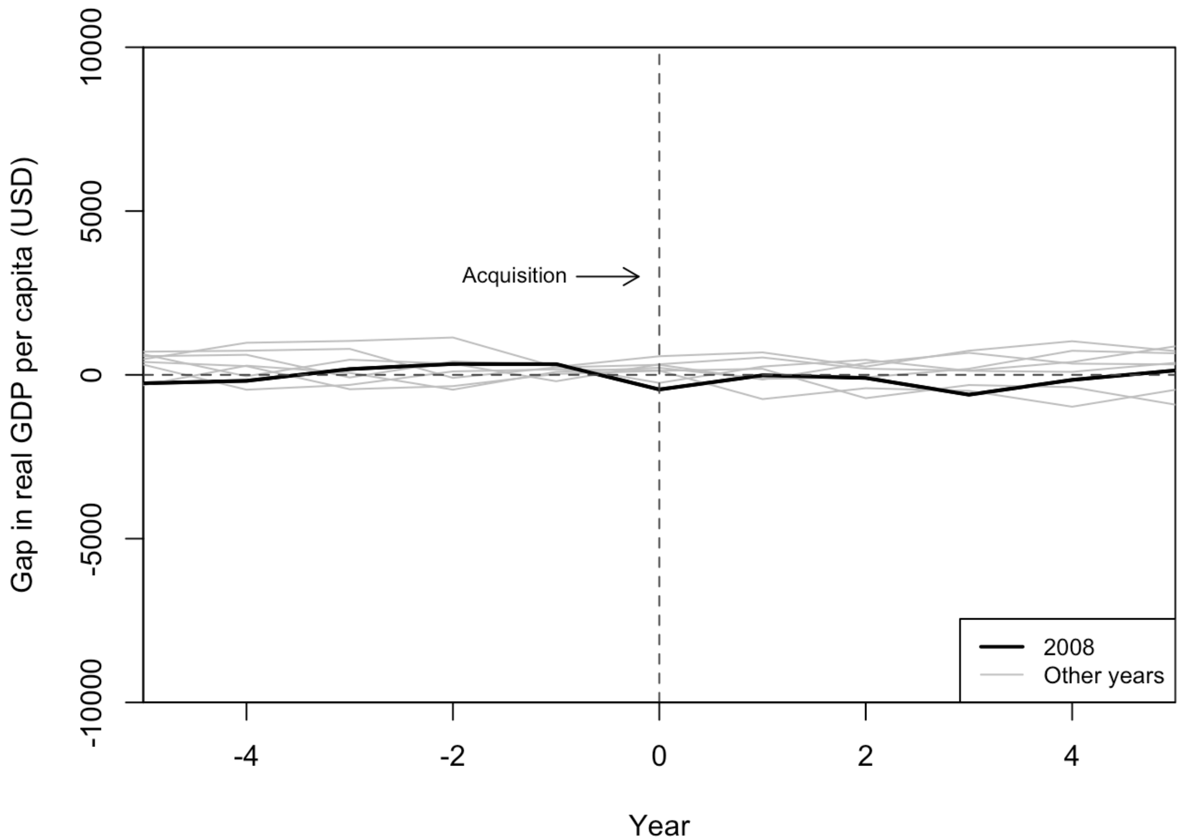


**Figure 10.** Placebo Test Assuming Treatment Year of 2006 to 2013 for Manchester. There is no significant treatment effect for 2008.

| | Count | Mean | Median | Min | Max | SD |
|---|---|---|---|---|---|---|
| **Output** | | | | | | |
| GDP per Capita | 648 | 37,458 | 34,588 | 23,317 | 81,224 | 9,565 |
| **Predicting** | | | | | | |
| Population Growth | 648 | 105.30 | 104.50 | 96.60 | 127.70 | 4.90 |
| Employment Rate | 648 | 70.68 | 70.60 | 59.40 | 83 | 4.48 |
| Schooling | 648 | 40.65 | 41.20 | 28.10 | 47.70 | 3.38 |

**Table 3.** Descriptive Statistics. Substantial variances are observed in GDP per capita.

| Year | GDP per Capita | | Population Growth | | Employment Rate | | Schooling | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| 2001 | 33,591 | 8,219 | 100.00 | 0.00 | 70.95 | 5.60 | 36.94 | 2.16 |
| 2002 | 34,551 | 8,439 | 100.31 | 0.35 | 70.91 | 5.48 | 37.49 | 2.17 |
| 2003 | 35,563 | 8,735 | 100.74 | 0.68 | 71.05 | 5.00 | 42.19 | 1.83 |
| 2004 | 36,318 | 8,485 | 101.24 | 1.01 | 71.22 | 4.67 | 41.78 | 1.69 |
| 2005 | 36,949 | 8,728 | 101.91 | 1.35 | 71.63 | 4.58 | 42.80 | 1.87 |
| 2006 | 37,745 | 9,042 | 102.63 | 1.70 | 71.48 | 4.37 | 42.75 | 1.89 |
| 2007 | 38,213 | 9,602 | 103.33 | 1.99 | 71.22 | 4.37 | 42.49 | 2.41 |
| 2008 | 37,838 | 9,512 | 104.08 | 2.29 | 70.96 | 4.53 | 42.35 | 1.95 |
| 2009 | 36,373 | 9,081 | 104.79 | 2.59 | 69.34 | 4.41 | 42.17 | 2.20 |
| 2010 | 36,703 | 9,160 | 105.53 | 2.96 | 68.66 | 4.02 | 42.23 | 2.08 |
| 2011 | 36,888 | 9,264 | 106.36 | 3.33 | 68.45 | 4.10 | 41.03 | 3.26 |
| 2012 | 37,314 | 9,396 | 107.13 | 3.65 | 68.73 | 3.75 | 40.81 | 3.42 |
| 2013 | 37,918 | 9,831 | 107.76 | 3.92 | 68.86 | 3.85 | 40.34 | 3.34 |
| 2014 | 38,771 | 10,482 | 108.45 | 4.26 | 70.05 | 3.81 | 40.24 | 3.98 |
| 2015 | 39,501 | 10,806 | 109.23 | 4.62 | 71.59 | 3.97 | 39.65 | 3.94 |
| 2016 | 39,616 | 10,268 | 110.07 | 4.95 | 71.80 | 3.32 | 38.79 | 3.89 |
| 2017 | 40,037 | 10,655 | 110.82 | 5.20 | 72.64 | 3.86 | 39.06 | 3.74 |
| 2018 | 40,355 | 11,050 | 111.59 | 5.58 | 72.77 | 3.67 | 38.65 | 3.89 |

**Table 4.** Annual Summary of All Variables.

| Year | Blackburn with Darwen | Bournemouth | Bristol | Cambridge | Cardiff | Coventry |
|---|---|---|---|---|---|---|
| 2001 | $ (253.21) | $ 920.91 | $ 923.85 | $ 887.06 | $ (191.39) | $ 1,116.21 |
| 2002 | $ (620.10) | $ 66.58 | $ 697.56 | $ 1,373.88 | $ 87.87 | $ 400.33 |
| 2003 | $ (62.04) | $ 490.37 | $ 361.73 | $ 281.24 | $ 170.56 | $ 614.16 |
| 2004 | $ (383.01) | $ (114.78) | $ 677.28 | $ (181.73) | $ (77.77) | $ 280.48 |
| 2005 | $ (779.37) | $ 657.69 | $ (219.23) | $ (1,158.81) | $ (157.38) | $ 459.21 |
| 2006 | $ (1,608.03) | $ (421.95) | $ (1,373.16) | $ (657.84) | $ (107.72) | $ (613.25) |
| 2007 | $ (969.97) | $ (986.60) | $ (729.76) | $ (813.75) | $ 249.24 | $ (1,661.07) |
| 2008 | $ (1,504.88) | $ (1,128.30) | $ (599.68) | $ (977.31) | $ (552.70) | $ (2,217.15) |
| 2009 | $ (2,412.08) | $ (596.74) | $ 522.08 | $ (530.66) | $ (285.22) | $ (2,749.08) |
| 2010 | $ (2,203.41) | $ (2,157.05) | $ 788.66 | $ 415.43 | $ (631.78) | $ (1,633.25) |
| 2011 | $ (2,157.29) | $ (2,787.33) | $ 324.29 | $ 525.05 | $ 392.55 | $ (534.11) |
| 2012 | $ (2,070.33) | $ (3,306.87) | $ (545.04) | $ 1,604.69 | $ 612.98 | $ (537.85) |
| 2013 | $ (2,268.29) | $ (3,446.57) | $ (1,532.75) | $ 393.62 | $ 746.86 | $ 178.23 |
| 2014 | $ (2,092.16) | $ (3,706.79) | $ (752.57) | $ 456.60 | $ (203.51) | $ 1,061.46 |
| 2015 | $ 33.45 | $ (3,343.56) | $ (2,483.89) | $ 964.38 | $ 577.15 | $ 2,991.90 |
| 2016 | $ 720.55 | $ (1,670.41) | $ (234.58) | $ 1,452.69 | $ 564.92 | $ 3,475.19 |
| 2017 | $ 872.75 | $ (681.10) | $ (728.34) | $ 1,059.09 | $ 871.90 | $ 3,474.32 |
| 2018 | $ 268.82 | $ (1,292.10) | $ (684.68) | $ 3,141.43 | $ 169.75 | $ 2,963.68 |

| Year | Derby | Exeter | Glasgow | Kingston upon Hull | Leeds | Manchester |
|---|---|---|---|---|---|---|
| 2001 | $ 126.93 | $ (437.37) | $ 408.06 | $ (276.16) | $ (282.48) | $ 775.12 |
| 2002 | $ 317.74 | $ (89.23) | $ (169.39) | $ 264.63 | $ (403.56) | $ 582.84 |
| 2003 | $ (457.72) | $ 60.41 | $ (500.58) | $ 633.33 | $ (519.66) | $ (176.66) |
| 2004 | $ (11.58) | $ 310.21 | $ (447.81) | $ (274.76) | $ (62.85) | $ (12.91) |
| 2005 | $ 914.87 | $ 185.58 | $ 330.78 | $ (595.10) | $ 298.07 | $ 436.03 |
| 2006 | $ (55.27) | $ 176.43 | $ 377.30 | $ 36.14 | $ 136.70 | $ 492.70 |
| 2007 | $ (677.40) | $ (17.11) | $ (37.44) | $ 240.48 | $ 654.46 | $ 565.19 |
| 2008 | $ (2,248.34) | $ (434.15) | $ 715.02 | $ 1,074.88 | $ (197.27) | $ (327.44) |
| 2009 | $ (2,277.08) | $ (833.23) | $ 392.87 | $ 1,461.27 | $ 131.52 | $ 13.53 |
| 2010 | $ (1,804.93) | $ (375.87) | $ (597.43) | $ (864.65) | $ (713.96) | $ 71.93 |
| 2011 | $ (919.96) | $ (411.24) | $ (192.24) | $ (1,609.50) | $ (588.77) | $ (392.80) |
| 2012 | $ (2,185.02) | $ (893.49) | $ (1,695.67) | $ (1,572.58) | $ (738.99) | $ 58.20 |
| 2013 | $ (2,440.67) | $ (859.07) | $ (1,507.06) | $ (2,146.19) | $ (896.26) | $ 243.29 |
| 2014 | $ (3,691.93) | $ (1,158.13) | $ (1,101.08) | $ (2,033.28) | $ (1,735.35) | $ (101.36) |
| 2015 | $ (4,090.54) | $ (739.79) | $ (985.04) | $ (1,605.99) | $ (1,603.28) | $ (105.63) |
| 2016 | $ (3,973.27) | $ (1,209.97) | $ (1,375.98) | $ (2,311.01) | $ (1,988.86) | $ 500.07 |
| 2017 | $ (5,495.42) | $ (1,045.38) | $ (239.03) | $ (1,688.19) | $ (2,551.37) | $ 1,005.70 |
| 2018 | $ (4,994.89) | $ (2,216.78) | $ (578.04) | $ (956.03) | $ (1,904.76) | $ 1,096.94 |

| Year | Newcastle upon Tyne | Nottingham | Preston | Southampton | Sunderland | West Midlands urban area |
|---|---|---|---|---|---|---|
| 2001 | $ (1,174.94) | $ (299.72) | $ (293.12) | $ (49.25) | $ (1,679.51) | $ 1,197.74 |
| 2002 | $ (830.03) | $ (526.80) | $ (204.90) | $ (98.01) | $ (270.42) | $ 1,075.62 |
| 2003 | $ (1,202.46) | $ (1,002.89) | $ 384.12 | $ (260.84) | $ (320.42) | $ 617.22 |
| 2004 | $ (756.57) | $ (586.48) | $ 1,222.01 | $ 378.75 | $ 673.34 | $ 204.91 |
| 2005 | $ (516.77) | $ (267.61) | $ 420.85 | $ 530.24 | $ 552.32 | $ (144.92) |
| 2006 | $ (586.81) | $ (679.34) | $ (1,166.04) | $ (662.26) | $ 439.72 | $ (1,045.93) |
| 2007 | $ (1,041.49) | $ (359.23) | $ (115.91) | $ 242.70 | $ 479.43 | $ (1,381.25) |
| 2008 | $ (1,688.70) | $ (100.97) | $ 330.31 | $ (141.67) | $ 379.16 | $ (1,722.67) |
| 2009 | $ (2,416.51) | $ (789.62) | $ 301.40 | $ 591.02 | $ 1,301.32 | $ (2,531.61) |
| 2010 | $ (1,548.23) | $ (368.14) | $ 379.68 | $ 1,236.42 | $ 1,483.40 | $ (2,081.13) |
| 2011 | $ (994.34) | $ 18.87 | $ 81.45 | $ 1,968.35 | $ 1,271.24 | $ (2,168.02) |
| 2012 | $ (947.38) | $ 398.73 | $ 1,372.34 | $ 882.16 | $ 1,438.26 | $ (2,541.54) |
| 2013 | $ (3,874.11) | $ 365.74 | $ (725.64) | $ (261.98) | $ 4,546.18 | $ (2,372.69) |
| 2014 | $ (4,424.27) | $ (542.16) | $ (1,170.70) | $ (676.08) | $ 4,815.37 | $ (2,904.61) |
| 2015 | $ (4,466.76) | $ (612.52) | $ (1,385.27) | $ (167.99) | $ 5,251.79 | $ (2,106.97) |
| 2016 | $ (4,221.25) | $ (1,035.76) | $ 1,053.34 | $ 79.12 | $ 4,955.53 | $ (1,675.06) |
| 2017 | $ (4,621.38) | $ (825.13) | $ (60.52) | $ (484.72) | $ 4,748.02 | $ (1,411.80) |
| 2018 | $ (5,748.81) | $ (1,790.68) | $ (121.73) | $ (1,181.54) | $ 6,799.12 | $ (726.39) |

**Table 5.** Gap in Real GDP per capita for Different Treated Units.

| T | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|---|
| -5 | 395.53 | 311.70 | -256.40 | 476.76 | 707.53 | 568.67 | 628.14 | -316.97 |
| -4 | 265.87 | -453.41 | -182.45 | 980.08 | 737.93 | 612.80 | -43.99 | 280.06 |
| -3 | -438.48 | -306.75 | 176.30 | 1035.77 | 793.11 | -80.53 | 461.90 | 60.03 |
| -2 | -344.40 | 105.79 | 333.33 | 1140.80 | -92.21 | 412.04 | 339.19 | -452.15 |
| -1 | 28.00 | 168.65 | 327.39 | 241.34 | 227.71 | 292.09 | -193.88 | 92.17 |
| 0 | 124.50 | 129.48 | -446.09 | 568.71 | 307.15 | -245.85 | 322.55 | 214.10 |
| +1 | 183.93 | -740.06 | -14.30 | 686.26 | -141.51 | 254.18 | 530.48 | -123.02 |
| +2 | -712.12 | -407.96 | -94.31 | 251.21 | 358.67 | 458.69 | 187.09 | -77.75 |
| +3 | -310.19 | -487.73 | -605.64 | 736.47 | 673.51 | 121.82 | 127.85 | 185.87 |
| +4 | -375.00 | -972.32 | -152.95 | 1027.61 | 343.36 | 91.86 | 393.65 | 735.61 |
| +5 | -909.73 | -455.37 | 134.66 | 725.70 | 319.80 | 367.25 | 872.55 | 658.49 |

**Table 6.** Gap in Real GDP per capita for Different Treatment Year.

## *Appendix B: R Code*

### Data Preparation

```r
##Data Preparation for the Synthetic Control Model
#importing libraries
library(tidyverse)
library(dplyr)

#creating a function for data parsing
parsing_oecd_records <- function(foo,column) {

  #filtering UK data
  foo <- filter(foo,Country=='GBR')

  #pivot longer by year
  foo <- foo %>%
    pivot_longer(c("X2001"
                   , "X2002"
                   , "X2003"
                   , "X2004"
                   , "X2005"
                   , "X2006"
                   , "X2007"
                   , "X2008"
                   , "X2009"
                   , "X2010"
```

```
                        , "X2011"
                        , "X2012"
                        , "X2013"
                        , "X2014"
                        , "X2015"
                        , "X2016"
                        , "X2017"
                        ,"X2018"), names_to = "year", values_to = column)

  #converting the data type of year to integer
  foo$year <- as.integer(substr(foo$year,2,5))

  #returning the parsed dataframe
  return(foo)

}

#GDP per Capita
gdp <- read.csv("gdp_per_capita.csv",skip = 1)
gdp <- parsing_oecd_records(gdp,"gdp_per_capita")

#Population Growth
pop <- read.csv("population_growth.csv",skip = 1)
pop <- parsing_oecd_records(pop,"population_growth")
pop <- pop[,-4]

#Employment Rate
emp <- read.csv("employment.csv",skip = 1)
emp <- parsing_oecd_records(emp,"employment_rate")

#joining the tables
data <- gdp %>% left_join(pop) %>% left_join(emp)

#Secondary education attainment
edu <- read.csv("secondary_attainment.csv")
head(edu)

#renaming Columns
edu <- edu[,c("Region","Year","Value")]
colnames(edu) <- c("Region","year","schooling")

#removing duplicates
edu <- edu %>% group_by(Region,year) %>% summarise(
  schooling = mean(schooling)
)

#assigning Region
data <- mutate(data,
        Region = case_when(
          data$Name == "Aberdeen" ~ "Scotland"
```

```
       ,    data$Name == "Blackburn with Darwen" ~ "Lancashire"
       ,    data$Name == "Bournemouth" ~ "Dorset And Somerset"
       ,    data$Name == "Brighton and Hove" ~ "Surrey East And West Sussex"
       ,    data$Name == "Bristol" ~ "Gloucestershire Wiltshire and
Bristol/Bath Area"
       ,    data$Name == "Cambridge" ~ "East of England"
       ,    data$Name == "Cardiff" ~ "Wales"
       ,    data$Name == "Cheshire West and Chester" ~ "Cheshire"
       ,    data$Name == "Colchester" ~ "Essex"
       ,    data$Name == "Coventry" ~ "West Midlands"
       ,    data$Name == "Derby" ~ "East Midlands"
       ,    data$Name == "Dundee City" ~ "Scotland"
       ,    data$Name == "Edinburgh" ~ "Scotland"
       ,    data$Name == "Exeter" ~ "Devon"
       ,    data$Name == "Glasgow" ~ "Scotland"
       ,    data$Name == "Kingston upon Hull" ~ "East Yorkshire And Northern
Lincolnshire"
       ,    data$Name == "Leeds" ~ "West Yorkshire"
       ,    data$Name == "Leicester" ~ "East Midlands"
       ,    data$Name == "Liverpool" ~ "Merseyside"
       ,    data$Name == "London" ~ "Greater London"
       ,    data$Name == "Manchester" ~ "Greater Manchester"
       ,    data$Name == "Medway" ~ "Kent"
       ,    data$Name == "Middlesbrough" ~ "North Yorkshire"
       ,    data$Name == "Milton Keynes" ~ "Berkshire Buckinghamshire and
Oxfordshire"
       ,    data$Name == "Newcastle upon Tyne" ~ "Northumberland and Tyne And
Wear"
       ,    data$Name == "Northampton" ~ "East Midlands"
       ,    data$Name == "Norwich" ~ "East of England"
       ,    data$Name == "Nottingham" ~ "East Midlands"
       ,    data$Name == "Oxford" ~ "Berkshire Buckinghamshire and
Oxfordshire"
       ,    data$Name == "Plymouth" ~ "Devon"
       ,    data$Name == "Portsmouth" ~ "Hampshire And Isle Of Wight"
       ,    data$Name == "Preston" ~ "Lancashire"
       ,    data$Name == "Sheffield" ~ "South Yorkshire"
       ,    data$Name == "Southampton" ~ "Hampshire And Isle Of Wight"
       ,    data$Name == "Stoke-on-Trent" ~ "Shropshire and Staffordshire"
       ,    data$Name == "Sunderland" ~ "Northumberland and Tyne And Wear"
       ,    data$Name == "Swansea" ~ "Wales"
       ,    data$Name == "West Midlands urban area" ~ "West Midlands"
       ,    data$Name == "Wirral" ~ "Merseyside"
       ))

#removing NA values
data[data==""] <- NA
data <- na.omit(data)

#joining the tables
```

```r
data_with_schooling <- data %>% left_join(edu)

#adding identifier for model
data$Code <- group_indices(data, Name)
```

```
## Warning: The `...` argument of `group_keys()` is deprecated as of dplyr
1.0.0.
## Please `group_by()` first
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_warnings()` to see where this warning was generated.
```

```r
data <- data[,-2]

#excluding cities without schooling data
data_with_schooling <- filter(data_with_schooling,!Name %in%
unique(data_with_schooling[is.na(data_with_schooling$schooling),]$Name))

#adding identifier for model
data_with_schooling$Code <- group_indices(data_with_schooling, Name)
data_with_schooling <- data_with_schooling[,-2]
```

### Synthetic Model

```r
## Synthetic Control Model Analysis
#importing libraries
library(Synth)

#filter(data_with_schooling,Code==19)
#length(unique(data_with_schooling$Code))

#getting dataprep
dataprep.out <-
  dataprep(
    foo = as.data.frame(data_with_schooling)
    ,predictors= c("population_growth",
                   "employment_rate",
                   "schooling"
    )
    ,predictors.op = c("mean")
    ,dependent     = c("gdp_per_capita")
    ,unit.variable = c("Code")
    ,time.variable = c("year")
    ,treatment.identifier  = 19
    ,controls.identifier   = c(1:18,20:36)
    ,time.predictors.prior = c(2001:2007)
    ,time.optimize.ssr     = c(2001:2007)
    ,unit.names.variable   = c("Name")
    ,time.plot            = c(2001:2018)
```

```
  )

#running synth
synth.out <- synth(data.prep.obj = dataprep.out)

#getting result tables
synth.tables <- synth.tab(
  dataprep.res = dataprep.out,
  synth.res = synth.out
)

#printing the result table
print(synth.tables)

#plotting results
path.plot(synth.res = synth.out,
          dataprep.res = dataprep.out,
          Ylab = c("Real GDP per capita"),
          Xlab = c("Year"),
          Legend = c("Manchester","Synthetic Manchester"),
          Legend.position = "bottomright",
          Ylim = c(30000,40000)
)

#intervention
Cex.set <- .75
abline(v   = 2008,
       lty = 2)

arrows(2006.5, 32000, 2007.5, 32000,
       col    = "black",
       length = .1)

text(2005.5, 32000,"Acquisition",cex=Cex.set)

gaps.plot(synth.res = synth.out,
          dataprep.res = dataprep.out,
          Ylab = c("Gap in real GDP per capita"),
          Xlab = c("Year"),
          Ylim = c(-2000,2000),
          title()
)

abline(v   = 2008,
       lty = 2)

arrows(2006.5, -1000, 2007.5, -1000,
       col    = "black",
       length = .1)
```

```
text(2005.5, -1000,"Acquisition")
```

### Placebo Test in Place

```
## Placebo Testing
#importing libraries
library(Synth)

#applying the synthetic control method after reassigning the intervention in
the data
#to units and periods where the intervention did not occur
store <- matrix(NA,length(2001:2018),36)
colnames(store) <- unique(data_with_schooling$Name)

#looping the model for all cities
for(iter in 1:36)
{
  dataprep.out <-
    dataprep(
      foo = as.data.frame(data_with_schooling)
             ,predictors= c("population_growth",
                            "employment_rate",
                            "schooling"
             )
             ,predictors.op = c("mean")
             ,dependent     = c("gdp_per_capita")
             ,unit.variable = c("Code")
             ,time.variable = c("year")
             ,treatment.identifier  = iter
             ,controls.identifier   = c(1:36)[-iter]
             ,time.predictors.prior = c(2001:2007)
             ,time.optimize.ssr     = c(2001:2007)
             ,unit.names.variable   = c("Name")
             ,time.plot            = c(2001:2018)
    )

  #running synth
  synth.out <- synth(
    data.prep.obj = dataprep.out,
    method = "BFGS"
  )
  #storing gaps
  store[,iter] <- dataprep.out$Y1plot - (dataprep.out$Y0plot %*%
synth.out$solution.w)
}

data <- store
rownames(data) <- 2001:2018
```

```
#setting bounds in gaps data
gap.start     <- 1
gap.end       <- nrow(data)
years         <- 2001:2018
gap.end.pre  <- which(rownames(data)=="2007")
#MSPE Pre-Treatment
mse        <- apply(data[ gap.start:gap.end.pre,]^2,2,mean)
manchester.mse <- as.numeric(mse[19])
#excluding states with 5 times higher MSPE than Manchester
data <- data[,mse<5*manchester.mse]
Cex.set <- .75
#plotting results
plot(years,data[gap.start:gap.end,which(colnames(data)=="Manchester")],
     ylim=c(-10000,10000),xlab="Year",
     xlim=c(2001,2018),ylab="Gap in real GDP per capita",
     type="l",lwd=2,col="black",
     xaxs="i",yaxs="i")
#adding lines for control states
for (i in 1:ncol(data)) { lines(years,data[gap.start:gap.end,i],col="gray") }
#adding Manchester Line
lines(years,data[gap.start:gap.end,which(colnames(data)=="Manchester")],lwd=2
,col="black")

legend("bottomright",legend=c("Manchester","Control cities"),
       lty=c(1,1),col=c("black","gray"),lwd=c(2,1),cex=.8)

#intervention
abline(v=2008,lty=2,col="#404040")
abline(h=0,lty=2,col="#404040")

arrows(2006.5, 3000, 2007.5, 3000,
       col    = "black",
       length = .1)

text(2005.5, 3000,"Acquisition",cex=Cex.set)

abline(v=2001)
abline(v=2018)
abline(h=-10000)
abline(h=10000)
```

### Placebo Test in Time

```
## Placebo Testing
#importing libraries
library(Synth)
#applying the synthetic control method after reassigning the intervention in
the data
#to units and periods where the intervention did not occur
```

```
store <- matrix(NA,length(1:11),length(2006:2013))
colnames(store) <- (2006:2013)
#looping the model for all cities
for(iter in 2006:2013)
{
  dataprep.out <-
    dataprep(
      foo = as.data.frame(data_with_schooling)
      ,predictors= c("population_growth",
                     "employment_rate",
                     "schooling"
      )
      ,predictors.op = c("mean")
      ,dependent     = c("gdp_per_capita")
      ,unit.variable = c("Code")
      ,time.variable = c("year")
      ,treatment.identifier  = 19
      ,controls.identifier   = c(1:18,20:36)
      ,time.predictors.prior = c((iter-5):iter)
      ,time.optimize.ssr     = c((iter-5):iter)
      ,unit.names.variable   = c("Name")
      ,time.plot            = c((iter-5):(iter+5))
    )
  #running synth
  synth.out <- synth(
    data.prep.obj = dataprep.out,
    method = "BFGS"
  )
  #storing gaps
  store[,(iter-2005)] <- dataprep.out$Y1plot - (dataprep.out$Y0plot %*%
synth.out$solution.w)
}
data <- store
rownames(data) <- -5:5
#setting bounds in gaps data
gap.start     <- 1
gap.end       <- nrow(data)
years         <- -5:5
gap.end.pre  <- which(rownames(data)=="0")
#MSPE Pre-Treatment
mse        <- apply(data[ gap.start:gap.end.pre,]^2,2,mean)
treated.mse <- as.numeric(mse[3])
Cex.set <- .75
#plotting results
plot(years,data[gap.start:gap.end,which(colnames(data)=="2008")],
     ylim=c(-10000,10000),xlab="Year",
     ylab="Gap in real GDP per capita",
     type="l",lwd=2,col="black",
     xaxs="i",yaxs="i")
#adding lines for control states
```

```
for (i in 1:ncol(data)) { lines(years,data[gap.start:gap.end,i],col="gray") }
#adding Manchester Line
lines(years,data[gap.start:gap.end,which(colnames(data)=="2008")],lwd=2,col="
black")
legend("bottomright",legend=c("2008","Other years"),
       lty=c(1,1),col=c("black","gray"),lwd=c(2,1),cex=.8)
#intervention
abline(v=0,lty=2,col="#404040")
abline(h=0,lty=2,col="#404040")
arrows(-0.8, 3000, -0.2, 3000,
       col    = "black",
       length = .1)
text(-1.4, 3000,"Acquisition",cex=Cex.set)
abline(v=2001)
abline(v=2018)
abline(h=-10000)
abline(h=10000)
```