The Effect of College Acquisitions and Mergers on Student Dropout Behaviour: Evidence from the UK

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Abstract

We investigate the effect of college acquisitions on the probability of students dropping out of college. Using administrative data for the further education sector, which covers multiple cohorts, we estimate matching models and combine them with difference-in-differences methods to remove the effects of unobserved student and college heterogeneity. Overall our findings show that acquisitions reduce the probability of dropout by 0.01 percentage points, but this varies in magnitude and direction over time. In general, positive effects of acquisitions on drop out behaviour tend to be small (e.g. 0.001 for acquisitions in 2004) and dissipate over time, whereas negative effects persist and tend to increase in magnitude over time (e.g. -0.05 one year later and -0.07 two years later). We discuss the implications for policy and practice in the sector, as well as suggesting a need for similar analyses in other education sectors, such as primary and secondary schooling.

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1. Introduction

Dropping out of college implies a high cost for both individual students and for society as a whole. Young people risk entering unemployment and economic inactivity (so-called NEET - Not in Education, Employment or Training) if they terminate college before they have achieved a qualification (see Bradley and Crouchley, 2019 for an analysis at secondary school level). This may have serious long-term consequences for their future labour market outcomes, such as reduced earnings and further spells of NEET. There have been many studies of the determinants of dropout behaviour amongst students but very few that focus on the role of 'mergers' between institutions. This is surprising given the importance of the education sector to the creation of human capital and innovation, and hence its impact on economic growth and development. Indeed, some governments have actively embarked on a policy of encouraging mergers between universities and colleges to focus public funding in an effort to create world class, research-led institutions. Moreover, tertiary education institutions spend substantial amounts of public funding and so the study of mergers in this sector is also important from a value for money perspective. For instance, the sector that we study in this paper - the further education (FE) sector, broadly equivalent to US community colleges but catering primarily for 16-19 year olds - was responsible for £6 billion in funding in 2016 (Association of Colleges, 2016).

Merger and acquisition activity in the tertiary education sector is not a new phenomenon and it is quite widespread. For the US, McBain (2009) describes this activity between universities and between universities and community colleges since 1971. One of the early examples was the merger process, which led to the creation of the University of Wisconsin system completed in 1974. One of the most recent mergers was between Georgia State

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University and Georgia Perimeter College. College and university mergers are so frequent in the US that McBain (2009) concludes that: 'Mergers are part of the historical cycle of American higher education.' and not simply a response to short-term economic fluctuations. Similarly, the European University Association documents 71 mergers since 2007 primarily in the EU between private universities, vocational education and professional education institutions, and public universities, for example, in Sweden, Denmark, Belgium, and France. In terms of the UK and its further education sector, there were 800 further education colleges in the 1960s, which fell to 500 in 1993, and by 2016 this number had declined again to 332 (Association of Colleges, 2016). As Figure 1 shows, merger and acquisition activity in this sector has increased in recent years. In sum, mergers and acquisitions between tertiary educational institutions are widespread, are not a new phenomenon, however, they are not well understood in terms of their consequences for staff and students.

In practice, many mergers in the FE sector in the UK are actually more like acquisitions or takeovers where a weaker institution is 'dissolved' and its staff and students are absorbed into a stronger (academically and financially) institution. These are known in UK policy circles as Model B mergers (Department for Business, Innovation and Skills, 2015), and contrast with Model A mergers where two or more institutions are dissolved and a new college with a new name is created. Figure 1 shows the numbers of each type of merger from 1995-2017. It is also worth noting that up to 2010 there were financial incentives provided by government to support dissolutions of colleges, essentially to remove the debts of the weaker institution. In our data we observe both acquisitions and mergers, however, there are only three mergers and the remainder are acquisitions.[1] We drop three mergers from our data and focus on the effect of acquisitions on student dropout behaviour.[2]

Traditionally, economists have argued that larger firms can benefit from economies of scale and scope (Lang, 2002 and Payne, 2008). According to the Department for Business Innovation and Skills (2015) college mergers have taken place for one of two reasons - ‘building a competitive edge’, including quality improvement, or to solve the problems associated with ‘failing colleges’. Specifically, it is possible that acquisitions will lead to falling average costs of production (of student outcomes) because administrative and support costs related to finance, marketing and HR are reduced. Similarly, economies of scope may arise because a wider range of courses can be offered - course choice for students’ increases. Similarly, larger colleges may have the funding to support innovations in new course provision and be able to improve the quality of existing provision. In combination these factors may contribute to a decrease in the probability of students dropping out of college, however, these benefits may take some time to be realised.

The downside of acquisitions is that they could lead to a reduction in competition between colleges, leading to complacency amongst college managers, which then adversely affects student welfare. In these circumstances, colleges may be less responsive to student needs, because the student voice is no longer heard by management. Insofar as this leads to student dissatisfaction, we then observe an increase in the probability of students dropping out of college. Diseconomies of scale may also occur if industrial relations problems arise between teachers and college management in the larger, acquired, college entities, which could spill over on to students through poor teaching, for instance. There is also the possibility that college acquisitions lead to a disruption to teaching, and its organisation, perhaps because of the poor ‘industrial relations’ between newly acquired staff and existing college management, which adversely affects students, so increasing the risk of dropout.

The effects of acquisitions may also be progressive, reflecting the dynamic nature of the process of a stronger college taking over a weaker college. Hence, it is entirely feasible that the short-term impact of college acquisitions on student dropout behaviour differs to their medium-term effects.

In our data, we observe around 18 acquisitions involving 36 colleges, over the period 2004-2007 and cumulatively these mergers have potentially affected approximately 76,000 students. However, there is very little evidence on the impact of college mergers and acquisitions in the UK (Payne, 2008), and none that we are aware of on the effects of acquisitions on student dropout behaviour.

This is the first econometric investigation of the effect of college acquisitions on student outcomes, and we hope that the paper opens up an agenda for future research on the effects of mergers and acquisitions in education. In this paper, we therefore seek to investigate the effect of college acquisitions on the dropout behaviour of students. A second objective of our paper is to investigate the effects of acquisitions over time. There have been changes in government policy with respect to college mergers over time. In the UK context, and since the publication of the Foster Report in 2005 there has been a clear commitment by the British Government to create regulatory incentives for further education colleges to focus on the achievement *and* progression of their students, and hence to reducing dropout rates, in addition to the financial incentives outlined above. All colleges are now regulated by Ofsted, who visit and evaluate the quality of the education provided. Since these grades are published, colleges have an incentive to improve, otherwise student recruitment can be affected. The Foster Report led to the encouragement of colleges to engage in merger and acquisition behaviour to enable them to exploit both economies of scale and of scope, in an attempt to improve student achievement and reduce dropout rates (Foster, 2005). A third objective of this paper is therefore to investigate both the short term and medium term effects of college acquisitions on dropout behaviour, and to investigate changes in the effect of acquisitions on the risk of dropout arising from changes in government policy.

To address these issues we use administrative data provided by the Learning Skills Council (LSC). These data cover the population of students enrolled in colleges of further education in England. Specifically, we use the Individualised Learner Record data set, and for our purposes we use six cross-sections of student data referring to the years from 2002-03 to 2007-08. To estimate the effect of college acquisitions on student dropout behaviour, it is important that we control for the biases that arise from the selection of colleges into the treatment group. We seek to do so by using matching methods at college level to select a sample of comparable colleges in terms of pre-treatment characteristics. We then try to address the issue of student selection into treated colleges by implementing an individual level propensity score matching estimation combined with difference-in-differences methods (Heckman et al., 1998). This approach enables us to find a suitable control group with whom to compare the treated group, students in merged colleges, and to allow for the existence of time-invariant unobserved bias.

We find that there is some variation in the estimated effects between cohorts and in terms of the magnitude of the effects pre- and post-Foster. Overall, our findings show that acquisitions reduce the probability of dropout by a modest amount (0.01 percentage points), but this effect varies in magnitude and direction over time. In general, positive effects of acquisitions on drop out behaviour tend to be small (e.g. 0.001 for acquisitions in 2004) and dissipate over time, whereas negative effects persist and tend to increase in magnitude over time (e.g. -0.05 one year later and -0.07 two years later). The Foster Report (2005) stimulated a change of government policy and this is partly reflected in our findings, insofar as acquisitions initiated in 2006, had a large positive, and statistically significant, effect on dropout rates for the 2006 and 2007 cohorts but fall away by 2007. Later acquisitions may therefore have been qualitatively different to those occurring pre-Foster. However, we do not claim that there is a causal effect of government policy, because the type of colleges involved in the acquisition might be structurally different which could be due to factors other than the Foster Report or changes in government policy. Furthermore, our research is exploratory since further work is needed on the underlying mechanisms linking college mergers and acquisitions to student outcomes.

The remainder of this paper is structured as follows. In the next section, we briefly review the extensive literature on the determinants of dropout behaviour. This is followed in Section 3 by a discussion of the institutional structure of the further education sector in England, and then discusses our data, including the ways in which we trim the sample so that we obtain comparable treatment and control groups. Section 4 discusses our econometric methodology, which combines matching methods with a difference-in-differences approach. The results of our analysis of the impact of mergers then follow, and we end with our conclusions and implications for policy.

2. A Review of the Literature on the Determinants of Dropout Behaviour

The literature on student dropout behaviour is extensive. There are numerous studies of the determinants of dropout behaviour, including the effects of personal, family, college and peer characteristics and labour market conditions. Most of the literature is based on the US and relates to high school students. Clearly, the implications of not having a high school diploma are not the same as not having completed a UK college diploma. Nevertheless, the US literature is instructive and so we provide a brief overview of the findings. However, most of the existing literature, for the UK, US and elsewhere is descriptive rather than causal in nature.

There is very little work on the determinants of dropout behaviour in the UK further education sector (an exception is Bradley and Lenton, 2007). In terms of personal characteristics, females and younger students are less likely to drop out (Smith and Naylor, 2001; Johnes and McNabb, 2004). Bradley and Lenton (2007) show that the probability of dropping out for all ethnic minorities is lower than for white students when ability and a set of family and socio-economic factors are taken into account. The debate about the effect of family characteristics and socio-economic indicators has been extensive. Its main starting point is the recognition that income could be endogenous to the schooling and drop out decisions due to the existence of unobserved family characteristics, which could contemporaneously affect income and dropout behaviour. However, a paper by Bratti (2007) on the relationship between parental income and their children's dropout behaviour shows that there are large effects of parental variables other than income, such as social class and education. Bingley et al. (2009) using twins' data in an attempt to deal with the endogeneity issue find a significant positive effect of parental education on children's school completion. (In contrast, Behrman et al. (2005) find no effect of parental education on dropout behaviour when using twin's data for the US).

There is no consensus in the literature about the effect of school size on dropout behaviour. Smith and Naylor (2001) find for the UK higher education sector that school size has no direct effect on student outcomes. The Department for Education (2003) report on mergers in the FE sector did analyse a series of mergers that happened between 1996 and 2000. Although based on a qualitative rather than quantitative approach, the report concludes that the effect of mergers on students' outcomes is often dependent on the specific programme area. Moreover, the report noted that mergers in the period under scrutiny did not seek to enhance student attainment.

With respect to the US literature, and after controlling for family background, Cameron and Heckman (2001) show that students from ethnic minorities are more likely to graduate than whites. In terms of ability, or more specifically prior attainment, it has been shown that this is one of the main determinants of dropout behaviour. Eckstein and Wolpin (1999) find that higher ability students are less likely to dropout. However, Heckman et al. (2006) suggest that the most recent work on the topic, including their own analyses, show that both cognitive and non-cognitive ability play an important role in determining the probability of dropping out from High School. They also show that non-cognitive ability has a much bigger effect on dropping out than cognitive ability.

In terms of labour market effects, Eckstein and Wolpin (1999) examine whether working while in High School influences attainment and dropout, concluding that it actually reduces student performance. Human capital theory suggests that students will drop out if the expected wage of doing so is greater than what might be expected following graduation, which implies that a higher unemployment rate, especially for youths, should reduce drop out rates (see the US evidence in Chan, Morissette and Lu, 201 and Cascio and Narayan, 2019). However, there are contrasting findings in the literature - some studies find no effect (Warren and Lee, 2003; Mocetti, 2012), others a negative relationship (Rees and Mocan, 1997; Peraita, 2000) whereas for the UK a positive relationship is found (Smith and Naylor, 2001). What we can conclude from this literature is that the relationship between unemployment and dropout is a complex one.

One factor often associated with student outcomes is the existence of peer effects. Evans et al. (1992) investigate whether peer effects play a role in predicting student dropout behaviour. They find that peers affect the decision to drop out of school, however, if the endogeneity of peer group formation with respect to the dropout decision is taken into account, these effects disappear. The effect of college and institutional characteristics on student dropout behaviour have been investigated less frequently. Rumberger and Palardy (2005) find that social and academic climate-related factors are correlated with dropout behaviour. Rumberger (1995) finds that there is no effect of academic climate on dropout behaviour. Rumberger and Palardy (2005) also find that the student-teacher ratio is a positive and significant determinant of dropout behaviour even when controlling for student background characteristics and other factors. In contrast to the UK literature, some early work by Rumberger (1995) finds a significant positive relationship between school size and dropout behaviour, and more recently, Rumberger and Thomas (2000) using the same data finds a positive, and statistically significant, relationship between size and dropout even after controlling for school resources, attendance level, and characteristics of the student body.

Thus, there is a long tradition of research into the determinants of student dropout behaviour, however, the evidence is mixed and, as far as we are aware, there has been no study of the effects of college acquisitions on dropout behaviour.

3. The Data and Institutional Framework

3.1 The institutional framework

Students in the further education sector in England are typically aged between age 16 and 19. There are also various types of providers. The largest group of providers are General FE and Tertiary colleges, typically the largest institutions, which offer a wide range of vocational and academic subjects at various levels, often with a significant adult or mature student population. Sixth Form colleges are another type of provider and they have traditionally catered for 16-19 year olds taking academic Advanced level courses. More recently, however, they have broadened both their course offering and their student profile. Specialist Colleges concentrate on specific vocational areas, such as art and design, dance, and drama or land based subjects. They often have well developed links with employers and industry because of the specialist nature of the subjects taught. Finally, Specialist Designated institutions focus mainly for adults, as do External Institutions. The latter, however, also cater to the needs of educationally disadvantaged students. Most colleges derive the majority (over 70%) of their income from central government, and these funds were distributed between providers by the local Leaning and Skills Council. Funding was allocated based on a formula, which has five components. First, a national base rate, reflecting the length and cost of the provision of various programmes. Second, a weighting for more costly programmes or courses (e.g. laboratory-based courses). Third, a weighting for learners *completing* the programme with a qualification. Fourth, an uplift applied for colleges taking learners from specified disadvantaged backgrounds, and lastly, an additional amount paid to colleges in geographical areas where provision is more costly (e.g. London). Funding in the FE sector is therefore based on both inputs and outputs. The majority of the acquisitions observed in our data occur between General FE and Tertiary colleges.

3.2 The data

We use a large administrative student dataset provided by the Learning Skills Council, and specifically the Individual Learner Record (ILR). These cross-section data provide detailed information about the population of students enrolled with providers in the further education sector in England between the years 2002 to 2009. We imposed various restrictions on the data insofar as our sample refers only to full-time, full year, non-working students because students enrolled in part time, or in short courses, are likely to behave differently with respect to their decision to drop out or not (Montmarquette et al., 2007). Similarly, our sample of students refers to those aged 16-24, since dropout rates are much higher for adult students. We drop students enrolled on Basic Skills only programmes, involving literacy and numeracy revision for similar reasons. Lastly, we exclude students who transferred to other courses since we do not know the courses they transferred to - these constitute a small proportion of the student population (i.e. less than 0.2%). This exclusion should reduce possible bias arising from the non-random nature of student transfers from a treated college to a college in the control group. We also exclude mergers in 2008/2009 because our data ends at the end of that academic year and hence we are unable to identify which students drop out.[3] Overall, these restrictions on the sample will ensure that our treatment and control groups are more comparable. Furthermore, as Mueser et al. (2007) note, the use of administrative data to obtain propensity score matching estimates of the average treatment effect on the treated can be very effective.

In our data, we observe all students and all of the modules, or 'learning aims', within a programme of study on which they enrol, as well as the outcomes for each module in terms of whether the student passes or fails. The majority of students enrol on either a one-year or a two-year programme of study. The data set includes a variable for each learning aim, which indicates whether the student has withdrawn. Students can drop out of some learning aims or they can drop out of all learning aims, equivalent to dropping out of the programme. Whenever a student drops out of *all* learning aims, we define that student as a dropout. However, a student from the 2002/03 cohort, for instance, can dropout in 2002-03 or in 2003-04 during his second year of study. Therefore, we construct a dropout variable that is equal to 1 if the student drops out of all learning aims in either the first year of study or their second (and final) year of study. Our definition excludes those students who switch to other providers but it includes students who switch programmes within a provider.

Given the focus of our paper, Table 1 shows the number of acquisitions over the period of our study, 2002-2007. The number of acquisitions between pairs of colleges has been small per annum, as one might expect, reaching a peak in 2007/2008 at 9 which affected 4% of the total further education student population. When looked at on a cumulative basis, however, the number of acquisitions over the period is 18 involving 36 colleges. Viewed on a cumulative basis, college mergers affected over 76,000 students, which is substantial.

Table 2 shows the size of our final samples for all the cross-sections as well as the percentage of students that dropped out by acquisitions and non-merged colleges. We can see from the Table 2 that the number of students enrolled in FE colleges has steadily increased over time, reflecting the rising staying-on rate, suggesting that more 'marginal' students may well be entering college towards the end of the study period. What this Table also shows is that the dropout rate is quite large at around 8-15% with very little difference in most years between non-merged colleges and those involved in an acquisition. However, the dropout rate tends to fluctuate over the period of this study.

Finally, Table 3, Panel A, shows how the probability of dropping out varies by personal characteristics and in Panel B by the number of colleges in the local Learning Skills Council (LLSC) area. The dropout rate is overall slightly higher for males than females, although, in the last three years we note an increase in the dropout rate for females. Older students are consistently more likely to drop out than younger ones. The same is true for Black Caribbean and Other Black students, whereas Chinese and Indian students have a lower incidence of drop out. Not surprisingly, students with lower level prior qualifications are more likely to drop when compared with students with higher qualifications. Panel B also shows the mean number of colleges in the local area, which is around 10-11, and implies that mergers have not reduced competition between further education colleges and shows that students still have choice and, in turn, colleges have an incentive to retain students.

Table 4 goes a step further in exploring the variation in dropout rates by acquisitions and non-merged colleges and shows the raw difference-in-differences estimates. This table tells a very different story with respect to the effect of mergers on student dropout behaviour. For the early cohorts (up to the 2005), college acquisitions reduce dropout rates by between 0.1-5 percentage points and these effects persist insofar as the lagged responses continue to be negative. For instance, the first block of estimates which refer to mergers in 2004 shows that the raw difference-in-differences estimate of the dropout rate for the treated group is 1 percentage point lower than for the control group, whereas two years later this has risen to -4.3 percentage points. From 2006 onwards, however, the raw difference-in-differences estimates are positive, large and statistically significant, the exception those in 2007. Generally, this implies that the acquisitions arising in 2006 may well have been qualitatively different when compared to those that occurred in the other periods. Of course, these effects are likely to be biased because we do not control for the other determinants of dropout behaviour amongst students, and the acquisition decision may be endogenous. The next section discusses our approach to reducing the impact of endogeneity bias.

4. Econometric Methodology

We use matching methods combined with difference-in-differences to estimate the effect of college mergers on student dropout behaviour. However, it is possible in our context that selection bias may influence our estimates in two ways. Firstly, this can arise insofar as colleges that ‘merge’ are inherently different from those that do not merge. A second source of potential selection bias arises because students attending a merged college may differ in systematic ways from their counterparts in non-merged colleges even in the absence of treatment. In order to deal with the first possible source of bias we apply propensity score matching at college level to select a restricted sample of non-merged colleges similar to the acquired ones in terms of pre-treatment college characteristics. College level matching is run only once on the panel of colleges with all cohorts included. Specifically, we match those colleges that never merge (the control group) against those involved in an acquisition between 2004-2008 using pre-treatment characteristics measured in 2002.[4] We then select all colleges that are on the common support and run the student level analysis on this sample. Therefore, at the second stage, we apply matching at the student level, which is combined with difference-in-differences analysis.

In fact, mergers and acquisitions may also affect the student population entering the institution leading to compositional changes in the treatment and control group. Table A1 in the appendix shows that we observe very little compositional change in the student populations. Formally, this is important because it raises implications for the way in which we interpret our results. In fact, we are estimating the effect of college acquisitions on student dropout behaviour conditional on having the same student population. Formally, the parameter that we estimate in our analysis is the average treatment effect on the treated, 'ATT', which is defined as:

$$\tau_{ATT} = E(\tau | D = 1) = E(Y(1)|D = 1) - E(Y(0)|D = 1) \qquad (1)$$

Therefore, the ATT is equal to the difference between the expected outcome of treated students, who have been treated, and the expected outcome of treated students who had not been treated. Matching methods involve the selection of a group of non-treated students similar to the treated in all the relevant *pre-treatment* characteristics (X). Therefore, the difference in outcomes between those students and the treated ones will be attributable to the treatment. Following Rosenbaum and Rubin (1983) we use a *balancing score* to ensure that at each of the values of the distribution of X for the treated and untreated students is the same. A key assumption of the matching approach is the conditional independence assumption, which suggests that matching is based on observable characteristics. Rosenbaum and Rubin (1983) also shows that the conditional independence assumption remains valid if, after controlling for p(X), instead of X, the treatment and potential outcomes are independent.

However, as noted by Imbens (2004), if this condition holds, conditioning on the propensity score removes all biases due to observable characteristics, X. It is not possible to test this condition directly. In a cross-sectional setting, one would employ the Rosenbaum bounds approach to assess how much a hypothetical unobserved characteristic changes the treatment probability in order to drive the estimated effect to zero. This method allows us to show that our estimates for each cohort are quite robust to the existence of 'hidden bias'. By way of example, for both the 2002 and 2004 cohorts, hidden bias that changed the probability of treatment by 50% would still not drive our propensity score estimates to zero. However, in the difference in difference setting this does not mean that the difference in the probability will be zero, even though we control for time-invariant unobserved heterogeneity.

A second key assumption of the matching approach is the overlap or common support condition. The basic intuition behind this assumption is that there has to be at least one similar student in the counterfactual state for each treated student. In other words, for every single value of X the probability of finding a treated and a control student must be greater than 0 (Heckman et al., 1999). Given these assumptions, the matching estimator for the ATT is:

$$\tau_{ATT} = E_{p(X)|D=1}\{E[Y(1)|D = 1, p(X)] - E[Y(0)|D = 0, p(X)]\} \quad (2)$$

Thus, computing the ATT entails taking the mean outcome of treated and control students, comparing them for each given value of p(X) in the common support and finally weighting them for the propensity score distribution. All matching estimators can be seen as a special case of the following where the weights, Wij, take different forms:

$$\tau_{ATT} = \sum_{i \in T}(Y_i - \sum_{j \in C} W_{ij} Y_j)W_i \quad (3)$$

T and C indicate, respectively, the treatment and control students, W_{ij} denotes the weights assigned to the control group when matching with the treated group, and w_i represent a re-weighting needed to rebuild the outcome distribution for the treated. For the college level matching analysis, we use the nearest neighbour approach, whereas for the student level matching we use the radius approach. We test the sensitivity of our estimates by adopting other weighting approaches and our estimates do not change dramatically.

4.1 **Matching with Difference-in-Differences Estimation**

As suggested above, the estimation of an average treatment effect on the treated using propensity score matching relies heavily on the validity of the conditional independence assumption. Therefore, it only estimates a causal effect in the absence of selection on unobservables. Rather than simply test for the presence of hidden bias, a more robust method for removing such bias is to combine propensity score matching with difference-in-differences methods. The difference-in-differences approach does allow for unobservables affecting treatment participation as long as this bias is constant over time (Heckman et al., 1998; Blundell and Costa Dias, 2009). Recall that a restricted sample of colleges is created through a college level propensity score matching to ensure that colleges in the control group, which have not merged, are similar to the merged ones in terms of pre-treatment college characteristics.

To perform matching with difference-in-differences we need at least one pre- and one post-treatment period. Moreover, we need to identify four different groups of students - one of which refer to the treated students and the remaining three groups are students in control groups. The treatment in this context refers to the event of college merger. Thus, we observe T_O and $C_{O,}$ which represent the treated and control groups in the pre-treatment period, whilst T_1 and C_1 are the treated and control group in the post-treatment period. As pointed out by Blundell and Costa Dias (2009) we can write our matching with difference-in-differences estimator as:

$$\tau_{ATT}^{DID} = \sum_{i \in T_1} \{ [Y_{it_1} - \sum_{j \in T_0} \tilde{W}_{ijt_0}^{T} Y_{it_0}] - [\sum_{j \in C_1} \tilde{W}_{ijt_1}^{C} Y_{it_1} - \sum_{j \in C_0} W_{ijt_0}^{C} Y_{it_0}] \} w_i \qquad (4)$$

where $\tilde{W}_{ijt_1}^{C}$ denote the weights assigned to student j in group C at time t when matching with the treated student i. $\tilde{W}_{ijt_0}^{T}$ refers to the same weight for students in group T. Finally, w_i represents a re-weighting needed to re-build the outcome distribution for the treated.[5]

5. Econometric results

5.1 Propensity score matching estimates

In this section of the paper, we discuss the estimates from the propensity score matching models for both the probability that a particular college acquires another college, and the probability that a particular student attends the combined college. We also report the associated covariate balancing tests (see Figures 2, 3 and 4). In practical terms, this means checking for covariate balance in the matched sample. Obtaining good covariate balance implies that the marginal distribution of each covariate is very similar for treated and untreated colleges or students. The most widely used method for checking the covariates balance is the so-called standardised bias, or standardised difference in means. This method, proposed by Rosenbaum and Rubin (1985), entails comparing the standardised difference in means for each of the covariates, between treated and untreated students before and after matching. A reduction in the standardised bias after matching demonstrates that covariate balance is improved by the matching procedures. Figure 2 shows the balancing test for matching at the college level, whereas Figures 3 and 4 show the tests at student level using cohorts 2002-03 and 2004-05 for illustration. These figures show that we achieve levels of the standardised bias which are well under the threshold considered as acceptable by Rosenbaum and Rubin (1985) for both college level matching and student level matching.

Figures 5 and 6 show that our matching at the student level fulfils the common support condition. We show the propensity score distribution before and after matching for the year before treatment – 2002 – and one selected year after treatment – 2004. The distribution for treated and controls is now very similar and we obtain so without having to discard many observations.

Following the suggestion of Rubin and Thomas (1996) and Heckman et al. (1998), the covariates included in the propensity score estimation were chosen because of the existence of a relationship with the outcome of interest. Table A1 in the Appendix shows illustrative descriptive statistics for all covariates included in the individual level propensity score estimation for the treated and control groups for cohorts 2002 and 2004. These data relate to pre-matching. They show that there is very little difference in the sample percentages for the treated and control groups for 2002 versus 2004. As Table A2 shows, virtually all of these covariates included in the individual level propensity score model are statistically significant, and the estimates are largely consistent over time. Mature students, males and disabled students are less likely to attend a college involved in an acquisition and these effects are consistent over time. Similarly, students from an ethnic minority background are generally less likely to attend merged colleges although interestingly for 2002-2006 the reverse is the case. The story with respect to prior qualifications is less clear-cut insofar as estimates are negative, positive or statistically insignificantly different from zero. The number of colleges in a local area (LLSC) has a variable effect sometimes increasing the risk of attending a 'merged' college, other times reducing this risk. Recall also our discussion of hidden bias, above. We conclude that the absence of key covariates in our dataset, such as family income, should not be a problem.

5.2 Difference-in-differences estimates of the effect of acquisitions on student dropout behaviour

This section presents the results of our matching with difference-in-differences estimation, initially for the whole time-period and then disaggregated by time-periods. To recap, we use student level data for our sub-sample of matched colleges. The next step consists in estimating a difference-in-difference radius propensity score matching model at the student level.[6] This approach has the advantage of generating a control group that is similar to the treated one in terms of pre-treatment observable characteristics and through the combination with difference-in-differences allows us to control for any time invariant unobserved heterogeneity. Given that we are unable to create a 'grandfathering instrument' as in Abdulkadiroglu et al. (2016) this approach is ensuring that we take care of most sources of potential bias.

Figure 7 investigates the common trends assumption. The students in colleges who are involved in the acquisition of other colleges ('mergers') exhibit a similar trend in dropout rates when compared with students from colleges who do not 'merge' (the control group), although we do note the modest convergence in the pre-treatment period.[7] Table 5 shows that overall acquisitions have a small, but statistically significant, negative effect on the probability of a student dropping out. However, as expected, we find that there is some variation in the estimated effects over time (between cohorts) in terms of the magnitude of the effects of acquisitions on student dropout behaviour (see Table 6). For acquisitions involving the 2004 cohorts of students we do observe initial, but small, increases in the risk of dropout, which then progressively dissipates over time. For instance, acquisitions taking place in 2004 reduce the risk of dropout for the 2005 and 2006 cohorts by between 5-7 percentage points. A similar story emerges with respect to acquisitions that took place in 2005, insofar as there is a decrease in the risk of student dropout, especially for the 2006 cohort (-6 percentage points) but also the 2007 cohort (-2 percentage points). These findings are consistent with the view that the possible negative effects of acquisitions, that is, an increase in the risk of student dropout, is eventually outweighed by the positive benefits of scale and scope – a reduction in the risk of student dropout. Specifically, it is possible that the takeover of one college by another needs time for the benefits to emerge – as suggested in the Introduction, there are likely to be organizational problems in the first year of the acquisition.

The Foster Report (2005) did lead to a change of government policy, as discussed in the Introduction, and so it is feasible that the 'type' of colleges involved in acquisitions after that report were structurally different to those preceding the publication of the Report, hence having a different effect on student dropout behaviour. Our results suggest that acquisitions initiated in 2006 had a positive effect on the risk of dropout for the 2006 and 2007 cohorts of students, which were quite large and statistically significant. However, this effect reduces substantially for acquisitions in 2007, suggesting that the Foster Report may have had an effect on the types of colleges involved in acquisitions but this effect was short lived. Furthermore, since factors other than the Foster Report, or government policy more generally, can affect the acquisition behaviour of colleges we do not claim that this is a causal effect.

To test whether there has been a structural break in the effect of mergers and takeovers on student dropout behaviour we estimate a difference-in-differences model where we combine data for the early period (2002-2003) with the later period (2005-2007).[8] Table 7 reports the results of this analysis and, interestingly, suggests that between these two time periods college acquisitions had the effect of increasing the probability of student drop out by about 1.3 percentage points.

Concluding remarks

This paper is the first substantial econometric investigation of the effect of college acquisitions on the probability of student drop out using administrative data obtained from the former Learning Skills Councils for the period 2002-2008. Our data refer to the population of students enrolled in further education colleges in England. We also explore whether the effect of acquisitions is short lived, dissipating over time, and whether there are differences in the effect following the publication of the Foster Report in 2005.

We find that there is some variation in the estimated effects between cohorts and in terms of the magnitude of the effects pre- and post-Foster. Overall, our findings show that acquisitions reduce the probability of dropout by a modest amount, but this effect varies in magnitude and direction over time. In general, positive effects of acquisitions on drop out behaviour tend to be small and dissipate over time, whereas negative effects persist and tend to increase in magnitude over time. These findings are consistent with the view that takeovers, or acquisitions, are likely to be more adversarial in the sense that the successful college in the arrangement wishes to acquire financial incentives from government, increase their market share in terms of student recruitment and achieve some of the benefits of scale. This can be disruptive for staff and students, however, over time this disruption is reduced as staff and students are assimilated by the acquiring college. The Foster Report (2005) stimulated a change of government policy and this is partly reflected in our findings, insofar as acquisitions initiated in 2006, had a large positive, and statistically significant, effect on dropout rates for the 2006 and 2007 cohorts but fall away by 2007. Later acquisitions may therefore have been qualitatively different to those occurring pre-Foster.

Our research is exploratory since further work is needed on the underlying mechanisms linking college mergers and acquisitions to student outcomes. These findings are important from a government policy perspective because the FE sector has and continues to face budget cuts, consequently forcing further 'mergers' to take place. Insofar as further rationalisation of the sector is sought, it can be argued that it is better to encourage voluntary merger between colleges rather than encourage acquisitions per se. Should acquisitions be encouraged then it is important to consider the quality of the match between successful and less successful colleges. This is especially important if the government wishes to protect the short-term interests of students in terms of progression and hence achievement. It is also important that should further acquisitions occur in the sector then it is important from a practice perspective that resources, policies and procedures are introduced to enable staff to proactively support those students at risk of failing and dropping out of college prematurely.

There is a need for further research on the effects of college mergers on student outcomes, in particular to identify the mechanisms linking merger events to student outcomes, which also draws a distinction between voluntary mergers and acquisitions. There is also a need to explore the effect of college mergers in the primary and secondary school sectors, especially given the introduction of quasi-markets in the UK.

Supplementary material

The supplementary material for our paper is available on the OUP website. This material comprises the Stata do files to assist researchers in replicating our results. The main data used in analysis is from what was the Learning and Skills Council, now replaced by the Education and Skills Funding Agency (ESFA), and refers to the Individual Learner Records. Researchers would have to apply to the Department for Education to use these data. The do files provided are for data preparation of individual learner aims records (data_prep.do), appending institutional level data (inst_append.do), college level matching models (college_lev_match_takeover.do) and several files needed to perform the difference-in-differences analysis for matched colleges and acquisitions (DiD*.do). Data requests should be made to the ESFA.

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Footnotes

[1] The spatial distribution of mergers and acquisitions in our data are: East Midlands (5), South West(3), Yorkshire & Humberside (2), North West (3), West Midlands (1), South East (5) and North East (3).This shows that the mergers are spatially distributed across England and occur in urban as well as rural areas.

[2] It is also worth noting that Abdulkadiroglu et al. (2016) describe trends in takeovers amongst charter schools and public schools in New Orleans and Boston, and also analyse their effect on student achievement.

[3]A student can drop out any time before achieving the qualification. Therefore a student enrolled in 2008/2009 can either drop out in 2008/2009 or in 2009/2010.

[4] The never merge category includes all colleges that have never merged since 1998. The following student level variables, measured in percentages, are used to estimate the college level propensity score model - females, aged 15-17, absence of a learning difficulty, no disability, no disadvantage, white, unknown prior attainment, no qualification, prior attainment below level 1, prior attainment level 2, prior attainment level 3, and prior attainment level 4 or 5. We also include the college disadvantage index and its squared term, the student-teachers ratio, the average age of teaching staff, the percentage of non- white teachers, the percentage of qualified teachers, average salary of permanent staff, the percentage of permanent teaching staff, and the rate of teaching to support staff.

[5] We report estimates using the radius matching algorithm with caliper=0.005. The use of this algorithm has the advantage of reducing bias while achieving a good precision. However, estimates using nearest neighbour, multiple neighbours or caliper matching are broadly comparable. We are unable to use non-parametric matching methods because of the computation burden.

6 The level of prior attainment corresponds to the NVQ classification used in the Individual Learner Records data set.

[7] Since we implement a non-parametric difference-in-differences analysis to investigate the impact of acquisitions on student dropout behavior within year and then again after 1 and 2 years. Given these data, we are unable to implement a test of the common trends assumption by interacting the treatment variable with time dummies (so called leads and lags). Consequently, we rely on visual inspection of the trends.

[8] Students enrolled in 2003 can drop out in 2003 or in 2004, therefore, we decided not to use the 2004 cohort to ensure a clear distinction between pre- treatment and post-treatment period.

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Table 1: The number of acquisitions and student population affected by year.

Years	No. of acquisitions	Proportion of students affected	Cumulative student population affected
2004/2005	3	1.41	11,433
2005/2006	3	1.27	22,394
2006/2007	3	1.76	38,508
2007/2008	9	4.04	76,045

Note: There were 2 colleges involved in each acquisition.
Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Table 2: Dropout rates by takeover and Non-takeover colleges, 2002-09.

		College Status		
		Non merged %[a)]	Acquisitions %	All
Year 2002/2003	Completers	383,542	6,908	390,450
		(90.30)	(88.11)	(90.26)
	Dropouts	41,211	932	42,143
		(9.70)	(11.89)	(9.74)
	Total	424,753	7,840	432,593
Year 2003/2004	Completers	423,687	8,985	432,672
		(90.71)	(90.11)	(90.69)
	Dropouts	43,407	986	44,393
		(9.29)	(9.89)	(9.31)
	Total	467,094	9,971	477,065
Year 2004/2005	Completers	435,931	9,424	445,355
		(91.17)	(89.95)	(91.14)
	Dropouts	42,242	1,053	43,295
		(8.83)	(10.05)	(8.86)
	Total	478,173	10,477	488,650
Year 2005/2006	Completers	499,500	5,780	505,280
		(91.68)	(91.33)	(91.68)
	Dropouts	45,311	549	45,860
		(8.32)	(8.67)	(8.32)
	Total	544,811	6,329	551,140
Year 2006/2007	Completers	541,228	9,204	550,432
		(89.42)	(84.47)	(89.33)
	Dropouts	64,047	1,692	65,739
		(10.58)	(15.53)	(10.67)
	Total	605,275	10,896	616,171

Year 2007/2008	Completers	544,498	26,679	571,177
		(89.89)	(90.62)	(89.93)
	Dropouts	61,212	2,761	63,973
		(10.11)	(9.38)	(10.07)
	Total	605,710	29,440	635,150
Year 2008/2009	Completers	595,592	11,071	606,663
		(90.58)	(87.39)	(90.52)
	Dropouts	61,906	1,598	63,504
		(9.42)	(12.61)	(9.48)
	Total	657,498	12,669	670,167

a) Column percentage in brackets.
Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Table 3: Dropout rates by pupil characteristics and year.

Panel A. Covariates	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08	2008-09
Age≤20	9.41	8.98	8.58	8.02	10.27	9.71	9.07
Age>20	13.68	13.39	12.61	12.59	16.6	15.56	15.24
Male	10.54	9.88	9.38	8.64	10.75	10.21	9.45
Female	8.99	8.77	8.37	8.02	10.6	9.95	9.49
Disability	9.64	9.39	8.62	8.04	9.93	10.08	9.23
No Disability	9.75	9.3	8.87	8.34	10.72	10.07	9.49
Ethnic origin:							
Bangladeshi	9.38	9.67	7.96	8.00	9.27	8.47	9.35
Black African	9.62	8.62	7.80	7.09	9.01	8.86	9.44
Black Caribbean	14.04	12.58	11.62	11.12	13.5	12.67	12.39
Black Other	14.93	13.28	12.67	11.73	15.14	13.58	13.42
Chinese	5.89	5.25	5.62	4.08	4.81	4.64	4.49
Indian	5.90	5.93	5.67	5.01	6.39	6.23	6.15
Pakistani	8.81	8.26	7.64	6.57	9.30	8.62	8.42
Asian Other	9.25	8.83	7.47	7.33	9.26	9.02	9.09
Other	10.37	10.65	9.03	8.46	9.26	11.1	10.51
White	9.75	9.32	8.95	8.43	11.16	10.17	9.41
Prior Qualification:							
None	11.22	10.49	11.53	11.29	10.78	13.67	12.74
< level 1	14.02	12.18	7.12	9.56	14.88	13.96	12.55
level 1	12.69	11.56	11.08	10.41	14.03	13.13	11.95
level 2	7.35	6.93	6.84	6.34	13.51	7.65	7.27
level 3	7.54	6.43	5.80	6.64	8.05	7.16	7.31
level 4 or 5	10.86	6.54	9.80	7.62	7.37	6.82	7.65
level unknown	10.84	10.87	10.3	10.00	11.78	12.53	11.57

Panel B. Number of colleges in the local area (LLSC)	Mean	St.	Min	Max
2002-03	10.978	6.074	1	25
2003-04	10.697	5.716	1	25
2004-05	9.98	5.322	1	24
2005-06	10.707	5.742	1	25
2006-07	10.723	5.89	1	24
2007-08	10.939	5.30	2	23
2008-09	11.33	5.207	2	22

a)The level of prior attainment corresponds to the NVQ classification used by the Institutional Learners Record data set.

Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Table 4. The raw DiD estimates of the effect of college acquisitions on student dropout behaviour.

	Proportion of Dropouts			
	Treated (s.e.)	Controls (s.e.)	Difference (s.e.)	N
Acquisitions in 2004				
2004 cohort	0.136	0.101	0.035	47,925
	(0.004)	(0.001)	(0.004)	
2002 cohort	0.149	0.108	0.041	39,795
	(0.005)	(0.002)	(0.005)	
DiD			-0.006	87,720
			(0.000)	
Acquisitions in 2004, lagged effect on 2005 cohort				
2005 cohort	0.114	0.098	0.016	50,424
	(0.004)	(0.001)	(0.003)	
2002 cohort	0.149	0.108	0.041	39,795
	(0.005)	(0.002)	(0.005)	
DiD			-0.025	90,219
			(0.000)	
Acquisitions in 2004, lagged effect on 2006 cohort				
2006 cohort	0.130	0.131	-0.002	56,400
	(0.004)	(0.002)	(0.004)	
2002 cohort	0.149	0.108	0.041	39,795
	(0.005)	(0.002)	(0.005)	
DiD			-0.043	96,195
			(0.000)	
Acquisitions in 2005				
2005 cohort	0.094	0.098	-0.004	49,907
	(0.004)	(0.001)	(0.004)	
2002 cohort	0.115	0.108	0.007	40,228
	(0.004)	(0.002)	(0.005)	
DiD			0.010	90,135
			(0.000)	
Acquisitions in 2005, lagged effect on 2006 cohort				
2006 cohort	0.084	0.131	-0.047	56,257
	(0.003)	(0.002)	(0.004)	
2002 cohort	0.115	0.108	0.007	40,228
	(0.004)	(0.002)	(0.005)	
DiD			-0.054	96,485
			(0.000)	
Acquisitions in 2005, lagged effect on 2007 cohort				
2007 cohort	0.125	0.121	0.004	59,025

	(0.004)	(0.001)	(0.004)	
2002 cohort	0.115	0.108	0.007	40,228
	(0.004)	(0.002)	(0.005)	
DiD			-0.003	99,253
			(0.000)	
Acquisitions in 2006				
2006 cohort	0.171	0.131	0.040	56,906
	(0.004)	(0.002)	(0.004)	
2002 cohort	0.139	0.108	0.032	40,067
	(0.005)	(0.002)	(0.003)	
DiD			0.008	96,973
			(0.000)	
Acquisitions in 2006, lagged effect on 2007 cohort				
2007 cohort	0.183	0.121	0.062	59,778
	(0.004)	(0.001)	(0.004)	
2002 cohort	0.139	0.108	0.032	40,067
	(0.005)	(0.002)	(0.003)	
DiD			0.030	99,845
			(0.000)	
Acquisitions in 2007				
2007 cohort	0.103	0.121	-0.018	73,722
	(0.002)	(0.001)	(0.003)	
2002 cohort	0.095	0.108	-0.012	48,103
	(0.003)	(0.002)	(0.003)	
DiD			-0.006	121,825
			(0.000)	

Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Table 5 The effect of acquisitions on student dropout behavior: An aggregate analysis,

Cohort	ATT (s.e.)	Treated	Controls	N
2005-2007	0.003 (0.002)	130,436	187,582	318,018
2002-2003	0.012 (0.006)	52,195	34,900	87,095
DiD	-0.009 (0.000)			405,113

Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Table 6: Student level matching and difference-in-differences estimates of the effect of college acquisitions on the probability of student drop out. Matched colleges.

Cohort		ATT (s.e.)	Treated	Controls	N
Acquisitions in 2004					
	2004	0.005	9,173	54,260	63,451
		(0.006)			
	2002	0.004	7,399	48,517	55,916
		(0.006)			
DiD		0.001			
		(0.000)			
Acquisitions in 2004, lagged effect on 2005 cohort					
	2005	0.003	4,972	44,274	49,246
		(0.007)			
	2002	0.045	4,895	34,900	39,795
		(0.007)			
DiD		-0.046			
		(0.000)			
Acquisitions in 2004, lagged effect on 2006 cohort					
	2006	-0.023	6,920	49,237	56,237
		(0.012)			
	2002	0.044	4,894	34,900	34,900
		(0.007)			
DiD		-0.068			
		(0.000)			
Acquisitions in 2005					
	2005	-0.01	5,630	59,534	65,167
		(0.004)			
	2002	-0.004	5,321	48,517	53,845
		(0.005)			
DiD		-0.006			
		(0.000)			
Acquisitions in 2005, lagged effect on 2006 cohort					
	2006	-0.055	7,005	49,237	56,242
		(0.006)			
	2002	0.003	5,328	34,900	40,228
		(0.007)			
DiD		-0.058			
		(0.000)			

Cohort	ATT	Treated	Controls	N

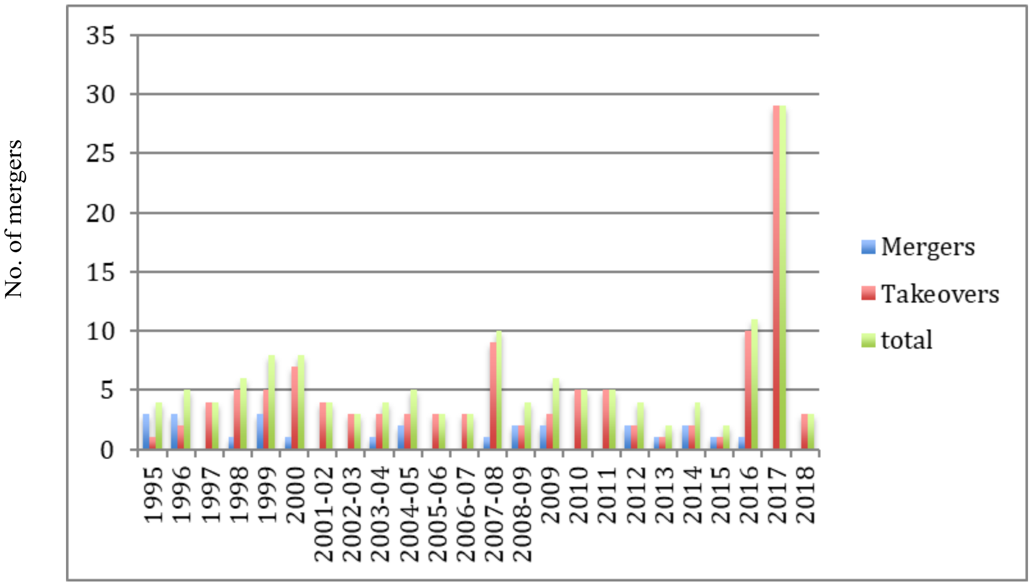
		(s.e.)			
Acquisitions in 2005, lagged effect on 2007 cohort					
	2007	-0.012	6,721	52,290	59,011
		(0.005)			
	2002	0.01	5,295	34,900	40,195
		(0.007)			
DiD		-0.023			
		(0.000)			
Acquisitions in 2006					
	2006	0.065	7,668	67,956	75,625
		(0.005)			
	2002	0.011	5,167	48,517	53,566
		(0.007)			
DiD		0.054			
		(0.000)			
Acquisitions in 2006, lagged effect on 2007					
	2007	0.077	7,488	52,290	59,290
		(0.005)			
	2002	0.016	5,295	34,900	40,195
		(0.007)			
DiD		0.061			
		(0.000)			
Acquisitions in 2007					
	2007	-0.017	24,812	67,081	91,893
		(0.002)			
	2002	-0.019	14,181	48,517	62,698
		(0.004)			
DiD		0.002			
		(0.000)			

Table 7: Student level matching and difference-in-differences estimates of the effect of college acquisitions on the probability of student drop out, post-Foster Report (2005-2007).

Cohort	ATT (s.e.)	Treated	Controls	N
2005-2007	-0.002 (0.002)	99,660	145,801	245,461
2002-2003	-0.01 (0.002)	49,719	79,941	129,660
DiD	0.013 (0.000)			375,121

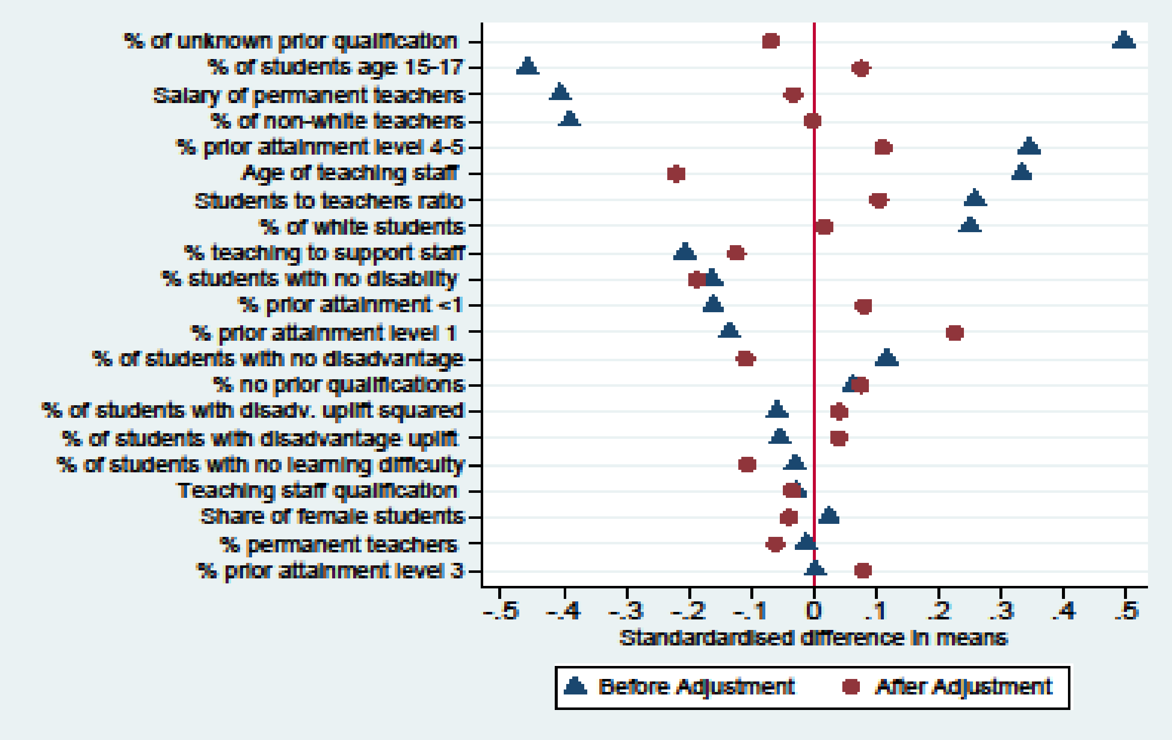
Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Figure 1: The incidence and type of college mergers in England, 1995-2018.



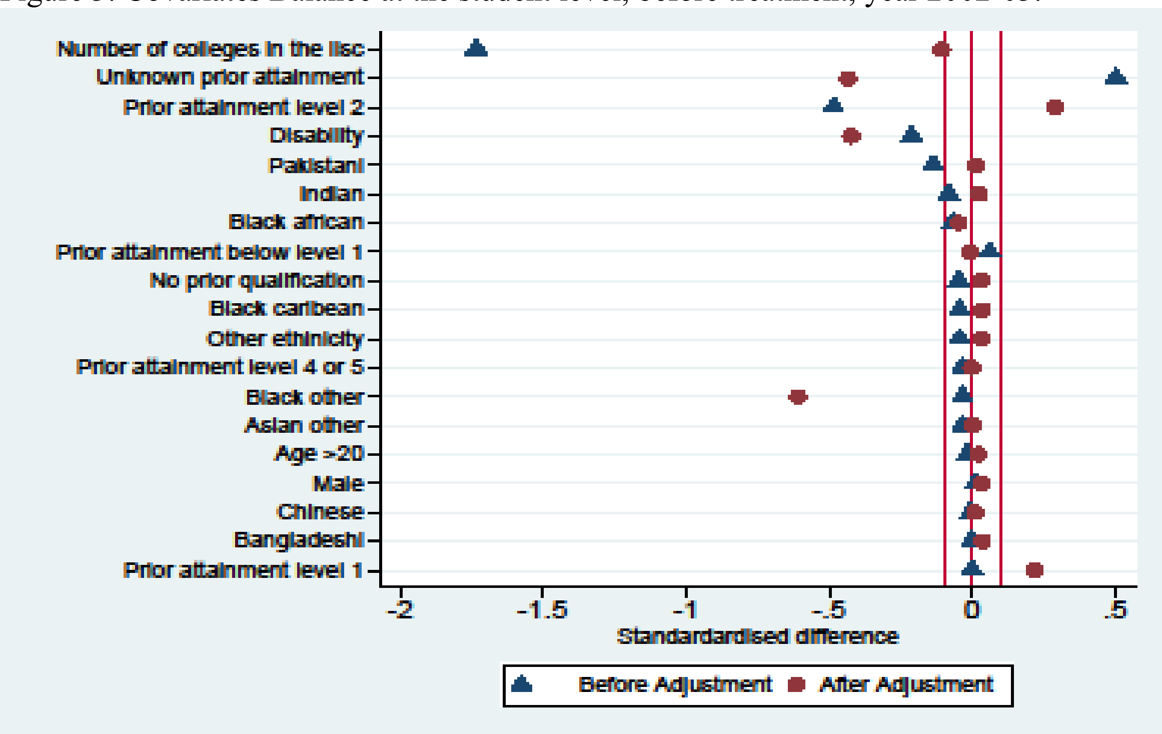
Source: Derived from the Association of colleges (2016)

Figure 2: Covariates Balance, matching at college level (covariates measured in year 2002/03). Nearest Neighbour, no replacement.



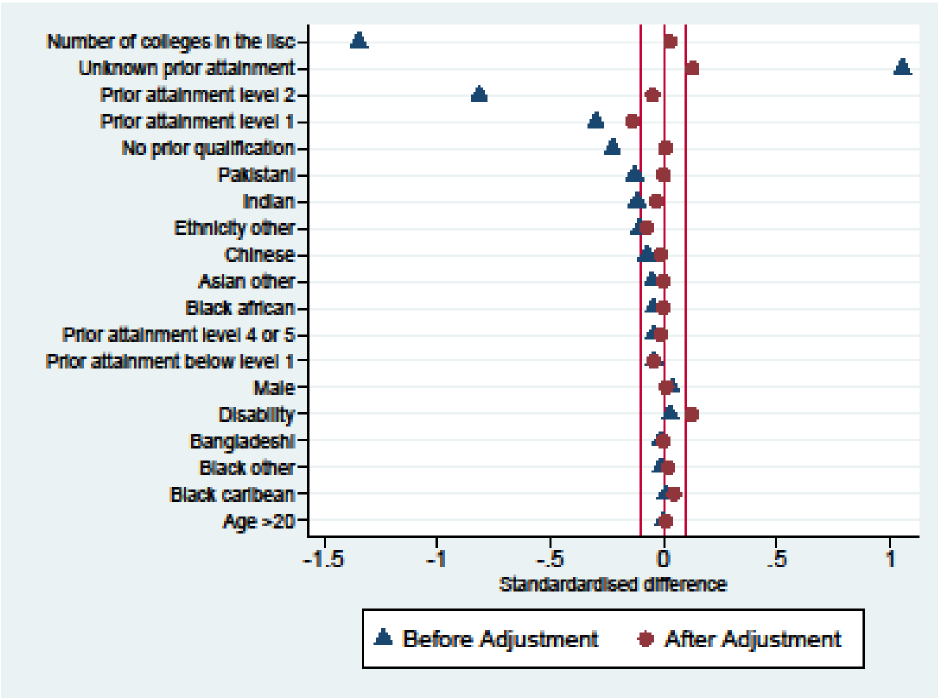
Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Figure 3: Covariates Balance at the student level, before treatment, year 2002-03.



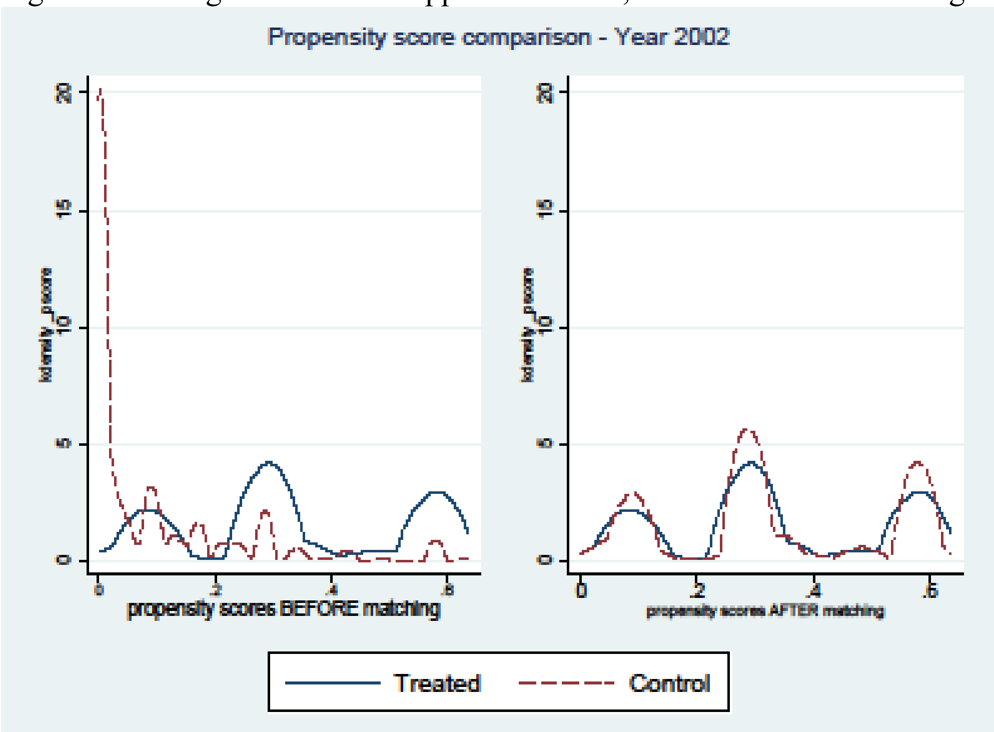
Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Figure 4: Covariates Balance at the student level, after treatment, year 2004-05.



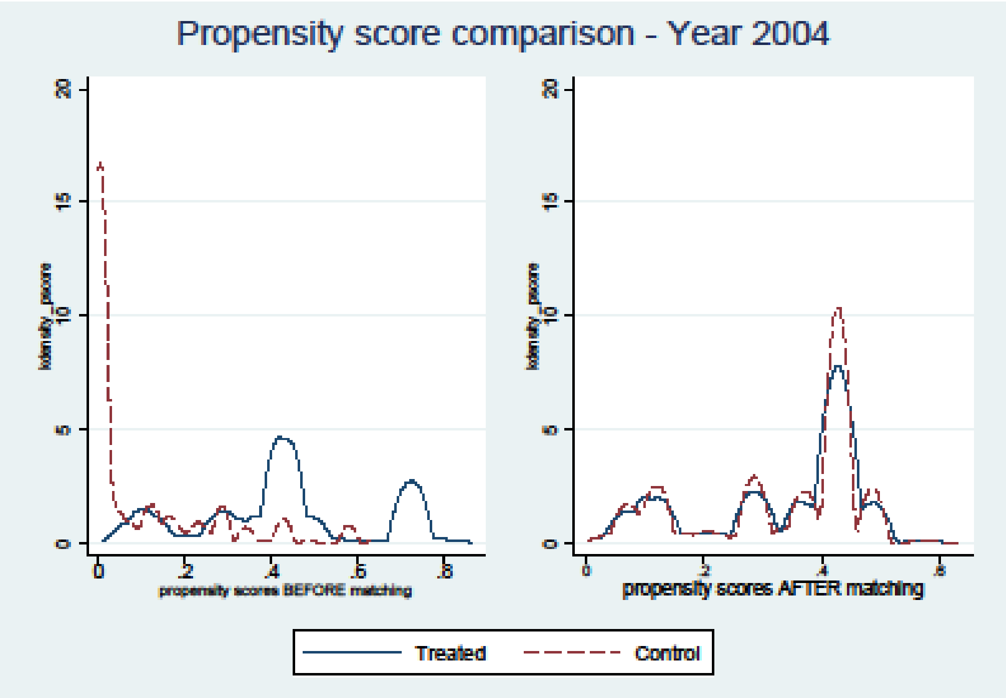
Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Figure 5: Testing the common support condition, individual level matching 2002



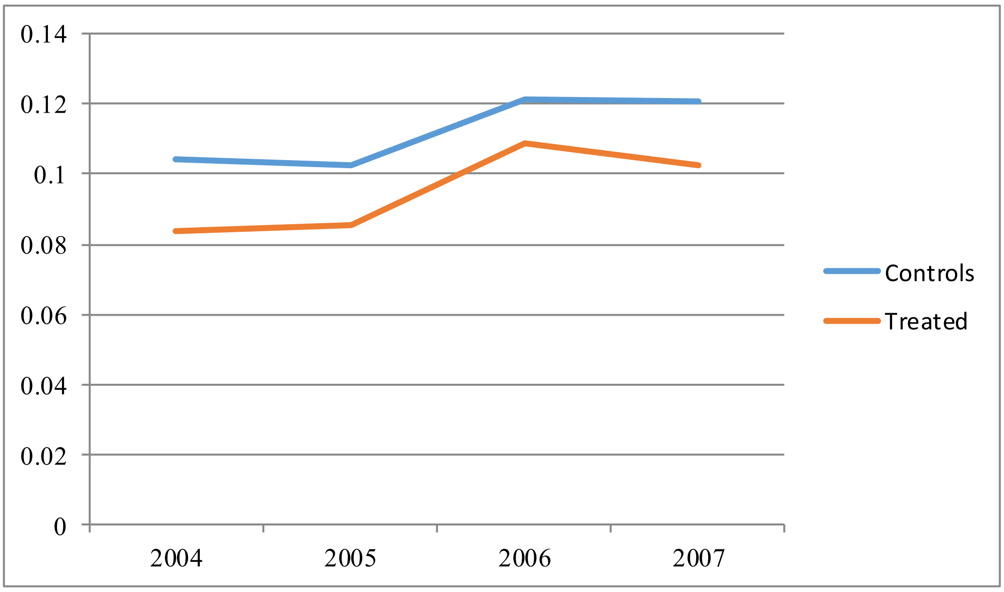
Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Figure 6: Testing the common support condition, individual level matching 2004



Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Figure 7: Testing for common trends in student dropout rates for 'merged' (Treated) and non-merged (Controls) colleges. Treatment in 2007-08



Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

A Appendix

Table A1: Descriptive statistics of treated and control students before and after treatment.

Variable	Before Treatment: 2002		After Treatment: 2004	
	Treated	Control	Treated	Control
Age 20+	3519	493	3504	487
%	10.08	10.07	8.39	7.93
Male	16757	2437	20043	2984
%	48.01	49.79	47.97	48.57
Disable	1896	298	2300	99
%	5.43	6.09	5.5	1.61
White	29093	4416	34908	5507
%	83.36	90.21	83.55	89.63
Bangladeshi	244	28	324	47
%	0.7	0.57	0.78	0.76
Black African	661	64	1016	92
%	1.89	1.31	2.43	1.5
Black Caribbean	460	70	629	62
%	1.32	1.43	1.51	1.01
Black Other or mixed	604	77	879	101
%	1.73	1.57	2.1	1.64
Chinese	383	22	247	34
%	1.1	0.45	0.59	0.55
Indian	742	36	841	62
%	2.13	0.74	2.01	1.01
Pakistani	1563	107	1638	103
%	4.48	2.19	3.92	1.68
Asian other	385	31	510	54
%	1.1	0.63	1.22	0.88
Ethnic Other or mixed	765	44	789	82
%	2.19	0.9	1.89	1.33
prior attainment:no qualification	1005	7	334	27
%	2.88	0.14	0.8	0.44
prior attainment: below level 1	30	0	113	43
%	0.09	0	0.27	0.7
prior attainment: level 1	2856	86	6307	928
%	8.18	1.76	15.1	15.1
prior attainment: level 2	10462	111	14281	864
%	29.98	2.27	34.18	14.06
prior attainment: level 3	1099	11	2028	51
%	3.15	0.22	4.85	0.83
prior attainment: level 4 or 5	66	2	68	3

%	0.19	0.04	0.16	0.05
prior attainment: unknown	19382	4678	18650	4228
%	55.54	95.57	44.64	68.82

Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).

Table A2: Estimated marginal effects from the propensity score models, in year effects from matched colleges sample.

Years (DiD)	2002-04 Estimates (s. e.)	2002-05 Estimates (s. e.)	2002-06 Estimates (s. e.)	2002-07 Estimates (s. e.)
Age over 20	0.005***	0.027****	-0.012***	0.000
	(0.001)	(0.004)	(0.003)	(0.005)
Male	0.000	0.005**	-0.013***	-0.04*
	(0.000)	(0.002)	(0.002)	(0.002)
Disable	-0.006***	0.025***	-0.056***	-0.028***
	(0.001)	(0.005)	(0.003)	(0.005)
Ethnic origin				
Bangladeshi	-0.011***	0.028***	0.246***	-0.066***
	(0.001)	(0.011)	(0.014)	(0.014)
Black African	-0.010***	0.040***	0.015**	-0.095***
	(0.001)	(0.006)	(0.007)	(0.008)
Black Caribbean	-0.011***	0.000	0.320***	-0.123***
	(0.001)	(0.009)	(0.011)	(0.009)
Black other or	-0.011***	0.018	0.142***	-0.095***
	(0.001)	(0.008)	(0.009)	(0.008)
Chinese	-0.005***	0.212***	0.046***	0.055***
	(0.002)	(0.016)	(0.014)	(0.015)
Indian	-0.013***	-0.062***	0.227***	-0.161***
	(0.001)	(0.005)	(0.010)	(0.007)
Pakistani	-0.012***	-0.011**	0.158***	-0.131***
	(0.001)	(0.005)	(0.007)	(0.006)
Asian other or	-0.009*	0.082***	0.052***	0.004
	(0.001)	(0.012)	(0.011)	(0.011)
Other or mixed	-0.012***	-0.028*	-0.025	-0.086***
	(0.001)	(0.007)	(0.006)	(0.008)
Prior attainment				
No qualification	0.005	-0.005	-0.016**	0.087***
	(0.005)	(0.003)	(0.007)	(0.010)
Below level 1	0.229***	0.127***	0.199*****	-0.179***
	(0.056)	(0.026)	(0.028)	(0.013)
Level 1 or entry	0.029***	0.098***	0.031***	0.039***
	(0.006)	(0.008)	(0.007)	(0.008)
Level 2	0.009****	0.000	0.025***	0.019***
	(0.003)	(0.006)	(0.006)	(0.007)
Level 4 or 5	0.002	0.236***	0.033	-0.086
	(0.010)	(0.036)	(0.033)	(0.031)
Unknown	0.044****	-0.003	0.104****	0.091***
	(0.004)	(0.005)	(0.000)	(0.008)

No. of colleges in the llsc	-0.013***	0.010***	-0.017***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.36	0.07	0.12	0.06
N.	87,720	90,135	96,973	121,825

* p<0.1, ** p<0.05, *** p<0.01

Source: Authors calculations from Learning Skills Council Individual Learner Records (ILR).