Appendix for *Assortative Mating and Turnout*

1 Descriptives

1.1 Variables

The variables used in the analysis are voting participation, partner's voting participation, education, income, age, marital status, sex, and year of election. Voting participation (of both partners) is asked "Did you vote in this (past) year's general election?", Education measures the individuals highest qualification (derived and harmonized across BHPS and UKHLS), income measures the total monthly personal income gross (derived and harmonized across BHPS and UKHLS), age is the age at time of interview, from the variable marital status I have used the categories "married" "living as a partner" and "never married", sex is measures as male or female, and year of election is the year of the last election (corresponding to the question asked about turnout). More information about variables, harmonization and the combined data set can be found in the (Fumagalli et al. 2017).

1.2 Relationship between socio-economic status and turnout

Table 2 shows the results from a pooled model using data from all waves. As expected from previous research, married people vote more often than those who are not married. Education, income, age, and being female are positively related to voting. Age^2 is negatively related to turnout. Turnout is highest in the 1992 election.

1.3 Sample restrictions and data structure

Limiting the sample to the individuals who had a change in relationship status (never married $\rightarrow$ cohabitation/marriage) and dividing the sample into two groups; the ones who's partner voted at T1 and the ones who's partner did not vote at T1 gives us figure 1. Figure 1 also shows the number of respondents who answered the survey about up to four elections before and after their first election in a relationship. It is clear that the n declines

Table 1

	Voted
Married	0.049*** (0.006)
Female	0.022*** (0.004)
Education	0.038*** (0.001)
Income	0.004*** (0.001)
Age	0.016*** (0.001)
Age × Age	-0.000*** (0.000)
1997	-0.073*** (0.005)
2001	-0.153*** (0.005)
2005	-0.206*** (0.006)
2009	-0.164*** (0.006)
2015	-0.161*** (0.006)
Constant	0.155*** (0.017)
Observations	59434
Clusters	31255
R^2	0.124

Standard errors in parentheses

Fixed effects for election, se's are clustered at the individual level, BHPS.

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

substantially in both directions. This has consequences for the analysis.

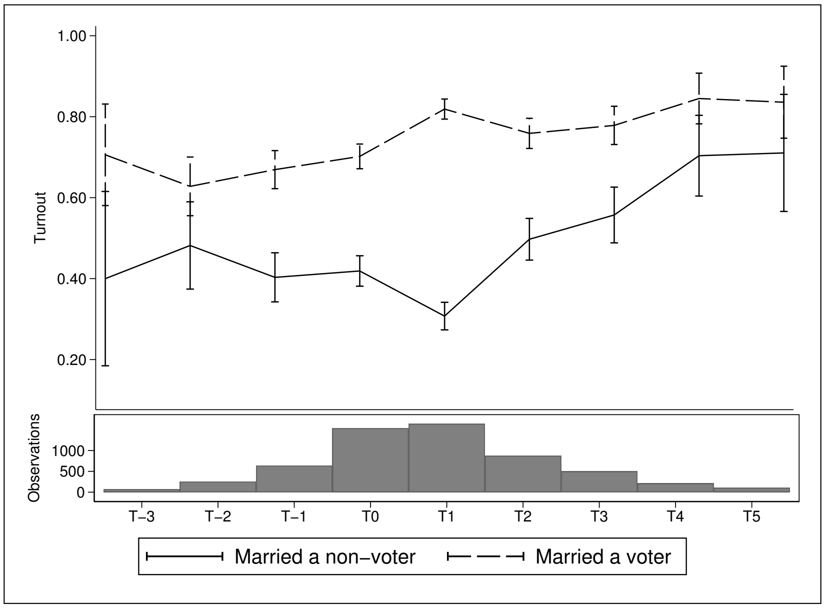

Figure 1

First, the panel attrition may not be at random. For example, it could be the case that marrying a non-voter correlates with panel non-response. Second, since the figure looks at the voting participation of the partner at T1 only it could be the case that the partner decides to vote at T2 and T3. Third, it is not known that all individuals stayed in the relationship after T1, they could be separated at T2 ot T3. Four, the same logic applies before T0, we do not know that the individuals who were never married at T0 were not in a relationship (without being married) at T-1 or T-2.

The models presented in the paper deals with most of these issues by adding covariates. This can be seen as a way of minimising a potential bias. However, there is no way to completely solve the problem.

2 Preprocessing the data

2.1 Details on the matching procedure

Following the work of Rosenbaum and Rubin (1983) matching methods have become popular in political science. The basic logic of the approach is to compare the treated units to similar untreated units in a way that mimics random assignment of treatment. Logically, if the treated and the control units are identical before treatment it ought not to matter if this is an artefact of randomization or of careful selection of the comparable units. In other words, one assumption is unconfoundedness; conditional on a number of variables, the outcome is independent from the treatment (Morgan and Winship 2007). A critique to this assumption is that model requires selection on observables, in other words, we can only match individuals on such information that is available to the researcher and thus there is a risk of omitted variable bias. In addition, there has to be an overlap; all the units in the population has to have some chance of being treated and some chance of not being treated (Morgan and Winship 2007). It can be difficult to achieve such overlap if matching is done using many covariates and if the data set is not extremely large. If comparing this to experimental studies we could look at this as a trade of between internal and external validity. If the sample is too big, we include units in the control group that would not have been part of the population in an experimental study. If the sample is too small, we may exclude individuals who would have been part of that population.

As described in the main paper the data for the difference-in-differences analysis with pooled panels has been preprocessed using genetic matching. The model has been estimated aslo using Coarsened Exact Matching (cem) as a robustness test. Genetic matching is a method using an genetic algorithm to improve covariate balance on so-called weighted Malahanobis distances (Diamond and Sekhon 2013, for technical details). The strength of this approach is that it automatically and iteratively improves balance instead of leaving this process up to the researcher (as in for example propensity score matching), which produces more balanced covariates (Diamond and Sekhon 2013). Cem is a type of matching method that uses so-called Monotonic Imbalance Bounding (MIB). The logic of this approach is based in exact matching where each observation is matched to another observation with identical values on a set of covariates. Exact matching requires very large data sets and/or a lot of overlap (common support). To solve this Cem uses coarsened variables (i.e age groups instead of age in years etc.) to find exact matches. The main benefits with this approach is that it automatically restricts the analysis to include only the areas of common support and the size of the groups used for matching is decided by the researcher. This provides an opportunity to create substantially meaningful groups, and, most importantly, it makes the matching process transparent (Iacus et al. 2012). [1]

This paper uses genetic matching, and adds cem as a robustness control, in combination with the difference-in-difference estimation. Genetic matching is a more efficient approach and is expected to exclude less of the available data. Cem, on the other hand, will restrict the model to including only the theoretically relevant commonly supported areas (as these are defined by the researcher).

The matching is done one to many, with replacement. The variables used for matching are some of the most common predictors of both turnout and mate choice; education, income, age, sex, and election. When combining matching and difference-in-difference estimation it has been shown that the models that produce the least bias are the ones not including pre-treatment outcome and that limits the matching to variables that are time-invariant (Chabé-Ferret 2017). All variables used for matching are measured before the individual enters marriage and the matching is done for one election at a time. The groups

[1] Genetic matching is estimated in R using the matchit package (Stuart et al. 2011)

used for cem are; up to lower secondary education vs higher secondary education and above, age has cut of points at 20, 30 and 40. As a robustness test, following Hobbs et al. (2014), the matching is preformed including a variable of the individual's previous turnout as a way of partially controlling for variables related to turnout. This can be thought of as one way of limiting the risk of causing bias due to omitting relevant but in this case unavailable variables. For example, personality type, genetics, and pre-adult socialisation. For cem results see section 2.3 and for further robustness tests see section 4.

2.2 Balance achieved by genetic matching

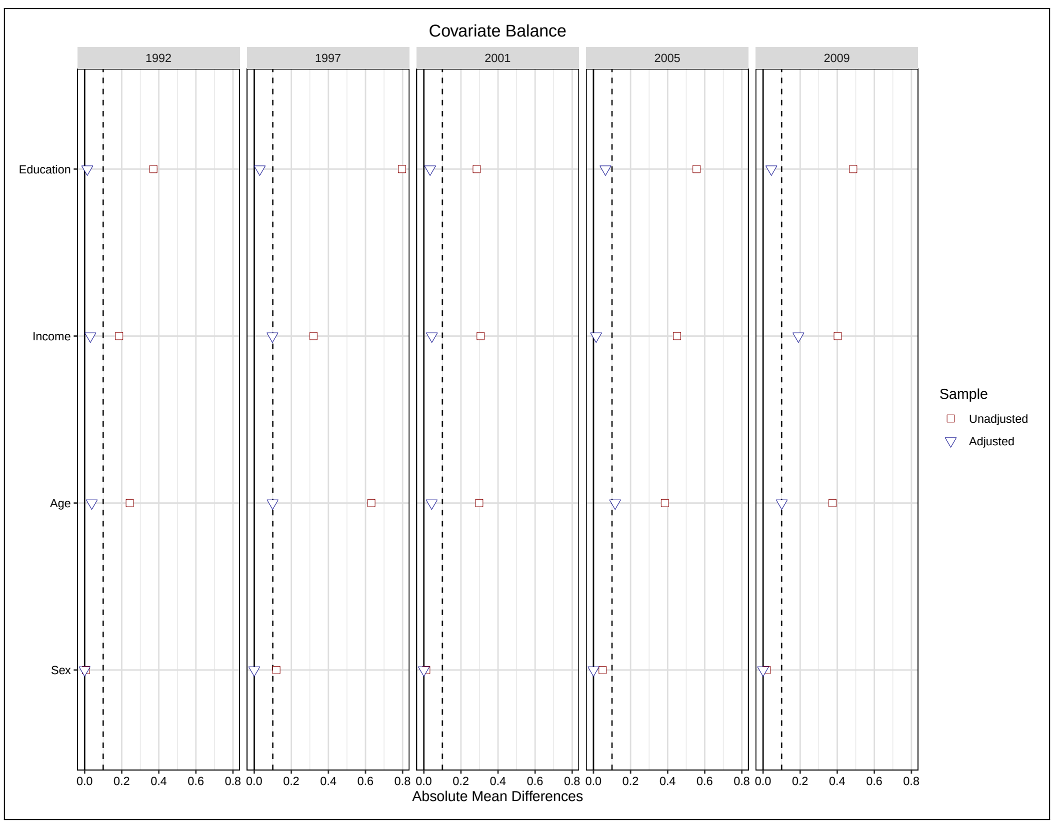

Figure 2

The main reason to preprocess data using matching is to make the treated and non-treated units as comparable as possible (to make the unconfoundedness assumption). A common way to determine the quality of the matching is so-called balance tests [2]. Figure 2 shows the covariate balance for each election. More specifically, the figure presents the standardized bias before and after matching for all covariates. The basic logic for interpreting the figure is that if the standardized estimates falls within the confidence bounds, the covariates are as balanced as they would have been in a randomized experiment. We can see that the matched estimates are within the bounds or very close to the bounds while the unmatched estimates falls far from the bounds for all covariates but sex. Thus, the matching has greatly improved the balance.

For a more detailed look at the balance achieved by genetic matching we can look at the numbers that figure 2 is based on. Table 2 shows the balance for the unmatched data while table 3 shows the balance for the matched data. In the last column in table 3 we can also find the percentages of improvement achieved. The first thing to note is that the standardized means in the matched data is remarkably more similar than the corresponding unmatched means. Overall, the percentage of improvement is high. However, we can also see that the number of observation in the control group declined from 635 to 368 when matching the data. The large number of observations lost is due to limited overlap. Since all of the covariates are interacted with the year of election the numbers may not be the easiest to interpret. Thus, for an overview figure 2 is preferable.

[2] simply comparing the means of the covariates is common, but not recommended (Imai et al. 2008)

Table 2: Summary of balance for all data

	Means Treated	Means Control	SD Control	Mean Diff
Distance	0.6080	0.4964	0.1669	0.1116
1992	0.3433	0.2378	0.4261	0.1055
1997	0.1219	0.2173	0.4127	-0.0954
2001	0.2687	0.3291	0.4703	-0.0605
2005	0.1057	0.0992	0.2992	0.0065
2009	0.1604	0.1165	0.3211	0.0439
Education	4.0137	3.4142	1.3492	0.5995
Income	1119.3114	832.7507	880.0078	286.5607
Age	25.2077	22.9024	5.9929	2.3053
Sex	0.5025	0.5213	0.4999	-0.0188
1997:Education	0.5274	0.7008	1.4856	-0.1734
2001:Education	1.0672	1.1654	1.8431	-0.0982
2005:Education	0.4465	0.3386	1.0834	0.1079
2009:Education	0.7239	0.4567	1.3217	0.2672
1997:Income	161.7409	178.6352	452.9726	-16.8942
2001:Income	295.4797	277.8565	561.3742	17.6232
2005:Income	155.4010	97.9830	371.5534	57.4181
2009:Income	262.2225	134.3349	709.5238	127.8876
1997:Age	3.1779	4.9307	9.6165	-1.7528
2001:Age	6.8060	7.6047	11.3916	-0.7988
2005:Age	2.7177	2.2961	7.1490	0.4216
2009:Age	4.5050	2.8992	8.4004	1.6058
1997:Sex	0.0473	0.1102	0.3134	-0.0630
2001:Sex	0.1418	0.1780	0.3828	-0.0362
2005:Sex	0.0572	0.0488	0.2157	0.0084
2009:Sex	0.0858	0.0646	0.2460	0.0213
Observations	804	635		

Table 3: Summary of balance for matched data

	Means Treated	Means Control	SD Control	Mean Diff	% Improvement
Distance	0.6080	0.6040	0.1410	0.0040	96.4440
1992	0.3433	0.3433	0.4755	0.0000	100
1997	0.1219	0.1219	0.3276	0.0000	100
2001	0.2687	0.2687	0.4439	0.0000	100
2005	0.1057	0.1057	0.3079	0.0000	100
2009	0.1604	0.1604	0.3675	0.0000	100
Education	4.0137	4.0199	1.3866	-0.0062	98.9627
Income	1119.3114	1058.6712	737.9209	60.6402	78.8386
Age	25.2077	24.9179	6.3791	0.2898	87.4292
Sex	0.5025	0.5025	0.5007	0.0000	100
1997:Education	0.5274	0.5323	1.5075	-0.0050	97.1312
2001:Education	1.0672	1.0808	1.9535	-0.0137	86.0662
2005:Education	0.4465	0.4366	1.3363	0.0100	90.7812
2009:Education	0.7239	0.7152	1.7097	0.0087	96.7414
1997:Income	161.7409	142.8778	447.0001	18.8632	-11.6544
2001:Income	295.4797	285.7866	609.5906	9.6930	44.9983
2005:Income	155.4010	153.7915	520.5756	1.6096	97.1967
2009:Income	262.2225	225.6801	583.8614	36.5424	71.4262
1997:Age	3.1779	3.1132	8.5080	0.0647	96.3102
2001:Age	6.8060	6.7214	11.5785	0.0846	89.4114
2005:Age	2.7177	2.7998	8.3891	-0.0821	80.5290
2009:Age	4.5050	4.3669	10.4396	0.1381	91.4022
1997:Sex	0.0473	0.0473	0.2125	0.0000	100
2001:Sex	0.1418	0.1418	0.3493	0.0000	100
2005:Sex	0.0572	0.0572	0.2326	0.0000	100
2009:Sex	0.0858	0.0858	0.2805	0.0000	100
Observations	804	368			

3 Regression tables that correspond to figures in paper

Table 4 presents the regression results an predicted probabilities that correspond to figure 1 in the main text (column one). The results are very similar when restricting to only the respondents who entered marriage (not cohabitation). Compared to staying never married entering a relationship in general decreases ones likelihood to vote if the partner is a non-voter, while it increases ones likelihood to vote if the partner is a voter. Figure 3 shows the predicted probabilities calculated from the married only (column 2).

Table 4: Regression results and marginal effects corresponding to figure 1

	Living together	Married only
Regression results		
Change among never married	0.030*** (0.006)	0.030*** (0.006)
Partner non-voter	-0.170*** (0.019)	-0.170*** (0.019)
Partner voter	0.059*** (0.018)	0.059*** (0.018)
T1 $\times$ Partner non-voter	-0.141*** (0.020)	-0.109*** (0.033)
T1 $\times$ Partner voter	0.082*** (0.018)	0.148*** (0.023)
Constant	0.708*** (0.012)	0.707*** (0.012)
Predicted probabilities		
Never married (T0)	0.625 [0.609,0.640]	0.624 [0.609,0.640]
Will live with non-voter	0.454 [0.419,0.490]	0.454 [0.419,0.490]
Will live with voter	0.683 [0.652,0.715]	0.684 [0.652,0.715]
Never married (T1)	0.655 [0.640,0.670]	0.654 [0.639,0.669]
Lives with non-voter	0.343 [0.309,0.377]	0.375 [0.312,0.438]
Lives with voter	0.795 [0.768,0.822]	0.861 [0.827,0.895]
Observations	14152	13177
Clusters	4753	4753
R^2	0.046	0.033

Standard errors in parentheses

Fixed effects for election, se's are clustered at the individual level, BHPS and UKHLS.

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

Table 5 shows the regression results from the model used to create figure 2 in the main text. The first column in the table corresponds to the first row in the figure (and so on).

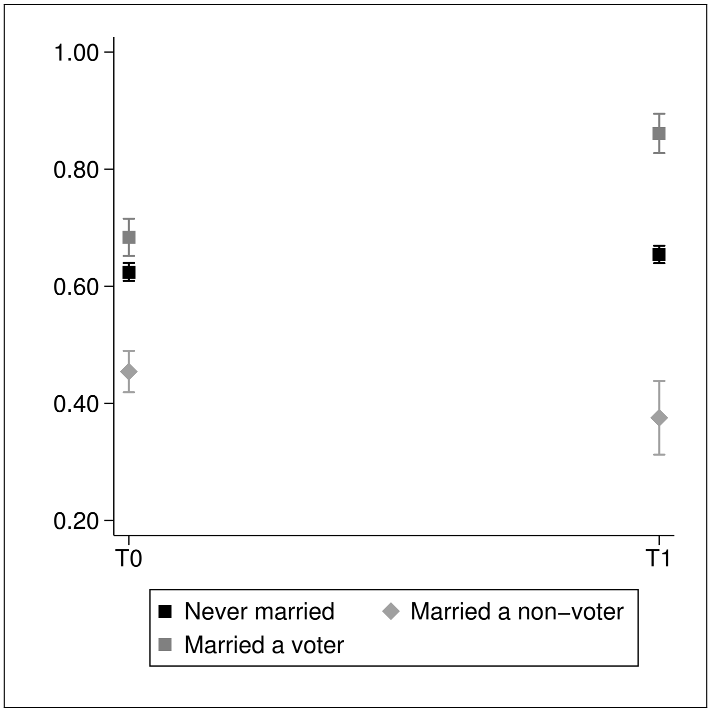

Figure 3

The interaction effects show the difference-in-differences at each time point compared to T0. We can see that compared to T0 there are no significant differences-in-differences when comparing to time periods before treatment (T-1 or T-2). However, all estimates at T1 show an significant increase in differences in the range from 0.21 to 0.37. The size of the estimates are thus similar to the ones using pooled panels with unmatched and matched estimates. The long term effects are less pronounced. In the second panel (T-1 to T2) the difference-in-difference estimate at T2 is positive but not significant. In the last panel (T0 to T3), that also has the largest number of observations there are significant differences in differences between T0 and T2, and between T0 and T3. However, the size of the estimates are roughly half of the difference at T1 (0.10 at T2 and 0.13 at T3).

Table 5

	T0 to T1	T-1 to T1	T-2 to T1
Partner voter	0.212*** (0.025)	0.190*** (0.044)	0.236*** (0.075)
T1	-0.129*** (0.023)	-0.176*** (0.041)	-0.135* (0.074)
Partner voter × T1	0.225*** (0.026)	0.242*** (0.046)	0.216*** (0.076)
T-1		0.011 (0.043)	0.005 (0.076)
Partner voter × T-1		0.004 (0.047)	0.032 (0.082)
T-2			0.147 (0.102)
Partner voter × T-2			-0.154 (0.100)
Degree	0.209*** (0.046)	0.192*** (0.071)	0.040 (0.151)
Other higher degree	0.108** (0.052)	0.055 (0.080)	-0.028 (0.162)
A-level etc	0.113*** (0.044)	0.084 (0.066)	-0.064 (0.143)
GCSE etc	0.046 (0.044)	-0.011 (0.068)	-0.088 (0.144)
Other qualification	-0.057 (0.050)	-0.182** (0.075)	-0.336** (0.144)
Income	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Age	0.013** (0.005)	0.011 (0.009)	-0.004 (0.012)
Age × Age	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Female	0.012 (0.019)	0.027 (0.029)	0.037 (0.046)
Constant	0.233** (0.095)	0.246 (0.169)	0.519* (0.286)
Observations	3031	1569	744
Clusters	1516	523	186
R^2	0.232	0.190	0.160

Standard errors in parentheses

Fixed effects for election, se's are clustered at the individual level, BHPS and UKHLS.

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

Table 6 shows the regression results from the model used to create figure 3 in the main text. Although age, sex, and previous voting participation is held constant the individuals with higher education and higher income are more likely to marry someone who votes. Since the model is estimated using logistic regression and interactions the size of the coefficients are not interpretable. For this reason interpretation of whether any significant relationships are substantive is better done using the predicted probabilities shown i figure 3.

Table 6

	Education	Income
Voted	0.785** (0.337)	1.111*** (0.190)
Education	0.200*** (0.067)	0.217*** (0.045)
Voted × Education	0.029 (0.086)	
Income	0.000 (0.000)	0.000*** (0.000)
Voted × Income		-0.000 (0.000)
Sex	0.028 (0.117)	0.033 (0.117)
Age	0.068* (0.041)	0.063 (0.040)
Age × Age	-0.001 (0.001)	-0.000 (0.001)
Constant	-2.019*** (0.624)	-2.143*** (0.595)
Observations	1439	1439
Clusters	1415	1415
Pseudo R^2	0.106	0.108

Standard errors in parentheses

Fixed effects for election, se's are clustered at the individual level, BHPS and UKHLS.

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

Table 7 shows the regression results that correspond to figure 4 in the main paper. To estimate heterogeneous treatment effects I use three way interactions between time, treatment and the variable of interest (education or income). All other variables are included as covariates. A significant three way interaction, put simply, means that the effect of going from time 0 to time 1 (entering marriage) between treated and non-treated (marrying voter vs non voter) is different depending on ones level of education or income. The regression results show a positive significant interaction for income but not for education. This means that high income individuals are on average more affected by entering marriage with a voter than are less well of individuals. The size of the effect is not interpretable from the table since it is estimated using logistic regression. For this reason the results are presented graphically in figure 4.

Table 7

	Education	Income
T1	-0.941*** (0.291)	-0.983*** (0.159)
Treated	0.876*** (0.339)	0.946*** (0.161)
T1 × Treated	0.997** (0.417)	0.825*** (0.231)
Education	0.266*** (0.065)	0.280*** (0.039)
T1 × Education	0.002 (0.074)	
Treated × Education	-0.002 (0.088)	
T1 × Treated × Education	0.061 (0.107)	
Income	0.000 (0.000)	-0.000 (0.000)
T1 × Income		0.000 (0.000)
Treated × Income		-0.000 (0.000)
T1 × Treated × Income		0.000** (0.000)
Female	0.092 (0.104)	0.099 (0.105)
Age	0.069* (0.037)	0.080** (0.036)
Age × Age	-0.000 (0.001)	-0.001 (0.001)
Constant	-2.069*** (0.569)	-2.252*** (0.543)
Observations	2879	2879
Clusters	1416	1416
Pseudo R^2	0.181	0.183

Standard errors in parentheses

Fixed effects for election, se's are clustered at the individual level, BHPS and UKHLS.

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

4 Robustness

4.1 The model using Coarsened Exact Matching

The first thing to note after running the model with the data pre-processed using cem is that the sample size is substantially decreased. We are left with only 398 individuals and 824 observations. This is not only lower than the unmatched model but also less than after the genetic matching. Nevertheless, the effect size in the difference-in-difference estimation is consistent through all models. The estimate is 27 for the cem model as compared to 23 in the unmatched data and 24 in the analysis using the genetically matched data (main paper). Thus, further restricting the sample does not change the results substantially, if anything it makes the effect stronger.

Table 8

	(1) CEM
Predicted probabilities	
Will live with non-voter	0.250 [0.087,0.412]
Will live with voter	0.397 [0.230,0.564]
Lives with non-voter	0.744 [0.564,0.923]
Lives with voter	1.158 [0.985,1.330]
Differences	
Difference before living together	0.147
Difference when living together	0.414
Difference in differences	0.267
Observations	824
Clusters	398
R^2	0.166

95% confidence intervals in brackets

Predicted probabilities to vote. Living together with voter. BHPS and UKHLS

4.2 Including pre-treatment outcome in the pre-processing of data

As a robustness test, following Hobbs et al. (2014), the matching is preformed including a variable of the individual's previous turnout as a way of partially controlling for variables related to turnout. This can be thought of as one way of limiting the risk of causing bias due to omitting relevant but in this case unavailable variables. For example, personality type, genetics, and pre-adult socialisation. As previously mentioned, the other variables used for matching are some of the most common predictors of both turnout and mate choice; education, income, age, sex, and election. All variables used for matching are measured before the individual enters marriage and the matching is done by election year.

Table 9: Genetic matching including pre-treatment outcome

	(1) Living together	(2) Married only
Predicted probabilities		
Will live with non-voter	0.754 [0.705,0.803]	0.782 [0.706,0.858]
Will live with voter	0.735 [0.704,0.766]	0.776 [0.731,0.821]
Lives with non-voter	0.398 [0.328,0.469]	0.444 [0.326,0.563]
Lives with voter	0.785 [0.755,0.815]	0.869 [0.830,0.907]
Differences		
Difference before living together	-0.019	0.010
Difference when living together	0.386	0.436
Difference in differences	0.405	0.425
Observations	2252	902
Clusters	1126	451
R^2	0.135	0.144

Standard errors in parentheses

Fixed effects for election, se's are clustered at the individual level, BHPS and UKHLS.

When combining matching and difference-in-difference estimation it has been shown that the models that produce the least bias are the ones not including pre-treatment outcome and that limits the matching to variables that are time-invariant (Chabé-Ferret 2017). For this reason the results should be interpreted with caution. Table 9 shows the estimates from a model using pre-processed data that included pre-treatment outcome. The first thing to note is that when including previous turnout in the pre-processing of data the differences in turnout between the individuals who will marry non-voters and the individuals who will marry voters before entering marriage are no longer substantial. However, after entering marriage there are large differences in turnout between the groups. The difference-in-difference estimates are now as large as approximately 40 percent. Figure 4

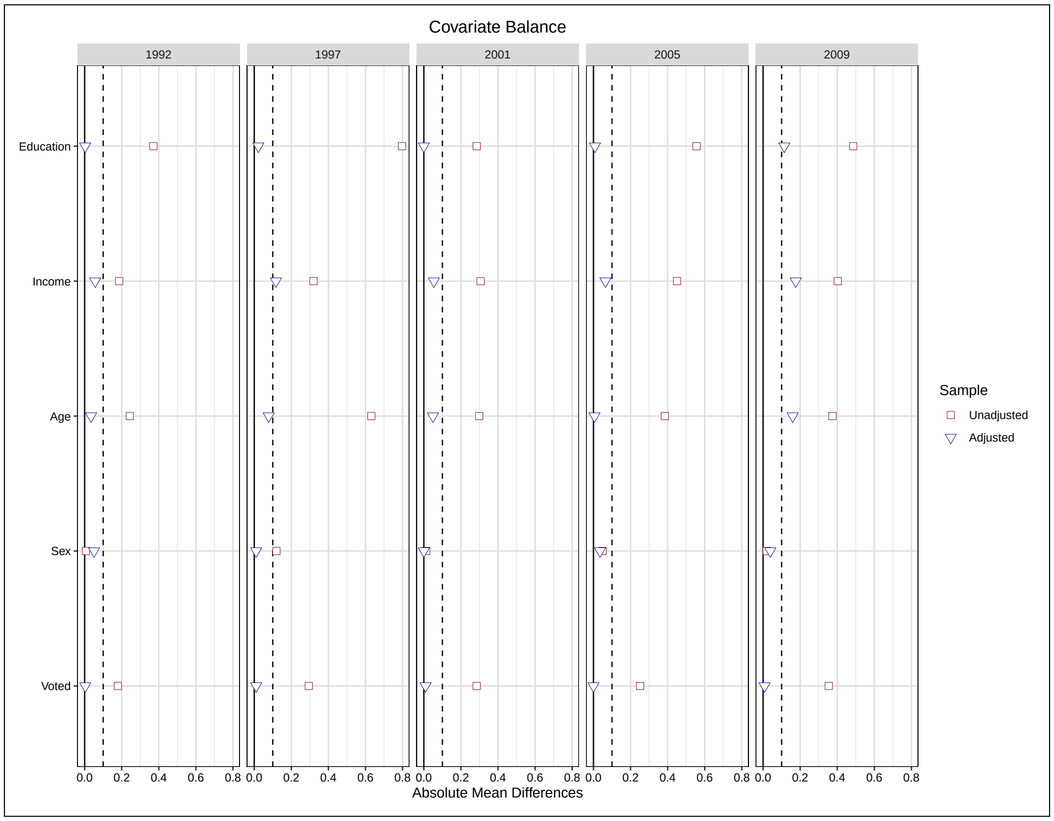

Figure 4

shows the covariate balance achieved by genetic matching by election. The figure presents the standardized bias before and after matching for all covariates. The basic logic for interpreting the figure is that if the standardized estimates falls within the confidence bounds, the covariates are as balanced as they would have been in a randomized experiment. We can see that the matched estimates are within the bounds or very close to the bounds while the unmatched estimates falls far from the bounds for all covariates.

4.3 Living together vs married

To make sure the results do not differ substantially depending on whether one entered marriage per se or a relationship in general some of the main models have been re-run using a sample limited only to those who entered marriage. Results are presented in table 4 and table 9. There are no substantive differences between the models.

4.4 Longer time trends with pre-processed data

Figure 5 shows results corresponding to Figure 2 in the main paper but now with data and weights from genetic matching. The benefits of using pre-processed data are that the assumption of unconfoundedness ought to hold when the treatment and control groups are made more similar. Matching is now done on T0 (the last election before entering

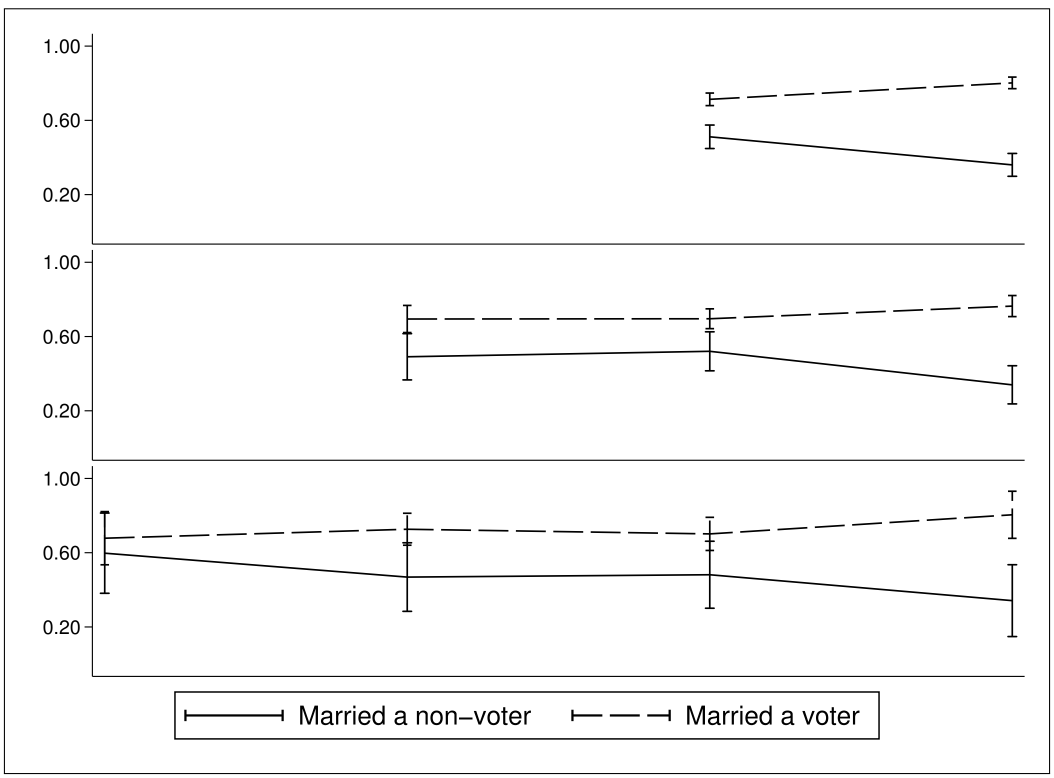

Figure 5

marriage). However, this approach has limitations when looking at more than two time periods. One possible limitation is that there is no perfect choice of time for the matching. Matching at T0 makes the approaches comparable across panels, however, it could be argued that matching should be done at the first panelwave in each panel (T-2, T-1 or, T0). The consequences of the choices are somewhat unclear. In addition, the panels has a low n to begin with and the matching procedure decreases the number of observations further. The results are, however, very similar to the results from the unmatched data in the main text.

Table 10

	T0 to T1	T-1 to T1	T-2 to T1
Partner voted	0.202*** (0.034)	0.175*** (0.059)	0.220** (0.097)
T1	-0.151*** (0.040)	-0.169*** (0.063)	-0.140 (0.100)
Partner voted × T1	0.240*** (0.041)	0.248*** (0.066)	0.242** (0.104)
T-1		-0.030 (0.067)	-0.013 (0.127)
Partner voted × T-1		0.029 (0.069)	0.038 (0.130)
T-2			0.116 (0.152)
Partner voted × T-2			-0.139 (0.142)
Other higher degree	-0.092** (0.042)	-0.122* (0.068)	0.004 (0.115)
A-level etc	-0.076*** (0.029)	-0.086** (0.040)	-0.057 (0.062)
GCSE etc	-0.146*** (0.031)	-0.161*** (0.049)	-0.112* (0.062)
Other qualification	-0.248*** (0.047)	-0.339*** (0.081)	-0.343*** (0.095)
Income	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
Age	0.013** (0.006)	0.012 (0.011)	-0.005 (0.014)
Age × Age	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Female	0.009 (0.023)	0.063* (0.034)	0.087* (0.051)
Constant	0.439*** (0.113)	0.431** (0.201)	0.554* (0.283)
Observations	2483	1365	676
Clusters	1242	455	169
R^2	0.173	0.134	0.133

Standard errors in parentheses

Fixed effects for election, se's are clustered at the individual level, BHPS and UKHLS.

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

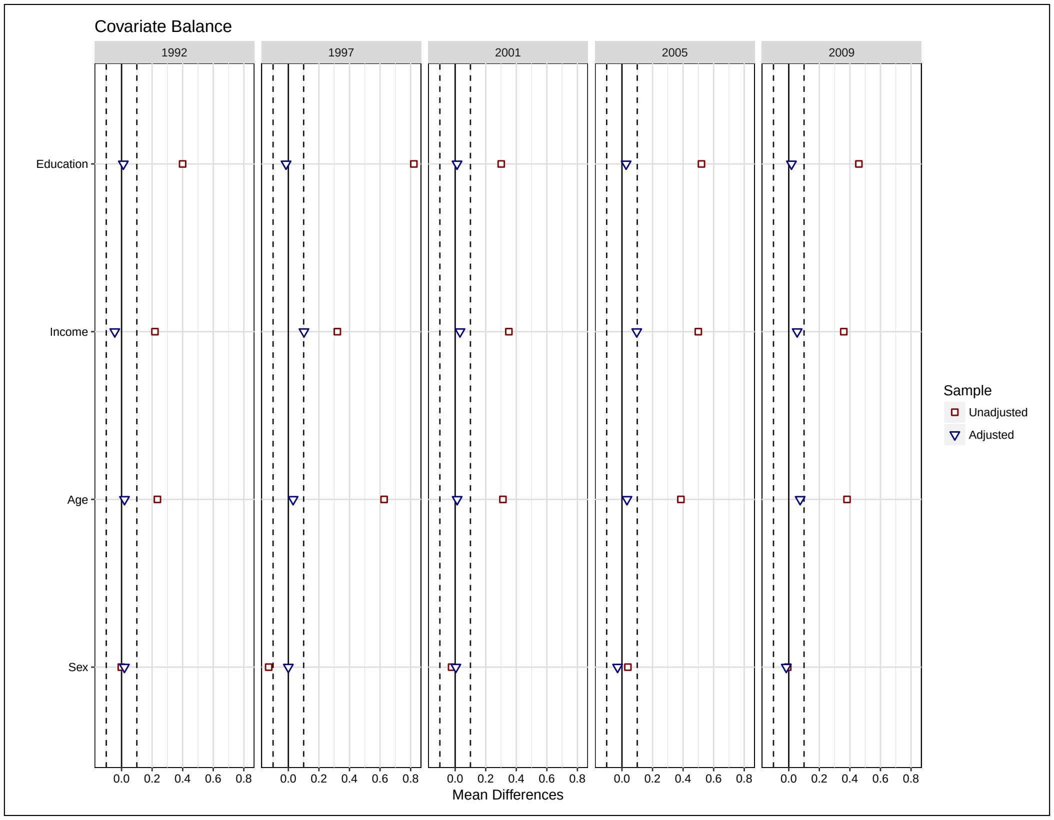

Figure 6

Figure 6 shows the balance for the matching used for 5. Balance improved substantially after matching.

4.5 Intent to vote

Table 11 show the results from a model with Voting Intention as the dependent variable (measured on a scale 0-10). The variable intent to vote is unfortunately only available in two panel waves in UKHLS. For this reason the analysis has a very low number of observations, only 83 individuals in total. The results are not contradictory to main analysis, however, the n is too low to draw any conclusions from this model.

Table 11

	Voting Intention
Treated	2.334*** (0.794)
T1	-0.506 (0.763)
Treated × T1	0.061 (0.879)
Age	0.259 (0.170)
Age × Age	-0.002 (0.002)
Education	0.369* (0.199)
Income	-0.000 (0.000)
Female	0.342 (0.649)
Constant	-2.126 (2.722)
Observations	166
Clusters	83
R^2	0.208

Standard errors in parentheses
Robust se's, UKHLS.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6 Selection model

One way to model all the analyses in the paper in one model would be using a selection model. Table 12 show the results from a Heckman probit estimation. The analysis consist of one main analysis with voting at T1 as the dependent variable and on selection regression with entering a relationship with an eventual voter (compared to a non-voter). As both dependent variables are binary both steps of the estimation is done using probit models. To use the panel component of the data all variables measured at T0 except the outcome variables that are measured at T1. To test the hypothesis about differential impacts in different socio-economic groups separated by previous voting participation I have included interactions between voted at T0 and income/education. Standard errors are clustered at the individual level. It is common practice when estimating Heckman models to include at least one variable in the selection equation that is not included in the outcome equation. The variable sex has been excluded from the outcome regression for computational reasons.

Table 12

	Model 1
Regression model: Voted at T1	
Age	0.020*** (0.006)
Education	0.133*** (0.047)
Income	0.000*** (0.000)
Voted T0	1.004*** (0.223)
Voted T0 × Education	0.023 (0.059)
Voted T0 × Income	-0.000** (0.000)
Constant	-1.621*** (0.208)
Selection model: Partnered with eventual voter T1	
Age	0.022*** (0.007)
Female	0.064 (0.043)
Education	0.109** (0.043)
Income	0.000*** (0.000)
Voted T0	0.553*** (0.209)
Voted T0 × Education	0.047 (0.056)
Voted T0 × Income	-0.000** (0.000)
Constant	-1.060*** (0.200)
Observations	1439
Selected	804
Rho	0.994
Prob > chi2	0.004

Standard errors in parentheses

Fixed effects for election, robust se's, BHPS and UKHLS.

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

Table 12 show the results from the heckman probit model. As expected from theory, and in line with the results in the main paper, we can see that there is a positive relationship between income/education and turnout, as well as income/education and entering a relationship with a voter. Entering a relationship with a voter is more common among those who have higher education and income levels. Moreover, within the group of individuals who entered such a relationship, individuals with higher education and income levels are more likely to vote. Figure 7presents the predicted probabilities of entering a relation-

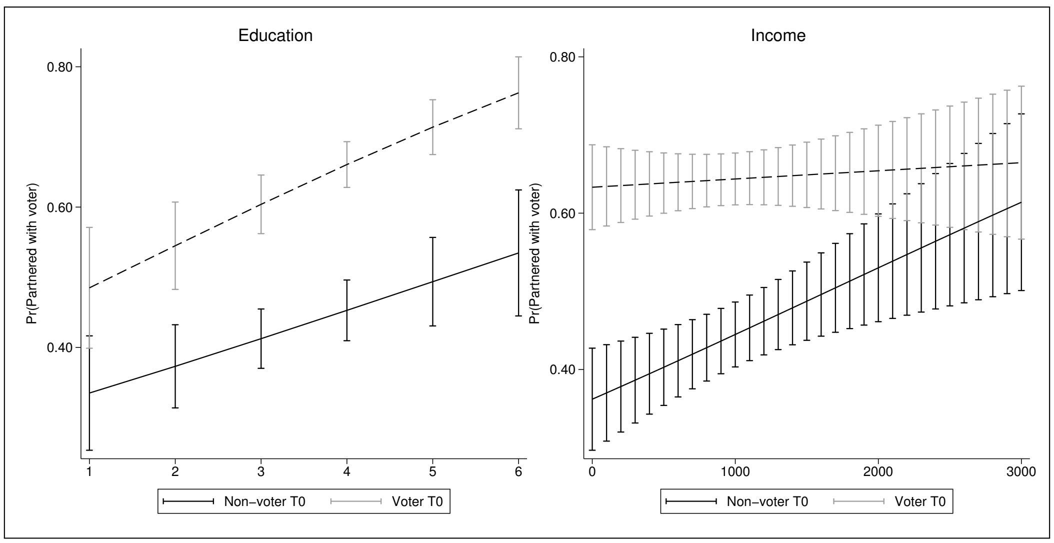

Figure 7: Predicted probabilities of entering a relationship with an eventual voter. Estimated from results in 12. BHPS and UKHLS

ship with an eventual voter in different levels of income and education. The results are estimated from the selection regression in table 12. The higher an individual's education level, the more likely one is to enter a relationship with a voter, regardless of one's previous turnout. In the case of income, the same is true for the previous non-voters. However, those who voted at T0 are equality likely to enter a relationship with a voter regardless of income level. Figure 8 show the predicted probabilities of voting among those who entered a relationship with a voter. The individuals of all income and education levels who voted at T0 are likely to vote again. However, in the group of individuals who did not vote

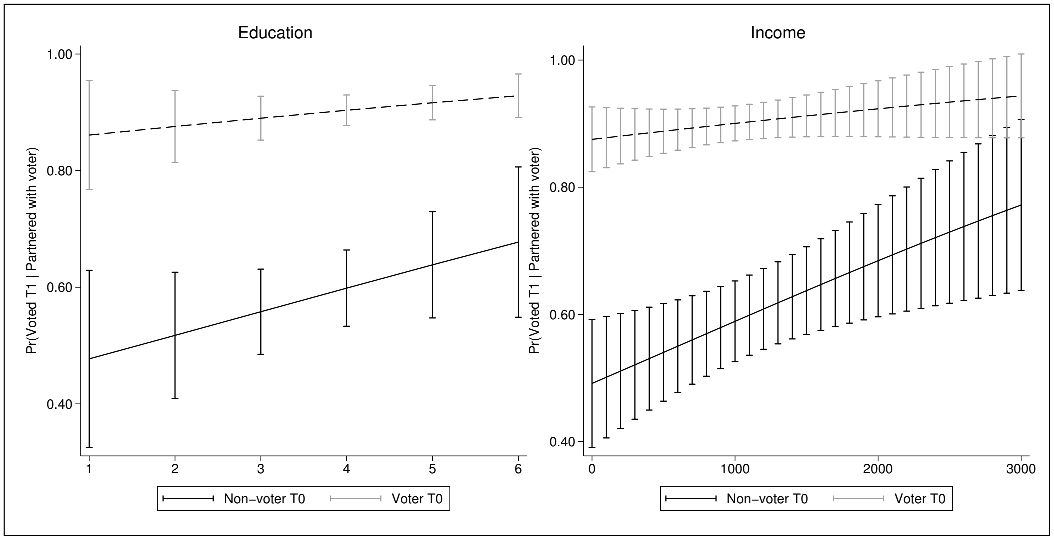

Figure 8: Predicted probabilities of voting at T1 given that the individual entered a relationship with an eventual voter. Estimated from results in 12. BHPS and UKHLS

at T0 the ones with higher education and income level are substantially more likely to vote at T1. THe results are in line with the main results presented in the paper.

While estimating both selection and outcome equations in one models has the benefit of clearly modeling the selection there are also possible drawbacks with this model. Most importantly, to properly model the causality the selection has to be identified correctly. Ideally there would have been a variable predicting who enters a relationship with a voter that is unrelated to individual voting participation (the exclusion restriction). In other words, to properly identify causality and to model the selection properly an instrumental variable is needed. Heckman models without such valid instrument risk producing inaccurate estimates (see for example Angrist and Krueger (2001)).

4.7 Placebo tests

One possible way to rule out that the results in the paper is due to the modelling strategy would be a placebo test. I have done this in two different ways. First, I re-run the analysis using a different ”treatment” variable. Instead of the partner’s turnout I model the effect of a partner characteristic that ought to be unrelated to turnout, sex. If I find an effect this would suggest that the effect is due to the modelling strategy. Second, I run a similar placebo test where I simulate the partner vote. The results from the simulation model is then compared to the real model. If the estimates from the simulated data overlap to a large extent with the true estimate this is a reason for concern.

4.7.1 Partner's sex as treatment

Table 13

	Placebo
T1	-0.107*** [-0.149,-0.066]
Treated (sex)	-0.045* [-0.094,0.004]
T1 × Treated (sex)	0.033 [-0.020,0.086]
Education	0.072*** [0.058,0.087]
Income	0.000** [0.000,0.000]
Age	0.023*** [0.011,0.035]
Age × Age	-0.000* [-0.000,0.000]
Constant	0.008 [-0.180,0.196]
Observations	2879
Clusters	1416
R^2	0.119

95% confidence intervals in brackets

Fixed effects for election

se's are clustered at the individual level, BHPS and UKHLS.

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

Table 13 shows the results from a difference-in-differences model of the same type as the pooled models. The only difference is that I have replaced the "treatment" of partner vote with the "treatment" of partner's sex. As sex ought to be unrelated to turnout, so is partner sex. If I when determining the treatment post facto (at T1) find that also a "treatment" that ought to be unrelated with turnout increases the probability of turning out to vote, this is problematic for the main results. The results from the model shows that there is no change in the probability of turning out to vote for the individuals who entered a relationship with a woman.

4.7.2 Simulation of partner vote at T1

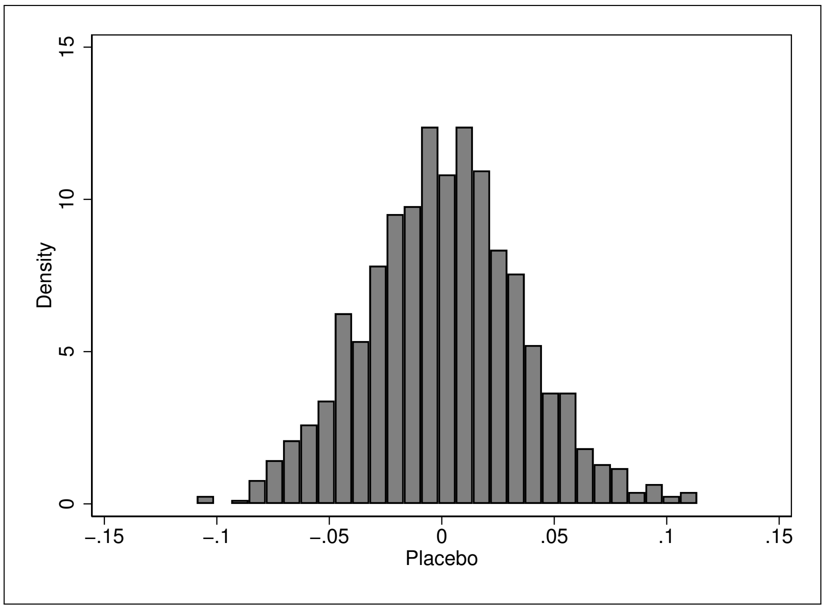

Figure 9: Histogram of coefficients form simulation. BHPS and UKHLS

To further assess the likelihood that the main results is due to the modelling strategy i have re-run the model using a simulation strategy. I simulated partner vote as random variation of voters and non-voters with a mean of 56 percent voters (as in the real sample). A repeated analysis of 1000 times generated 1000 coefficients for the difference-in-difference estimate. The result can then be compared to the true estimate at 0.23. The distribution of estimates from the simulation is shown in figure 9. Almost all of the estimates from the simulation can be found within the range of -0.1 and 0.1. The simulation results show that it is very unlikely that the true estimate is an artefact of random noise in the model.

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