Online Appendix

"Towards the Greater Good? EU Commissioners' Nationality and Budget Allocation in the European Union" (Kai Gehring and Stephan A. Schneider)

A1. The Selection Procedure

A closer look at the assignment of our treatment, the Agricultural Commissioner, reveals a very complex selection process. While the Heads of State or Government and the Commissioner candidates usually try to lobby the designated President of the EC to assign them one of their preferred portfolios (see Nugent, 2001), it is the President who finally decides on the portfolio distribution. The position of the President of the EC in the appointment process was strengthened in the Treaty of Amsterdam. Napel and Widgrén (2008) provide an in-depth description of the appointment procedure for the EC President and the Commissioners. The complicated bargaining process has to take internal demands and political power into account and often results in surprising outcomes. Which country out of all members is assigned *one particular post* is nearly unpredictable *ex-ante*.

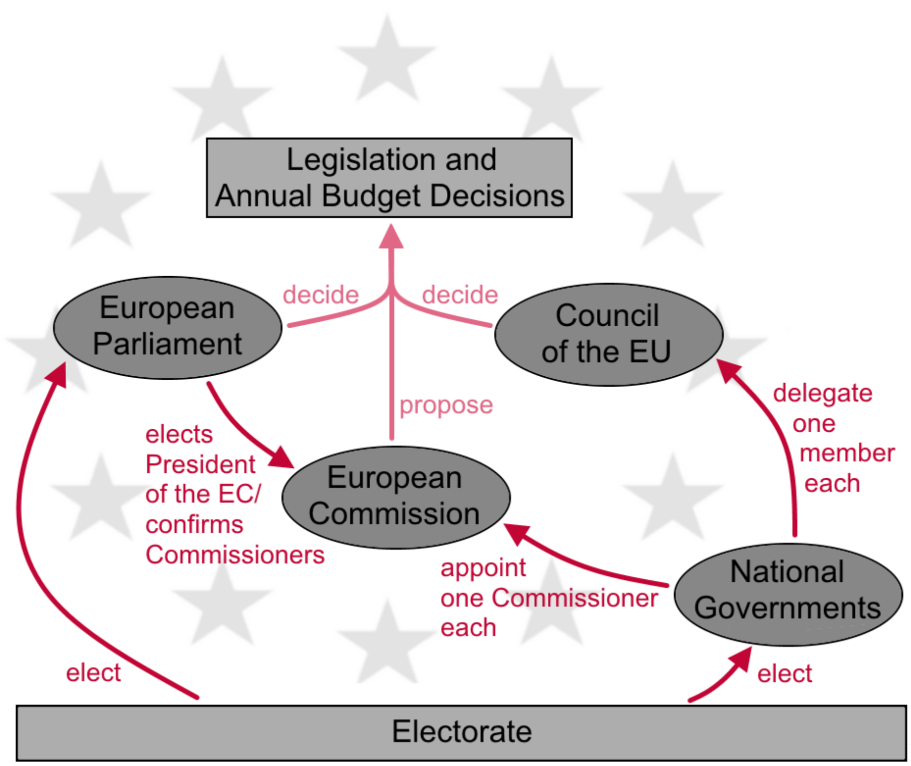

Figure 1: **Simplified Structure of the EU**
The main actors and the structure of decision-making in the European Union (own illustration); compare e.g. Baldwin and Wyplosz (2012) and Tömmel (2014).

This is illustrated by the example of the current Commissioner for Agriculture, Phil Hogan, from Ireland. Several states had nominated candidates suitable for the Agricultural position, including Romania and Spain (http://www.independent.ie/irish-news/politics/phil-hogans-big-job-interview-in-brussels-30560917.html, last accessed December 15, 2015), along with Eastern European states. Another recent example is the appointment of the current German Commissioner Günther Oettinger in 2014. The German Government and Oettinger himself had expressed a preference for the trade portfolio and, until a few days before the decision, media expected him to be the next Trade Commissioner. To general surprise, Oettinger was appointed as Commissioner for Digital Economy and Society, instead. See, for example, on the common expectations: *Wirtschaftswoche* at http://www.wiwo.de/politik/europa/eu-kommission-merkel-will-oettinger-als-handelskommissar/10219282.html (German). For the surprise after the final decision see e.g., *Borderlex* at http://www.borderlex.eu/trade-commissioner-malmstrom-appointment-comes-surprise/ (last accessed on April 30, 2015).

A2. Chronological List of Commissioners

Table 1: List of Agricultural Commissioners

Name	Nation	from	to
Finn Olav Gundelach[1)]	Denmark	January 6, 1977	January 13, 1981
Poul Dalsager[2)]	Denmark	January 20, 1981	January 6, 1985
Frans Andriessen[3)]	Netherlands	January 7, 1985	January 5, 1989
Ray MacSharry[4)]	Ireland	January 6, 1989	January 5, 1993
René Steichen[5)]	Luxembourg	January 6, 1993	January 24, 1995
Franz Fischler[6)]	Austria	January 25, 1995	November 21, 2004
Sandra Kalniete[7)]	Latvia	May 1, 2004	November 21, 2004
Mariann Fischer Boel[8)]	Denmark	November 22, 2004	February 9, 2009

The exact dates were cross-verified using the following sources:

1) http://www.spiegel.de/spiegel/print/d-14319885.html, https://www.munzinger.de/search/document?index=mol-00&id=00000013522&type=text/html&query.key=szU1dQFW&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

2) http://www.denstoredanske.dk/Dansk_Biografisk_Leksikon/Samfund,_jura_og_politik/Myndigheder_og_politisk_styre/Landbrugsminister/Poul_Dalsager, https://www.munzinger.de/search/document?index=mol-00&id=00000016216&type=text/html&query.key=rjym3Qji&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

3) http://www.vieuws.eu/food-agriculture/frans-andriessen-former-commissioner-\penalty\z@{}for-agriculture-on-the-common-agricultural-policy-of-the-1980s/, https://www.munzinger.de/search/document?index=mol-00&id=00000017522&type=text/html&query.key=mQRbHaNY&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

4) https://www.munzinger.de/search/document?index=mol-00&id=00000019420&type=text/html&query.key=5qx1jVy4&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

5) https://www.munzinger.de/search/document?index=mol-00&id=00000020594&type=text/html&query.key=i6NxSr1K&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

6) https://www.munzinger.de/search/document?index=mol-00&id=00000019235&type=text/html&query.key=KJFjpiKp&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

7) https://www.munzinger.de/search/document?index=mol-00&id=00000024374&type=text/html&query.key=NF9rcU0k&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

8) https://www.munzinger.de/search/document?index=mol-00&id=00000024988&type=text/html&query.key=LJmscBcr&template=/publikationen/personen/document.jsp&preview=

Table 2: List of Regional Commissioners

Name	Nation	from	to
Antonio Giolitti[1)]	Italy	January 6, 1977	January 6, 1985
Grigoris Varfis[2)]	Greece	January 7, 1985	December 31, 1985
Alois Pfeiffer[3)]	Germany	January 1, 1986	August 1, 1987
Peter Schmidhuber[4)]	Germany	September 22, 1987	January 5, 1989
Bruce Millan[5)]	United Kingdom	January 6, 1989	January 24, 1995
Monika Wulf-Mathies[6)]	Germany	January 25, 1995	September 17, 1999
Michel Barnier[7)]	France	September 17, 1999	April 1, 2004
Jacques Barrot[8)]	France	April 26, 2004	November 21, 2004
Péter Balázs[9)]	Hungary	May 1, 2004	November 21, 2004
Danuta Hübner[10)]	Poland	November 22, 2004	July 4, 2009

The exact dates were cross-verified using the following sources:

1) https://www.munzinger.de/search/document?index=mol-00&id=00000010572&type=text/html&query.key=AXXBQgGY&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/
2) http://aei.pitt.edu/1535/
3) https://www.munzinger.de/search/document?index=mol-00&id=00000017405&type=text/html&query.key=IFSCDeRs&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/
4) https://www.munzinger.de/search/document?index=mol-00&id=00000015616&type=text/html&query.key=icfj3I1o&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/
5) http://aei.pitt.edu/1535/
6) https://www.munzinger.de/search/document?index=mol-00&id=00000016843&type=text/html&query.key=eBQGuQmx&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/
7) https://www.munzinger.de/search/document?index=mol-00&id=00000023033&type=text/html&query.key=BL9HJPas&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/
8) https://www.munzinger.de/search/document?index=mol-00&id=00000014939&type=text/html&query.key=QDYGnRiO&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/
9) https://www.munzinger.de/search/document?index=mol-00&id=00000024894&type=text/html&query.key=2yKNVSDn&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/
10) https://www.munzinger.de/search/document?index=mol-00&id=00000024792&type=text/html&query.key=o09MaerS&template=/publikationen/personen/document.jsp&preview=

Table 3: List of Budget Commissioners

Name	Nation	from	to
Christopher Tugendhat[1)]	United Kingdom	January 6, 1977	January 6, 1985
Henning Christophersen[2)]	Denmark	January 7, 1985	January 5, 1989
Peter Schmidhuber[3)]	Germany	January 6, 1989	January 24, 1995
Erkki Liikanen[4)]	Finland	January 25, 1995	September 17, 1999
Michaele Schreyer[5)]	Germany	September 17, 1999	November 22, 2004
Marcos Kyprianou[6)]	Cyprus	May 1, 2004	November 22, 2004
Dalia Grybauskaite[7)]	Lithuania	November 22, 2004	July 1, 2009

The exact dates were cross-verified using the following sources:

1) https://www.munzinger.de/search/document?index=mol-00&id=00000014946&type=text/html&query.key=WGH1rUUZ&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

2) https://www.munzinger.de/search/document?index=mol-00&id=00000015397&type=text/html&query.key=6jbFAztz&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

3) https://www.munzinger.de/search/document?index=mol-00&id=00000015616&type=text/html&query.key=eNQY73fw&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

4) https://www.munzinger.de/search/document?index=mol-00&id=00000022864&type=text/html&query.key=Vl57hKR4&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

5) https://www.munzinger.de/search/document?index=mol-00&id=00000019158&type=text/html&query.key=1J9aTjbF&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

6) https://www.munzinger.de/search/document?index=mol-00&id=00000024888&type=text/html&query.key=mopXdm6j&template=/publikationen/personen/document.jsp&preview=, http://aei.pitt.edu/1535/

7) https://www.munzinger.de/search/document?index=mol-00&id=00000024892&type=text/html&query.key=WwKYz4qa&template=/publikationen/personen/document.jsp&preview=

EC collectively resigned on March 15, 1999 and remained in office executively until September 1999. All weblinks last accessed on May 1, 2015.

A3. Variable Description

Description of Variables used:

Agricultural Fund Share[1)]	Each member state's annual agricultural fund (EAGGF) receipts as a share of the overall annual EU budget (in percent).
Agricultural Fund Share (100)	Each member state's annual agricultural fund (EAGGF) receipts as a share of the overall EAGGF budget (in percent).
Overall Funds Share[1)]	Each member state's annual budget receipts as a share of the overall annual EU budget (in %).
Regional/Social Funds Share[1)]	Each member state's regional and social fund (ERDF/ESF) receipts as a share of the overall annual EU budget (in percent).
Commissioner	Proportion of the year in which a country appointed the Agricultural Commissioner (0 if country i did not appoint the Agricultural Commissioner in year t, 1 if the country appointed the Agricultural Commissioner during the whole year). A month is counted, if the respective Commissioner was in office for the major part of this month.
Commissioner (Binary)	Dummy for appointing the Agricultural Commissioner (1 if country i appoint the Agricultural Commissioner in in year t and if *Commissioner* is not 0, 0 otherwise).
Commissioner (B)	Proportion of the year in which a country appointed the Budget Commissioner (0 if country i did not appoint the Budget Commissioner in year t, 1 if the country appointed the Budget Commissioner during the whole year). A month is counted, if the respective Commissioner was in office for the major part of this month.
Commissioner (R)	Proportion of the year in which a country appointed the Regional Commissioner (0 if country i did not appoint the Regional Commissioner in year t, 1 if the country appointed the Regional Commissioner during the whole year). A month is counted, if the respective Commissioner was in office for the major part of this month.
Time in Office	Cumulated years in office as Agricultural Commissioner (1 in the first year, 2 in the second year,...).
Commissioner (Binary) × *Time in Office*	Interaction of *Commissioner (Binary)* and *Time in Office.*

Description of Variables used (continued):

Election Year	Dummy for election years (1 in years with a national election in country i, 0 otherwise).
Preelection Year	Dummy for preelection years (1 in the year before the national election in country i, 0 otherwise).
Employment Agriculture (ln)[2)]	Logarithmized number of employees in the agricultural sector (in millions).
GVA Agriculture[2)]	Gross value added of the agricultural industry as a percentage of GDP.
Number of EU Members	Number of EU Member States.
Unemployment Rate[2)]	Unemployment Rate (in percent).
Per Capita GDP (EU=100)[2)]	Normalized per capita gross domestic product (EU average = 100).
New Member State	Dummy for the newest member states (1 for all new members until the next enlargement, 0 otherwise).
Voting Power Council	Shapley-Shubik index of country i in the Council in year t (in %).
Domestic EU Support[4)]	The percentage of citizens who think that "EC/EU membership is a good thing" minus the percentage of those who think that "EC/EU membership is a bad thing."
Commission President	Binary variable that takes the value 1 if the country provides the president of the Commission in year t.
European Council Presidency	Binary variable that takes the value 1 if the country holds the EU Council presidency in year t.

Original Sources:

1) All budget data are from the annual reports of the European Court of Auditors.
2) Eurostat and World Development Indicators
3) Data from Indices of Power IOP 2.0. Available at http://www.tbraeuninger.de/download/
4) Eurobarometer

All remaining variables are adapted from Schneider (2013).

A4. EU Accession

Table 4: EU Accession

Year	New Member States	∑
1957	Belgium, France, Germany, Italy, Luxembourg, Netherlands	6
1973	Denmark, Ireland, United Kingdom	9
1981	Greece	10
1986	Portugal, Spain	12
1995	Austria, Finland, Sweden	15
2004	Estonia, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia, Czech Republic, Hungary, Cyprus	25
2007	Bulgaria, Romania	27
2012	Croatia	28

The table lists the enlargement rounds of the EU. Column 3 shows the cumulative number of member states after the respective enlargement.
Source: http://ec.europa.eu/enlargement/pdf/publication/factsheet_en.pdf

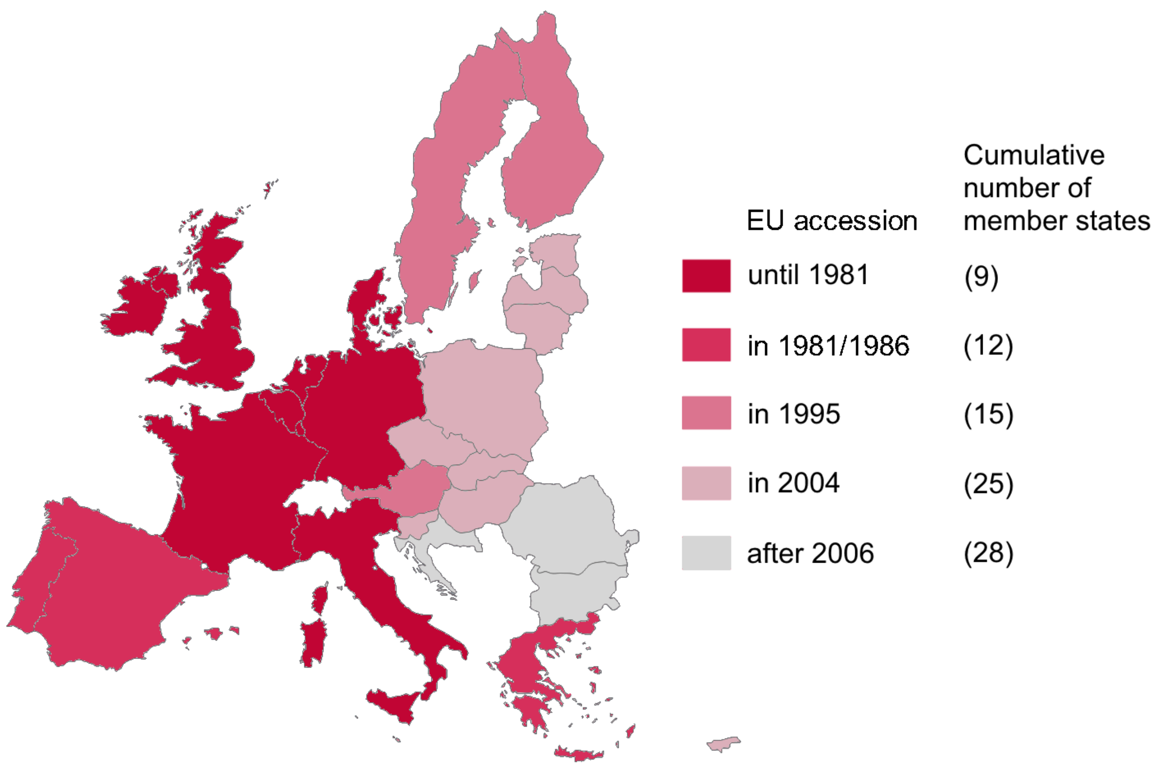

Figure 2: **Dates of EU Accession**
Own graphic based on data provided by the European Commission.

A5. Evolvement over Time

With regard to the Agricultural Commissioner, it seems possible that the Commissioners' effectiveness in redirecting funds to their home country is enhanced with the time they stay in office. In practice, Commissioners differ in terms of the degree of power they develop in office. Smith (2003) identifies several crucial factors, including their personal network, or their ability to learn to use their latent power effectively. Suvarierol (2008) highlights that international contacts in Brussels are especially potent in this regard. Based on this our hypothesis is the Commissioners' personal networks (both within and outside of the EC) improves with their time in office. This could improve their ability to pursue national interests.

Table 5: **Regression Results**

	(1)	(2)	(3)
Dependent Variable	*AFS*	*AFS*	*AFS*
Commissioner	0.557***	–	–
	[0.154]		
Commissioner (Binary)	–	0.495***	0.340***
		[0.128]	[0.125]
Commissioner (Binary)	–	–	0.057
X Time in Office			[0.072]
Adj. R-Squared	0.78	0.78	0.78
Number of Observations	385	385	385

The table displays regression coefficients with standard errors in brackets. *AFS* refers to *Agricultural Fund Share*. All columns use the fixed-effects within estimator. Standard errors are multiway-clustered to allow for arbitrary correlation at the country and year level using the xtivreg2 command in Stata. Controls includes all control variables in Table 2, column 4. This includes country and year fixed-effects, plus country-specific time trends. The time trends comprise a set of linear time trends which are allowed to vary by country. * p<0.10, ** p<0.05, *** p<0.01.

Table 5 shows the test of this hypothesis. First, column 2 demonstrates that our main results remain qualitatively unchanged when using a binary variable instead of the monthly shares of the year that the respective country provided the Commissioner. This binary variable allows for a more straightforward interpretation of the interactions with time in office. We can see in column 3 that the interaction is positive, as expected, with a value of 0.057, but insignificant at conventional levels. Figure 3 shows the marginal effect of *Commissioner* conditional on time in office for 1 to 4 years in office and the 99 percent confidence intervals. The reason for restricting the periods to 4 years is that, in all except one case, the Commissioners remain in office for 4 years or less.

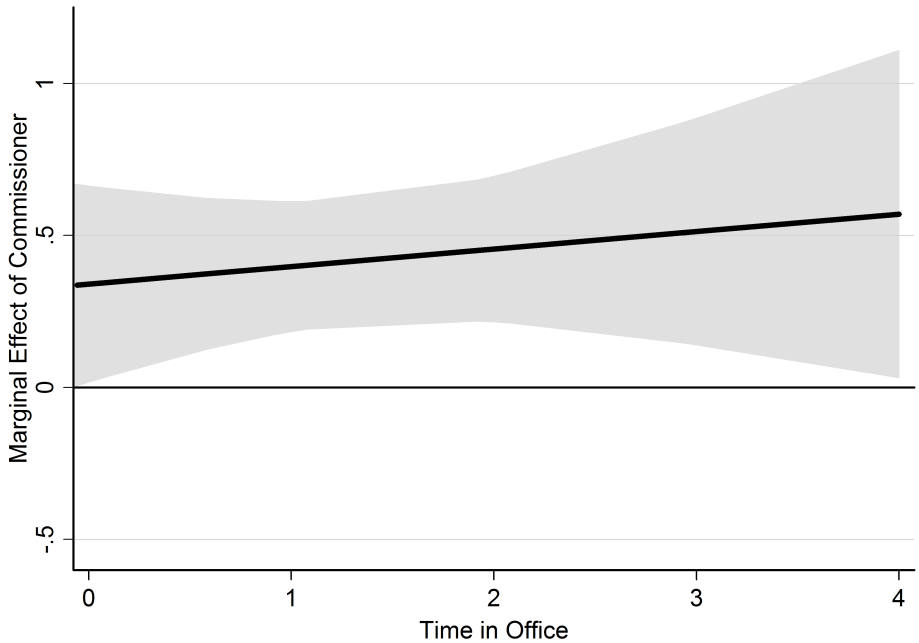

Figure 3: **Marginal Effect of *Commissioner* Conditional on *Time in Office***
The marginal effect is based on Table 5, column 3. *Time in Office* is measured in years. The grey shaded area indicates the 99 percent confidence interval, the fact that it widens towards the right end indicates that there are fewer observations.

A6. Wild Cluster Bootstrap and Randomization Inference

This is a more detailed description of the alternative approaches to statistical inference that we outline in the paper. As mentioned there, potential inference problems are based on the issue of having relatively few clusters. Only a limited amount of those receive the treatment, and of those the treatment is switched on only in certain years. This should be taken into account when estimating standard errors. The main approach of using two-way clustered standard errors already allows for arbitrary correlation within each cluster and across clusters at each point in time. However, due to the two specific challenges raised directly above, these rather standard ways to compute standard errors might lead to misleading statistical inference. More specifically they could lead to quite severe under- or overrejection.

A good summary of problems and challenges arising under circumstances which feature clustered data is provided by Cameron and Miller (2015). Besides small cluster size, other issues that the literature has examined are few treated clusters (MacKinnon and Webb, 2016*a*) and different cluster sizes (MacKinnon and Webb, 2016*a*). The most recommended procedure to tackle this issue is the so-called restricted wild cluster bootstrap (WCRB). The advantages of this approach are, for example, discussed in Cameron, Gelbach and Miller (2008). They use simulation evidence to demonstrate that the wild cluster bootstrap with the null-hypothesis imposed provides valid inference even with cluster sizes smaller than 50 under many circumstances typical to applied research. Webb (2013) provides a useful further advancement related to how to construct the bootstrap sample based on a 6-point rather than a 2-point distribution.

As we argue, the WCRB also seems to be the most reliable and conservative approach in our case. Simulation results comparing the reliability of different methods are always contingent on the assumptions and the specific case that is modeled. Real world applications necessarily differ to some degree from any specific simulation. Still, looking across different papers which conducted experiments for different settings, the evidence is accumulating that the wild cluster bootstrap procedure provides reliable inference even under unusual circumstances. Cameron and Miller (2015)'s Table 2 shows that for small numbers of clusters, for instance ten clusters, the cluster-robust standard error overrejects a null-hypothesis at a level of 0.103 instead of 0.05. Depending on the specific assumptions, the WCRB only rejects with rates of 0.065 to 0.067, so with a much milder overrejection.

Regarding problems with differing cluster sizes, as in our case, MacKinnon and Webb (2016*b*)'s Figure 3 shows that the WCRB tends to reject correctly once the number of treated observations within the cluster is greater than five or less than 95 percent. This condition is fulfilled in our application. MacKinnon and Webb (2016*b*)'s Figure 6 and 7 show that the restricted version WCRB procedure should lead to more conservative p-values than the unrestricted (WCUB), which does not impose the Null and tends to overreject. Their Figure 10 shows that the WCRB performs "extremely well" for $G \geq 5$.

An alternative to the wild cluster bootstrap approach is randomization inference. For an introduction and application of this approach to economics, we refer to Conley and Taber (2011). In simple terms, randomization inference is an approach to tackle inference problems that can arise when the treatment occurs only rarely. In our case, the share of countries that receive the treatment at least once is 6 out of 25 countries, hence, not small in the original definition of Conley and Taber (2011). Most importantly, we cannot assume the number of untreated control countries to approach infinity as in their setting. The share of years in which the treatment is switched on within these countries is small, however. Thus, while our case does not exactly resemble the setting in Conley and Taber (2011), we might still learn something from applying a modification of their method. Thus, we applied their approach to compute another set of p-values to test for the significance of our treatment, the provision of the *Commissioner*.

Based on Conley and Taber (2011) and MacKinnon and Webb (2016*a*) we programmed a routine that computes p-values based on randomization inference. As this is an area of ongoing research, we had to combine approaches from both sets of authors to fit them to our specific case as good as possible. This was done in coordination and with support by the authors of the respective papers. We thank all of them for their advice, detailed comments, and help. Our approach is most similar to the Wild Bootstrap Randomization Inference procedure in MacKinnon and Webb (2016*a*), section 2.9. We partial out time and country dummies from the outcome as well as the treatment variable as in Conley and Taber (2011) to resemble their original approach. To spare the reader with unnecessary details about the need to adjust the procedures, we refer them to the original papers which provide many important insights. Our procedure runs through the following steps.

1. Run the baseline regression $Y_{i,t} = \alpha + \beta C_{i,t} + X_{i,t}^{\prime}\gamma + \vartheta_i + \tau_t + \epsilon_{i,t}$, and store the original β_M and t-value t_M.

2. Create vectors d_k with the treatment patterns for each treated state and assign numbers to them, for all $k = 1, ...N_t$. N_t refers to the number of states which receive the treatment at least once. Partial out averages across time and country from the treatment to get N_t vectors $\tilde{d}_k$ and adjust for the effect of the treatment (cf., Conley and Taber 2011, p. 117). Then partial out the country and time fixed-effects, and the controls from the outcome variable $Y_{i,t}$ to form residuals $\hat{\eta}_{i,t}$ for each of the $N = N_t + N_{nt}$ states. N_{nt} refers to the states that never receive the treatment.

3. For each b of B bootstrap rounds, draw randomly with replacement one of the vectors $\tilde{d}_k$ and assign it to country i. Do this for each of the $i = 1, ..., N$ countries, conditional that it is not the vector of the country itself, i.e. $k \neq i$, until there are N $\{\hat{\eta}_i, \tilde{d}_k\}$ combinations in the bootstrap sample.

4. Run the regression of $\hat{\eta}$ on $\tilde{d}$. Store the coefficient and t-value in vectors β_{boot} and t_{boot}.

5. Repeat this procedure B times.

6. Use the distribution of the coefficient estimates β_{boot} and t-values t_{boot} to compute a p-value. We used a symmetric test. The p-value is thus the proportion of times that $|\beta_{boot}| > |\beta_M|$, or more formally $\hat{p}^*_{boot} = \frac{1}{B}\sum_{b=1}^{B} I(|\beta_{boot}| > |\beta_M|)$. Bootstrapping the t-value which offers asymptotic refinement analogously gives the p-value as $\hat{p}^*_{boot} = \frac{1}{B}\sum_{b=1}^{B} I(|t_{boot}| > |t_M|)$. For details see, among others, Cameron and Miller (2015).

The most conservative and based on the simulation evidence best approach to statistical inference in our case should be the WCRB. Our wild cluster bootstrap procedure is exactly analogous to the one described in Cameron and Miller (2015), section C.2. In addition to using the standard Rademacher weights $w_g = \{-1, 1\}$, we also use a 6-point distribution based on Webb (2013). In this approach, the weights have the equal likelihood to take on any of the values $\{-\sqrt{1.5}, -\sqrt{1}, -\sqrt{0.5}, \sqrt{0.5}, \sqrt{1}, \sqrt{1.5}\}$, which reduces problems with few clusters. We also conducted the procedure without imposing the null hypothesis that $\beta = 0$, the so-called unrestricted WCUB, but do not report the results here. The unrestricted version uses unrestricted estimates and residuals and tests the hypothesis that $\beta_{boot} = \beta$ instead of $\beta_{boot} = 0$. As, for example, Davidson and MacKinnon (1999) argue, the restricted version is usually preferable regarding efficiency and also produces more conservative estimates of the standard errors. We verified this as the unrestricted version yielded consistently lower p-values.

Figures 4 to 8 show the distribution of the coefficient values and t-values from the randomization inference procedures. The first two display the distribution of placebo coefficients, and the latter three the placebo t-values. They show the empirical probability density function as well as the empirical cumulative distribution function. Looking at the pdf in absolute value in Figure 5 and 8 helps to understand how the p-values are computed. The formula computes the fraction of rounds that yielded coefficients or t-values more extreme (or larger in absolute terms) than the actual treatment effect or its t-value.

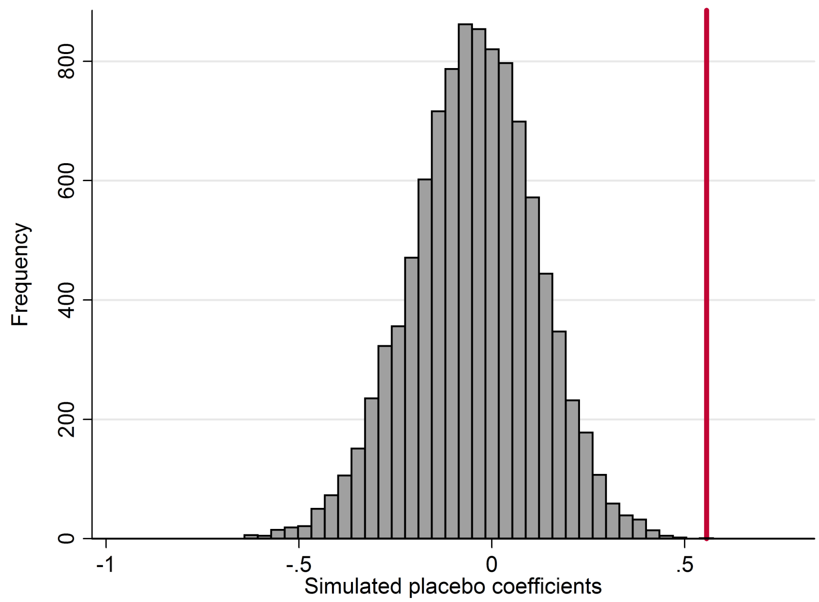

Figure 4: **Simulated Placebo Coefficient Density**
Displays coefficient size on the horizontal axis and the empirical probability density function based on 10,000 repetitions on the vertical axis. The red line indicates the coefficient in our preferred specification in Table 2, column 4.

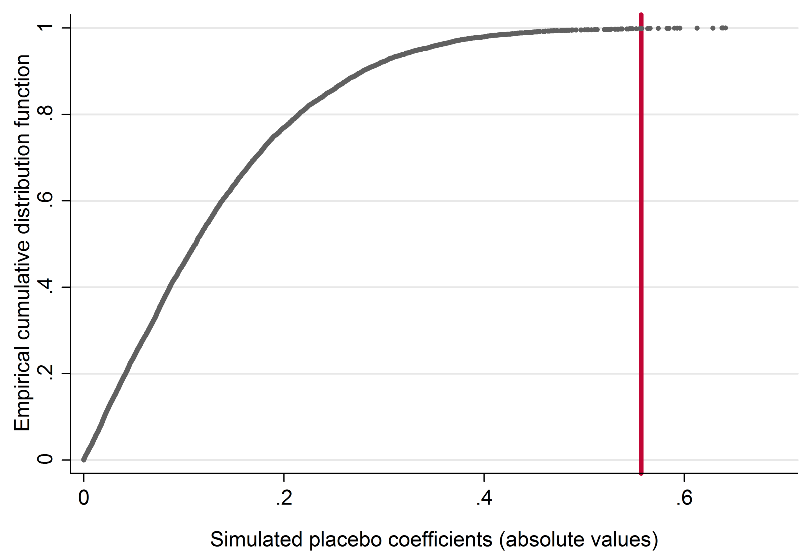

Figure 5: **Simulated Placebo Coefficient Distribution (absolute values)**
Displays coefficient size on the horizontal axis and the empirical cumulative distribution function on the vertical axis. The curve is not an interpolation: it is looking smooth due to the high number of repetitions (10,000). The red line indicates the coefficient in our preferred specification in Table 2, column 4. Note that for the computation of the p-value with a two-sided test we add up all coefficient values larger in absolute value than the treatment effect. Accordingly, this graph shows the distribution of the absolute values of the coefficient estimates over all repetitions. The p-value is the share of placebo coefficient estimates larger than the real treatment effect.

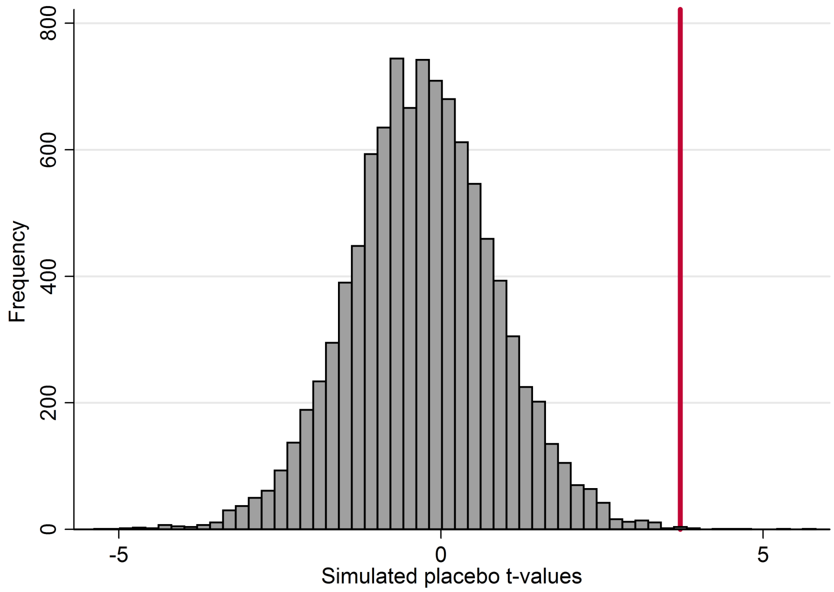

Figure 6: **Simulated Placebo t-value Distribution**
Displays t-values on the horizontal axis and the empirical probability density function based on 10,000 repetitions on the vertical axis. The red line indicates the t-value of the Commissioner coefficient in our preferred specification in Table 2, column 4. Using t-values provides asymptotic refinement compared to using placebo coefficient estimates.

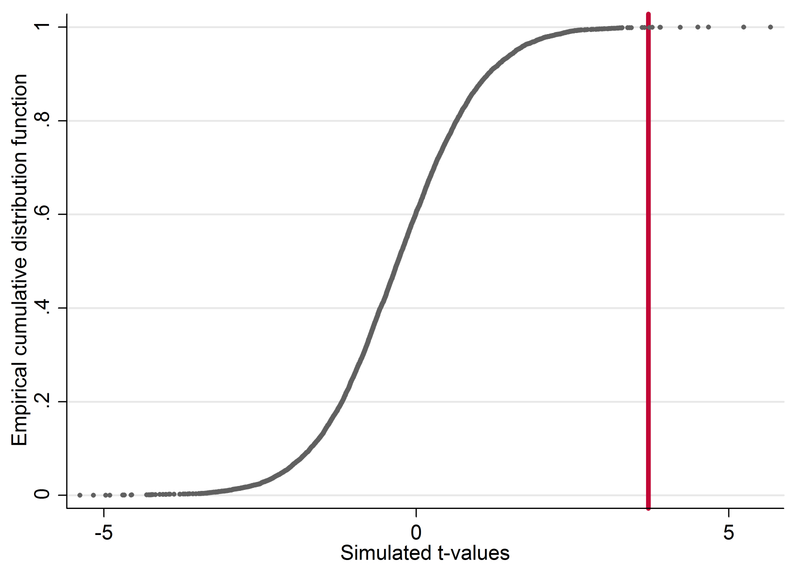

Figure 7: **Simulated Placebo t-value Distribution**
Displays t-values on the horizontal axis and the empirical cumulative distribution function on the vertical axis. The curve is not an interpolation: it is looking smooth due to the high number of repetitions (10,000). The red line indicates the t-value of the Commissioner coefficient in our preferred specification in Table 2, column 4. Using t-values provides asymptotic refinement compared to using placebo coefficient estimates.

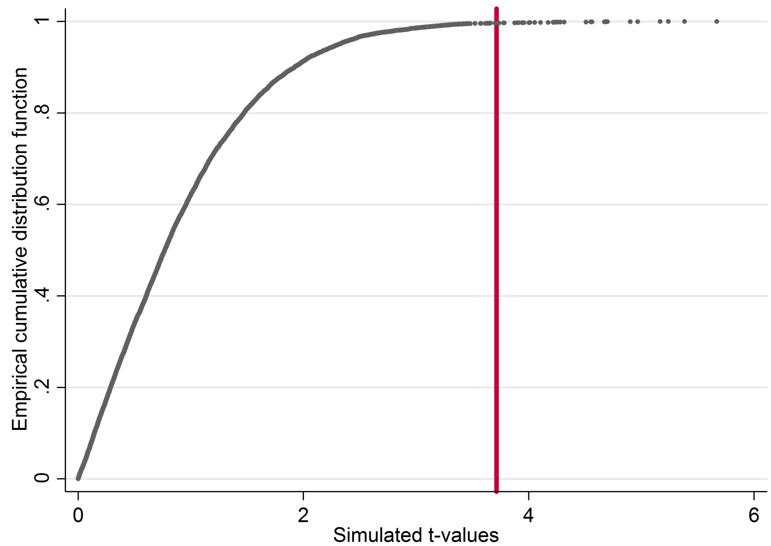

Figure 8: **Simulated Placebo t-value Distribution (absolute values)**
Displays absolute values of t-values on the horizontal axis and the empirical cumulative distribution function on the vertical axis. The curve is not an interpolation: it is looking smooth due to the high number of repetitions (10,000). The red line indicates the t-value of the Commissioner coefficient in our preferred specification in Table 2, column 4. Using t-values provides asymptotic refinement compared to using placebo coefficient estimates. This graph shows the distribution of the absolute values of the t-values over all repetitions. The p-value is the share of placebo t-value estimates larger in absolute value than the t-value in the real regression.

A7. Robustness to Varying Specifications Randomly

While our main robustness test for outliers is leaving out each individual country once, we also programmed a more extensive procedure that varies both the choice of countries and of control variables many times to systematically assess the sensitivity of our results to alternative specifications. Our additional simulations randomly drop an individual country and control variable in each repetition, then run the regression and store the coefficient and p-value. Figure 9 shows the distribution of coefficients when repeating this 10,000 times, and figure 10 the distribution of p-values. An overwhelming share of p-values is below 0.05, and only a tiny share of cases is above 0.10. This arbitrary omission of control variables is not without problems in our opinion, as can be seen from some very large or small coefficient estimates. As can be seen in Figure 9, this on average seems to lead to higher rather than lower coefficients. The fact that our results are that robust to simultaneously varying both the composition of countries and control variables further increases our confidence that such choices are not driving the results.

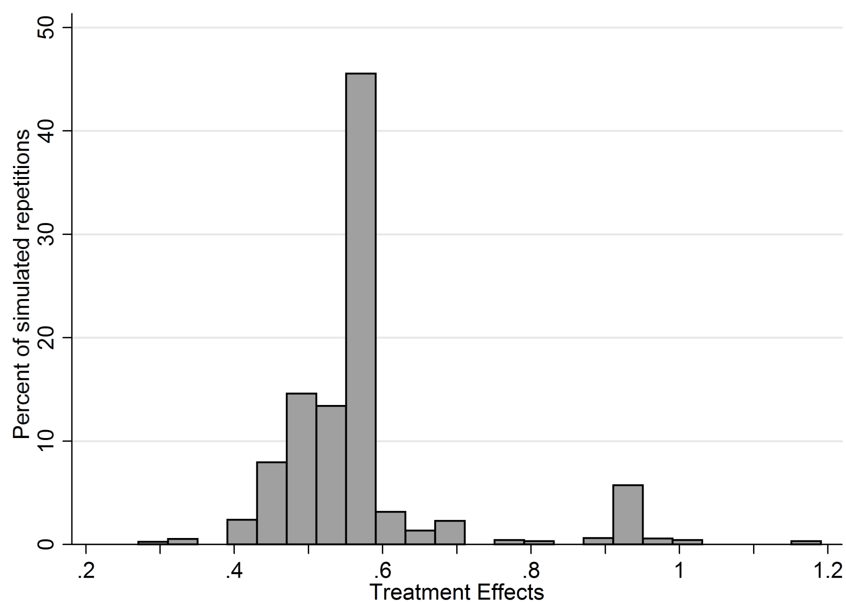

Figure 9: **Varying Country Composition and Control Variables – Coefficients** Shows the histogram of coefficients when repeating a procedure 10,000 times that randomly omits one country and one control variable in each round. The height of the bins indicates the percentage share of repetitions during which the coefficient was within the thresholds of a particular bin.

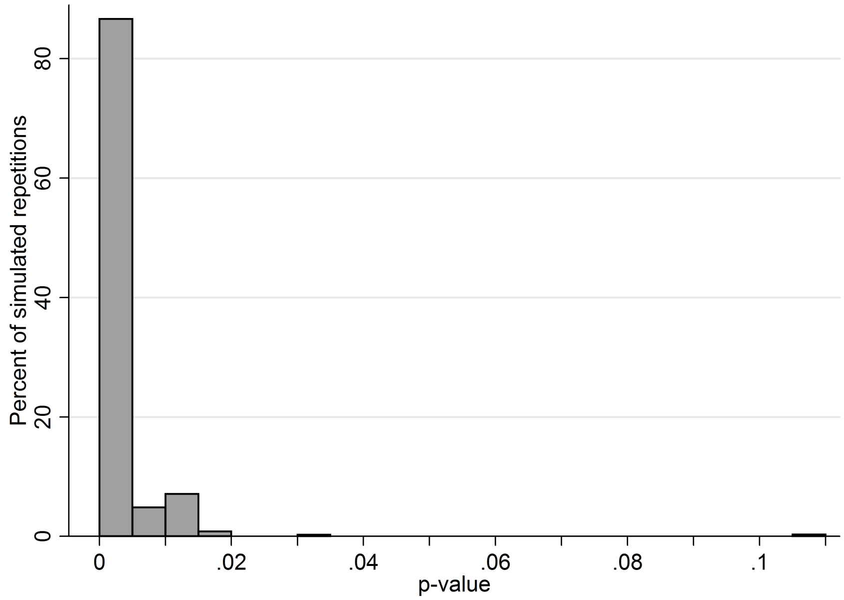

Figure 10: **Varying Country Composition and Control Variables – p-values**
Shows the distribution of p-values when repeating a procedure 10,000 times that randomly omits one country and one control variable in each round. The height of the bins indicates the percentage share of repetitions within the respective range of p-values of a bin. It can be clearly seen that the vast majority of repetitions yields p-values smaller than 0.05.

A8. Robustness

Table 6: **Separate Pre- and Posttreatment Trends**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	*AFS*	*AFS*	*AFS*	*AFS*	*AFS*	*AFS*	*AFS*
Commissioner (t-2)	−0.149	–	–	–	–	–	–
	[0.262]						
Commissioner (t-1)	–	−0.068	–	–	–	–	–
		[0.354]					
Commissioner	0.549***	0.553***	0.557***	0.635***	0.586***	0.562***	0.566***
	[0.153]	[0.145]	[0.154]	[0.194]	[0.170]	[0.152]	[0.156]
Commissioner (t+1)	–	–	–	0.634	–	–	–
				[0.585]			
Commissioner (t+2)	–	–	–	–	0.372	–	–
					[0.234]		
Commissioner (t+3)	–	–	–	–	–	0.073	–
						[0.050]	
Commissioner (t+4)	–	–	–	–	–	–	0.119
							[0.209]
Adj. R-Squared	0.78	0.78	0.78	0.78	0.78	0.78	0.78
Number of Observations	385	385	385	385	385	385	385

The table displays regression coefficients with standard errors in brackets. *AFS* refers to *Agricultural Fund Share*. All columns use the fixed-effects within estimator. Standard errors are multiway-clustered to allow for arbitrary correlation at the country and year level using the xtivreg2 command in Stata. They include all control variables from Table 2, column 4. This includes country and year fixed-effects, plus country-specific time trends. The time trends comprise a set of linear time trends which are allowed to vary by country. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: **Separate Pre- and Posttreatment Trends**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	*AFS*	*AFS*	*AFS*	*AFS*	*AFS*	*AFS*	*AFS*
Commissioner (t-2)	−0.264	–	–	–	–	–	–
	[0.307]						
Commissioner (t-1)	–	−0.191	–	–	–	–	–
		[0.400]					
Commissioner	–	–	0.557***	–	–	–	–
			[0.154]				
Commissioner (t+1)	–	–	–	0.442	–	–	–
				[0.542]			
Commissioner (t+2)	–	–	–	–	0.230	–	–
					[0.190]		
Commissioner (t+3)	–	–	–	–	–	−0.045	–
						[0.100]	
Commissioner (t+4)	–	–	–	–	–	–	−0.017
							[0.212]
Adj. R-Squared	0.78	0.78	0.78	0.78	0.78	0.77	0.77
Number of Observations	385	385	385	385	385	385	385

The table displays regression coefficients with standard errors in brackets. *AFS* refers to *Agricultural Fund Share*. All columns use the fixed-effects within estimator. Standard errors are multiway-clustered to allow for arbitrary correlation at the country and year level using the xtivreg2 command in Stata. They include all control variables from Table 2, column 4. This includes country and year fixed-effects, plus country-specific time trends. The time trends comprise a set of linear time trends which are allowed to vary by country. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 8: **Robustness to Outliers and Selection Effects**

	Belgium	*Denmark*	*Germany*	*Greece*	*Spain*	*France*	*Ireland*
Commissioner	0.557***	0.572***	0.560***	0.531***	0.547***	0.585***	0.683***
	[0.152]	[0.216]	[0.169]	[0.144]	[0.142]	[0.200]	[0.209]
Number of Observations	357	357	357	360	364	357	357
	Italy	*Luxembourg*	*Netherlands*	*Austria*	*Portugal*	*Finland*	*Sweden*
Commissioner	0.497***	0.591***	0.411***	0.555***	0.577***	0.561***	0.565***
	[0.150]	[0.180]	[0.101]	[0.158]	[0.144]	[0.156]	[0.156]
Number of Observations	357	357	357	373	364	373	373
	United Kingdom	*Cyprus*	*Malta*	*Czech Republic*	*Poland*	*Slovenia*	*Slovakia*
Commissioner	0.538***	0.557***	0.557***	0.557***	0.557***	0.557***	0.557***
	[0.161]	[0.154]	[0.154]	[0.154]	[0.154]	[0.154]	[0.154]
Number of Observations	357	382	382	382	382	382	382
	Hungary	*Estonia*	*Latvia*	*Lithunia*	*Large Countries*		
Commissioner	0.557***	0.557***	0.561***	0.557***	0.440**		
	[0.154]	[0.154]	[0.155]	[0.154]	[0.181]		
Number of Observations	382	382	382	382	252		

The table displays regression coefficients with standard errors in brackets. Dependent variable is *Agricultural Fund Share*. All columns use the fixed-effects within estimator. Standard errors are multiway-clustered to allow for arbitrary correlation at the country and year level using the xtivreg2 command in Stata. They include all control variables from Table 2, column 4. This includes country and year fixed-effects, plus country-specific time trends. The time trends comprise a set of linear time trends which are allowed to vary by country. Large Countries include Germany, France, UK, Italy, Spain. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

A9. Further Robustness Tests

Overall, we find no reason to doubt the interpretation of our coefficient as a causal effect of EU Commissioners' nationality on budget allocation behavior. Most importantly, we saw that while our treatment is relatively rare, the coefficient estimate is surprisingly robust to the omission of each member state individually or all large countries jointly. In this section, we also test how move further we can extend our set of control variables.

First, not only the level of factors like the importance of the agricultural sector or EU support in a member state, but also the change in these variables might affect the selection of the Agricultural Commissioner. When adding the changes to the levels, country and year fixed-effects, and linear time trends, our coefficient is barely affected and remains significant at the 1 percent level (see Table 7, Appendix D). Second, while the country-specific linear trends control for important changes like the decline or rise of the agricultural sector in a member state, they might not fully capture these changes. Adding further polynomials captures further potentially unobserved trend differences, but at the risk of capturing more and more of the variation caused by the treatment, and inflating standard errors.[1] In column 2-4 of Table 7, Appendix D, we first add quadratic, then cubic and finally quartic trends. As expected, this captures part of the variation and slightly decreases the point estimates, but the coefficients remain significant at the 5 percent level. Third, the results are nearly identical when we combine all time trends and the changes in the control variables (see column 5, ibid.).

Finally, we expect similar results when taking the logarithm of our dependent variable. It is possible that the "value" of the Commissioner is to some degree relative, i.e. smaller countries profit less from having it. However, it seems more likely that there is some value to each Commissioner position regardless of country size. It is of course still true that for a Commissioner from a very small country shifting money to the domestic agricultural sector might be much harder to organize and justify. In our sample, the only relevant such case is Luxembourg, which arguably offers less potential for acquiring agricultural fund spending than the other member states due to its tiny size. The results when using the logarithm are similar: the coefficient is positive and varies between 0.113 and 0.164 in columns 8 to 10, referring to an increase of 11-16 percent in the budget share. Adding more controls and time trends decreases the coefficient, but makes the estimation more precise so that the p-value decreases from 0.111 to 0.031 in column 9 and 0.079 in column 10. Overall, while the common trend assumption cannot hold for both the normal and the log value, we take this as further support for the robustness of the relationship.

[1] Mora and Reggio (2012) show that adding time trends and polynomials of further time trends is a more flexible way to account for heterogenous unobserved variation. They also state that this procedure alters the assumptions of the DiD framework. In addition, the correct average treatment effect would add the changes in the treated units captured by the time trend. We abstain from doing so here, and do not test the adjusted assumptions. Rather, we are interested in the stability of our point estimate and the significance level, which do not signal problematic divergences.

Table 9: **Regression Results**

PANEL A	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*AFS*	*AFS*	*AFS*	*AFS*	*AFS*
Commissioner	0.571***	0.471***	0.359***	0.387***	0.333**
	[0.180]	[0.168]	[0.125]	[0.147]	[0.169]
Year FE	*yes*	*yes*	*yes*	*yes*	*yes*
Changes in Controls	*yes*	*no*	*no*	*no*	*yes*
Country-specific Time Trends	*yes*	*yes*	*yes*	*yes*	*yes*
Country-specific Time Trends^2	*no*	*yes*	*yes*	*yes*	*yes*
Country-specific Time Trends^3	*no*	*no*	*yes*	*yes*	*yes*
Country-specific Time Trends^4	*no*	*no*	*no*	*yes*	*yes*
Adj. R-Squared	0.79	0.82	0.84	0.85	0.84
Number of Observations	368	385	385	385	368
PANEL B	(6)	(7)	(8)	(9)	(10)
Dependent Variable	*OFS*	*RFS*	*ln(AFS)*	*ln(AFS)*	*ln(AFS)*
Commissioner	–	–	0.133	0.164**	0.113*
			[0.084]	[0.076]	[0.064]
Commissioner (B)	0.111	–	–	–	–
	[0.882]				
Commissioner (R)	–	0.102	–	–	–
		[0.121]			
Year FE	*yes*	*yes*	*yes*	*yes*	*yes*
Changes in Controls	*no*	*no*	*no*	*no*	*yes*
Country-specific Time Trends	*yes*	*yes*	*yes*	*yes*	*yes*
Country-specific Time Trends^2	*no*	*no*	*no*	*yes*	*yes*
Country-specific Time Trends^3	*no*	*no*	*no*	*yes*	*yes*
Country-specific Time Trends^4	*no*	*no*	*no*	*yes*	*yes*
Adj. R-Squared	0.57	0.59	0.52	0.87	0.86
Number of Observations	403	385	385	385	368

The table displays regression coefficients with standard errors in brackets. All columns use the fixed-effects within estimator. *AFS* refers to *Agricultural Fund Share*, *OFS* to *Overall Funds Share*, and *RFS* refers to *Regional Funds Share*. Standard errors are multiway-clustered to allow for arbitrary correlation at the country and year level using the xtivreg2 command in Stata. 'Controls' includes all control variables in Table 2, column 4. This includes country and year fixed-effects, as well as country-specific time trends. The time trends comprise a set of linear time trends which are allowed to vary by country. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 10: **Robustness – Placebo Tests**

	Agricultural Fund Share	*Agricultural Fund Share*
Commissioner (R)	0.024	–
	[0.264]	
Commissioner (B)	–	−0.370
		[0.299]
Controls	*yes*	*yes*
Adj. R-Squared	0.77	0.78
Number of Observations	385	385

The table displays regression coefficients with standard errors in brackets. All columns use the fixed-effects within estimator. Standard errors are multiway-clustered to allow for arbitrary correlation at the country and year level using the xtivreg2 command in Stata. 'Controls' includes all control variables in Table 2, column 4. This includes country and year fixed-effects, as well as country-specific time trends. The time trends comprise a set of linear time trends which are allowed to vary by country. * p<0.10, ** p<0.05, *** p<0.01.

A9. Graphics

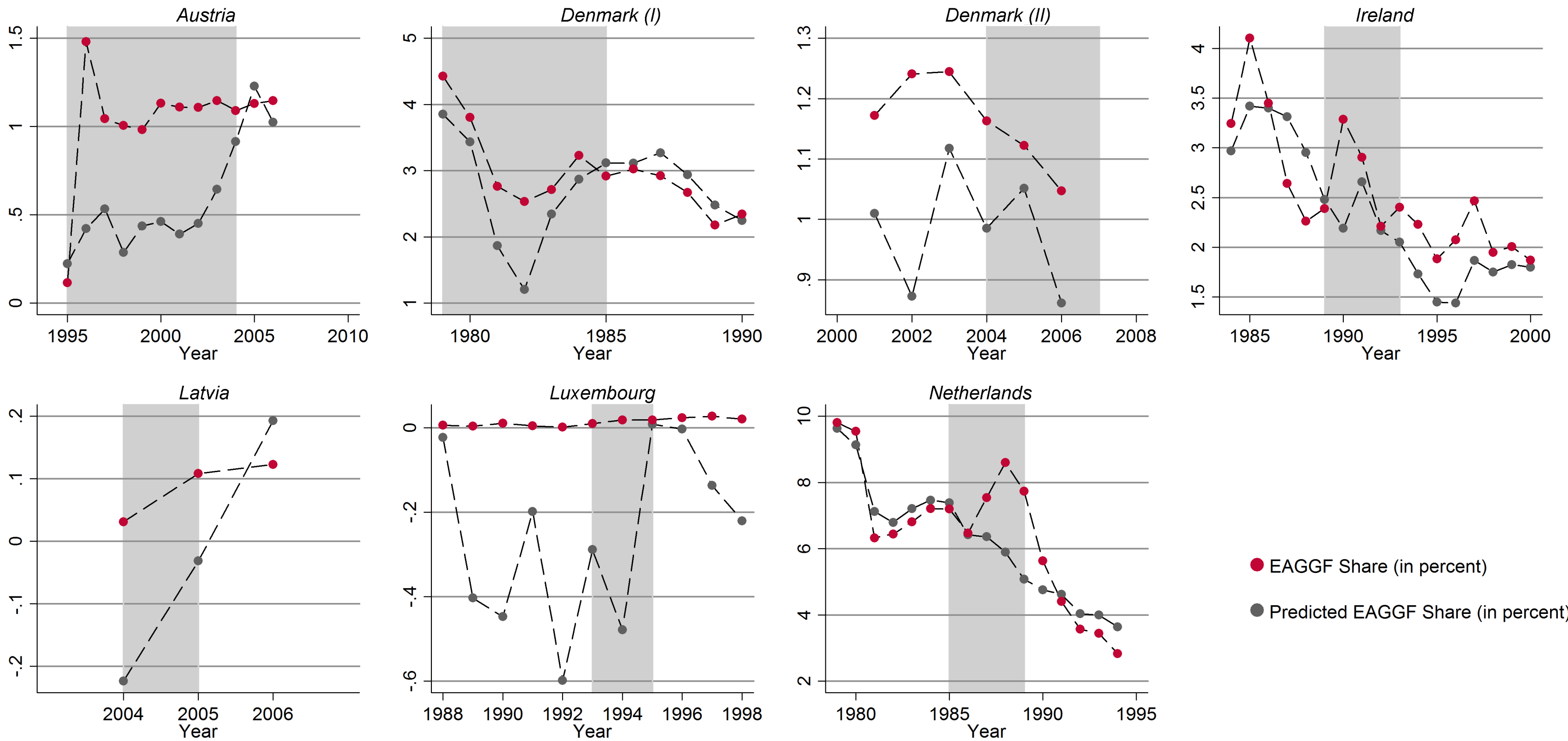

Figure 11: **Actual and Predicted Shares for Treated Countries**
This figure depicts the actual (red dots) and predicted (grey dots) share of the respective country based on the control variables in Table 2, column 4. The grey area shows the time period during which a country provided the Commissioner for Agriculture.

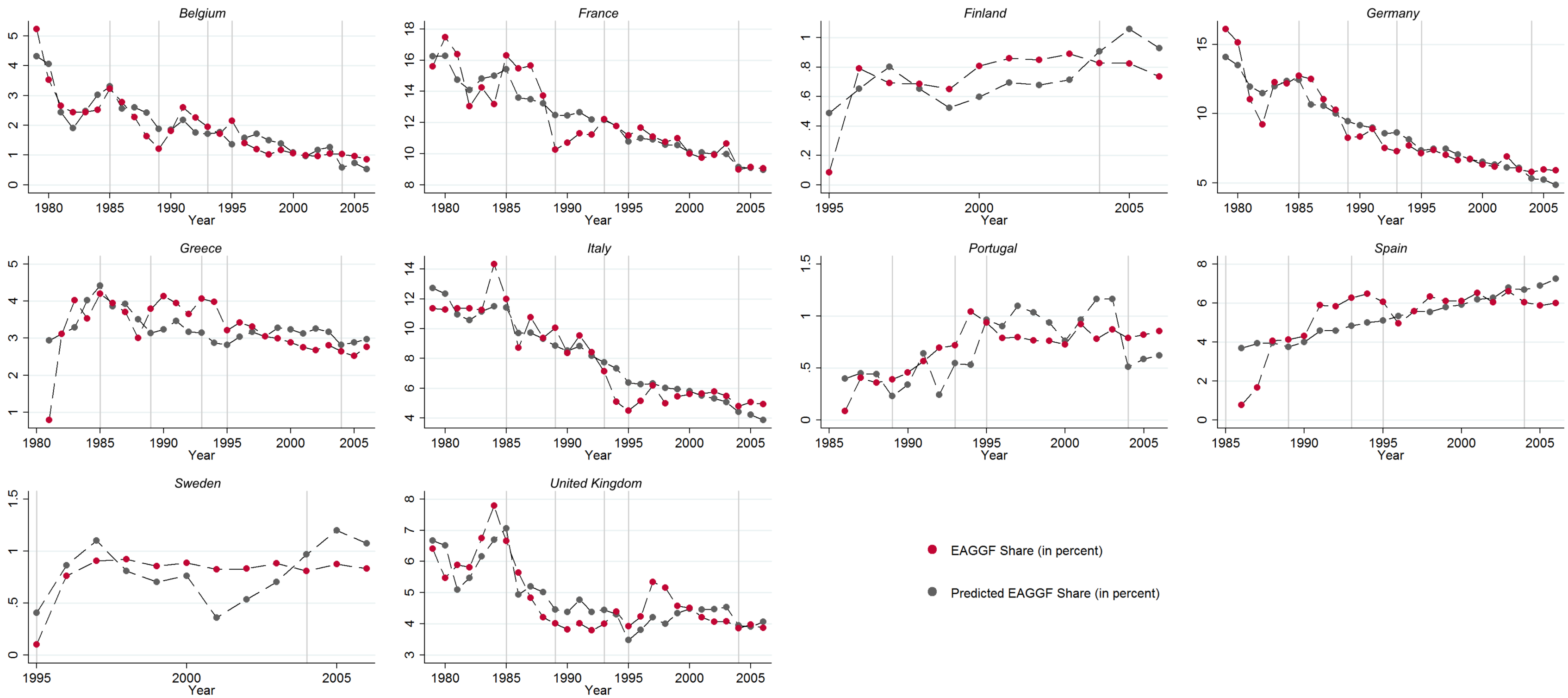

Figure 12: **Actual and Predicted Shares for Control Countries**
This figure depicts the actual (red dots) and predicted (grey dots) share of the respective country based on the control variables in Table 2, column 4. The grey vertical bars indicate changes in the nationality of the Commissioner for Agriculture and serve as a graphical placebo test. There is no apparent pattern related to changes in the nationality of the Commissioner for Agriculture for the member states in the control group.

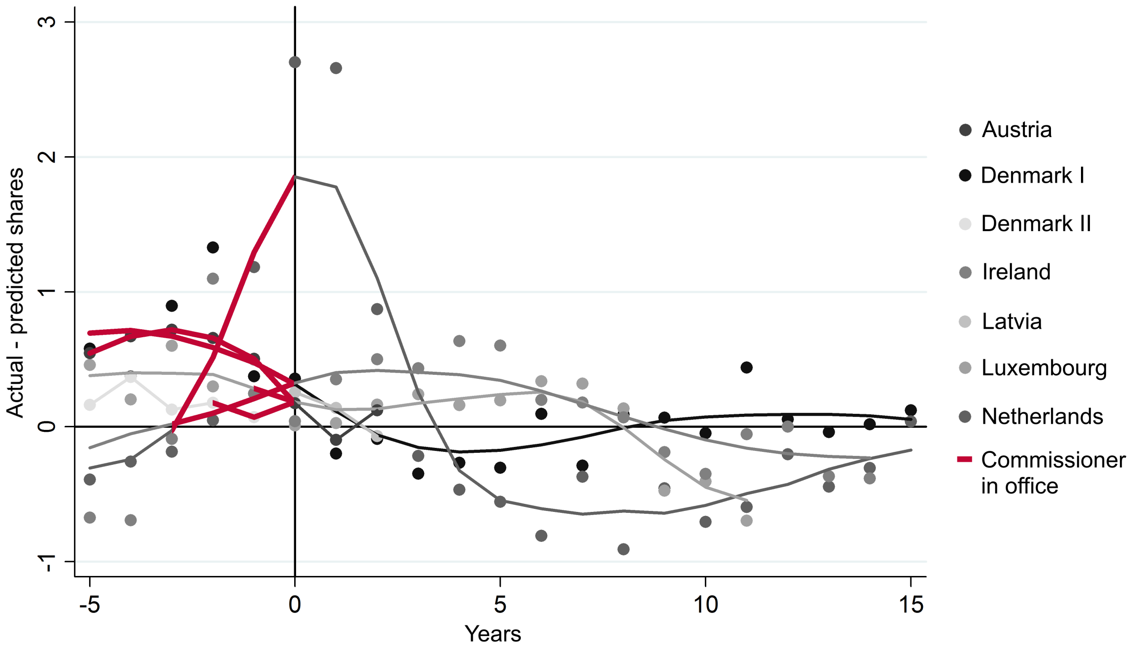

Figure 13: **Share of Treated Countries Centered around Event Time**
The vertical axis indicates the difference between the predicted and the actually observed budget shares of the respective country. Predictions are based on a regression on the observable control variables as defined in Table 2, column 4, country and year fixed effects as well as country-specific time trends. The lines provide nonparametric approximations to the development within the countries and the bold/red segments signal the period during which the respective country provided the Commissioner. All observations are centered around the termination of the treatment (years of leaving office), so that the 0 on the horizontal axis indicates the year in which a country stops providing the Commissioner for Agriculture.

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