Essays on Cooperation, Migration and Trust

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Abstract

This dissertation presents three studies related to cooperation, trust and social preferences. It can be summarized in two main topics, namely, cultural assimilation and cooperation in public good games.

The first two studies explore how migrants assimilate in their social preferences towards those that are prevalent in their host place. The first study refers to an international context and focuses on altruism, positive and negative reciprocity and trust. The second study focuses on internal migrants in Switzerland and how they assimilate in their trust on strangers. I find evidence of a causal relationship in line with the assimilation hypothesis.

The last study focuses on cooperation in social dilemmas. Here I explore how people respond in terms of beliefs, preferences and behaviour when they participate in public good games in groups of different sizes. For this, I develop a new version of the strategy method and conduct an online experiment with different parameters. I find the preferences to be rather stable with a stronger effect on beliefs. Finally, I find some evidence of a negative effect of group size on contributions.

Acknowledgements

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Chapter 1

Introduction

In a broad sense, this thesis studies important drivers of human behaviour, namely beliefs and preferences. Chapter 2 studies how immigrants assimilate in their social preferences (SPs) towards those that are prevalent in their host countries. Relying on a global and experimentally validated survey I show that migrants' preferences strongly correlate with their host population's SPs and provide suggestive evidence of a causal relationship in line with the assimilation hypothesis. This paper was published in Economics Letters with my coauthor and friend Matias Morales.

Chapter 3 digs deeper in identifying the causal effect of moving to a place with higher (lower) trust for the immigrants' level of trust. Here I focus on internal migrants in Switzerland which allows me to use a difference-in-differences approach. The cultural differences in the country plus the data available regarding migrants before migration provides a unique opportunity for my research question. The results, which are in line with the first chapter, show that internal migrants assimilate in their trust level when they move to a new place. I show also that the migrants who assimilate the most are the younger ones, which is consistent with the impressionable years hypothesis in psychology.

Chapter 4 departs from the migration context and studies how people react in terms of beliefs, preferences and behavior when they face social dilemmas in groups of different sizes. For this, I run an online experiment using public good games with different group sizes and elicit subject's preferences and beliefs using the traditional and a new version of a strategy method. This is joint work with my supervisor and friend Simon Gächter.

Chapter 2

Migration and Social Preferences

2.1 Introduction

Social preferences –e.g., altruism, trust, positive and negative reciprocity– shape individuals' behavior within societies; as a consequence, they are a key component of a country's culture. Since anti-immigrant sentiment is frequently motivated by the idea that migrants are a threat to the host country's culture (Rapoport et al., 2020), the question we aim to answer in this article is whether or not migrants adapt their social preferences (SPs) to those prevalent in their host country. Importantly, since a correlation between migrants and natives' SPs might be confounded by sorting -i.e., migration to places with similar SPs- it becomes relevant to distinguish whether such a finding would indeed be due to migrants sorting based on culture or, as we argue below, to assimilation.

We aim to overcome this empirical challenge with a combination of three approaches. First, with a regression specification based on the epidemiological approach (Fernández and Fogli, 2006; Giuliano, 2007), complemented with a falsification test using people that have not migrated yet but plan to do so in the near future. If migrants' SPs remain constant across cohorts, the test provides evidence against the sorting hypothesis, as their SPs should not correlate with the destination's SPs before being exposed to them (provided that the migrants that effectively migrate are not selected in terms of SPs). Second, we use host country fixed effects to compare migrants from the same country of origin that moved to the same host country but to different regions, which allows to hold all host country characteristics constant. Third, we check whether assimilation increases with time spent in the host country.

Our results suggest that cultural assimilation -as opposed to cultural sorting- is the main driver of migrants' social preferences. This conclusion is in line with other studies using different measures of assimilation in particular contexts. For instance, Jaschke et al. (2021), exploits the random allocation of refugees in Germany and finds that cultural assimilation occurs in more hostile places, and Abramitzky et al. (2020) find that immigrant mothers in the US shift toward native-sounding names for their children as they spend more time abroad. Klöble (2021) and Docquier et al. (2020) find that migrants are selected into migration but do not explore the sorting *per-se*.[1]

Our paper contributes to this ongoing academic debate in four ways. First, it uses measures of SPs that were specifically selected so that they correlate the most with actual behavior in experimental settings (Falk et al., 2018, 2016); this alleviates the concern that individuals might report SPs that do not match their behaviour. Second, it extends the number of SPs studied in Helliwell et al. (2016) from two to six; hence, this study allows for a more comprehensive understanding of SPs. Third, it focuses on regular migrants (as opposed to refugees or other context-specific migration situations) coming from and moving towards a large sample of countries which provides a higher external validity of the results.

This paper also contributes to a broader literature on how social preferences are shaped by network-based connectedness (Turati, 2020), natural disasters (Kuroishi et al., 2019; Hanaoka et al., 2018; Cassar et al., 2017; Callen, 2015; Cameron and Shah, 2015; Eckel et al., 2009), exposure to violence (Callen et al., 2014; Gneezy and Fessler, 2012; Voors et al., 2012), COVID-19 (Shachat et al., 2021; Bu et al., 2020), and financial situations (Andersen et al., 2019; Carvalho et al., 2016; Malmendier and Nagel, 2011; Chetty and Szeidl, 2007).

2.2 Data

We combine two data sources. First, we use the World Gallup Poll (WGP), a repeated cross-section survey collecting data representative of 99% of the world's adult population using ran-

[1]Docquier et al. (2020) finds that emigrants from MENA are less religious and more gender egalitarian than non-migrants and Klöble (2021) finds that migrants are positively selected in risk-taking, patience, positive and negative reciprocity, and negatively associated with trust.

domly selected and nationally representative samples.[2] This data set contains rich information on demographics and opinions on diverse topics such as politics, economics, religion, social issues, etc. Second, we use the Global Preferences Survey (GPS), which in 2012 collected the SPs of a sub-set of the individuals in the WGP from 76 countries (1141 sub-national regions). It included patience, risk aversion, altruism, trust, positive reciprocity, and negative reciprocity. The elicitation was based on questions that were previously experimentally validated (Falk et al., 2018, 2016), meaning that the questions asked in the survey were the ones that maximized the adjusted R-squared for behavior in an incentivized laboratory experiment ran in Germany. The results are also in line with evidence from the trust literature and validated against other similar surveys such as the World Values Survey.

It is common knowledge that there is a deficit in data regarding migration flows and decisions to migrate (Willekens et al., 2016). Fortunately, the WGP includes a module on migration decisions, containing individuals' country of origin and intentions to move abroad in the following 12 months (and to which country). This allows us to use future migrants in a falsification test that rules out the possibility that future migrants self-select into countries based on SPs. Tjaden et al. (2019) validates the questions regarding the intention to migrate using inflow and outflow data from the OECD International Migration Database, EUROSTAT and UNDESA.[3] Reassuringly, the WGP data has been recently used to study the determinants of migration decisions in a range of contexts (Smith and Floro, 2020; Migali and Scipioni, 2019; Ruyssen and Salomone, 2018; Bertoli and Ruyssen, 2018; Manchin and Orazbayev, 2018; Docquier et al., 2014; Dustmann and Okatenko, 2014).

Upon merging both datasets, we are left with 3255 migrants in 62 locations coming from 155 countries of origin. Of these migrants, 343 have moved within the past five years since the interview. The dataset also contains 1050 people in 51 countries that are about to move to one of 98 countries.

[2] Gallup World Poll (2019). See `https://www.gallup.com/178667/gallup-world-poll-work.aspx`.

[3] Creighton (2013) and Van Dalen and Henkens (2013) also show that intention to migrate correlates with actual migrations in other datasets.

2.3 Migrants: before and after moving

In Table 1.1, we compare all migrants with individuals that plan to migrate in the following 12 months controlling for country of origin fixed effects.[4] We find that migrants are older and are more likely to be female, to earn a higher income, to be married, and to have an elementary level of education. However, when we focus on recent migrants (i.e., those that migrated within the past five years), the characteristics are more balanced. Noticeably, observed characteristics that remain significantly different are mechanically related, as older people are more likely to be married and earn more than their younger (before moving) counterparts.

	(1)		(2)			(3)		
	Future Migrants (N=1050)		Migrants (N=3255)		(2)-(1)	Recent Migrants(N=343)		(3)-(1)
	Mean	SD	Mean	SD	Cond. Diff.	Mean	SD	Cond. Diff.
Age	30.91	11.55	45.84	17.18	13.892***	34.87	14.27	3.614***
Female	0.47	0.50	0.57	0.50	0.095***	0.55	0.50	0.074
Income	11625	15493	34514	38190	10181 ***	24363	27366	7337***
Married	0.36	0.48	0.58	0.49	0.137***	0.44	0.50	0.102**
Elementary	0.22	0.42	0.16	0.36	0.037*	0.18	0.39	0.037
Secondary	0.63	0.48	0.56	0.50	-0.007	0.56	0.50	-0.006
Tertiary	0.15	0.36	0.28	0.45	-0.031	0.26	0.44	-0.031

Table 1.1: Summary statistics for Migrants, Future migrants and Recent migrants
Income: Household annual income in US dollars. Elementary: Completed elementary education or less (up to 8 years of basic education). Secondary: Secondary to 3-year tertiary education and some education beyond secondary education (9-15 years of education). Tertiary: Completed four years of education beyond high school and/or received a 4-year college degree. Cond. Diff. stands for the conditional difference between different groups after including country of origin fixed effects.

2.4 Regressions specifications

We study whether migrants assimilate to their destination countries using alternative specifications of the following equation based on the epidemiological approach (Fernández and Fogli, 2006; Giuliano, 2007):

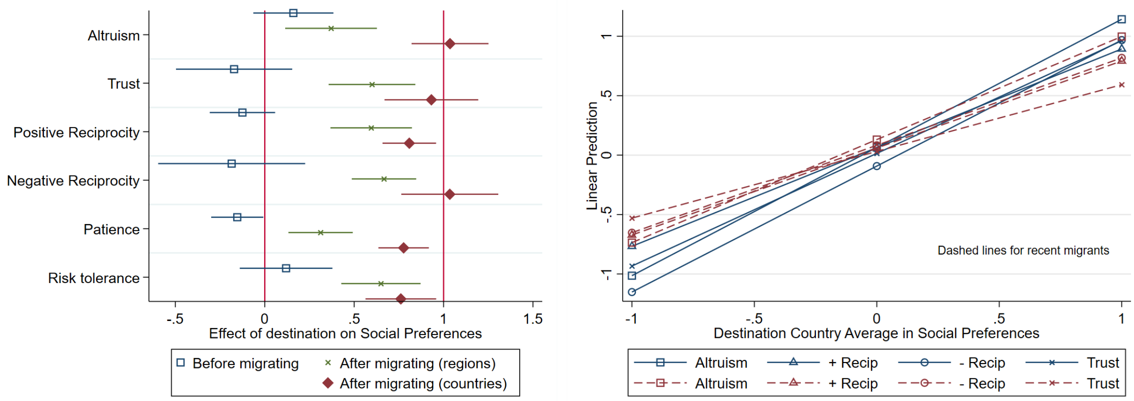
$$Y_i = \alpha + \beta \bar{Y} + H_i + \gamma \mathbf{X}_i + \epsilon_i. \tag{2.1}$$

Y_i is the trait of interest for individual i (e.g., trust), $\bar{Y}$ is the average trait in the destination country, $\mathbf{X}_i$ is a vector of individual-level demographic covariates (age, gender, log of income,

[4] See Table 1.A1 and Table 1.A4 in the Appendix for the tests without controls and an extended version of the table including SPs and non-migrants, respectively. As expected, non-migrants are different from migrants in many aspects, including altruism and negative reciprocity, but not trust and positive reciprocity. Note however, that we will not use non-migrants in our analysis.

marital status, and dummies for three education levels), H_i are country of origin fixed effects, and ϵ_i is an individual specific error term. The rationale is to compare migrants coming from the same country of origin with similar characteristics who migrated to countries with different SPs. Our coefficient of interest, β, captures the average effect of the SPs prevailing in the destination country on those of immigrants. Standard errors are clustered by country of destination in all regressions.

We estimate four different specifications of Equation 2.1. First, we use the sample of migrants that have already migrated. Second, we add country of destination fixed effects, D_i, in the regression to exploit a different source of variation, i.e., the regional variation within countries. Hence, $\bar{Y}$ becomes the sub-national average in the destination country. Third, we use the sample of future migrants (i.e., those that have not yet migrated but report to have intentions to do so in the following 12 months) and their reported destinations. This specification works as falsification test to check the selection of migrants into destination countries; if there is no selection, we should find no effect of the destination SPs on their individual preferences. Fourth, we repeat the first specification but interact $\bar{Y}$ with an indicator variable that takes the value 1 if the individual is a recent migrant (i.e., moved within five the past years) and 0 otherwise; this allows us to study whether assimilation increases with time spent in the host country.



(a) Regressions coefficients

(b) Predictions of SPs

Figure 1.1: Effect of host population's Social Preferences on individual Social Preferences
Panel (a) depicts the regression coefficients along their 95% confidence intervals. Vertical reference lines indicate no assimilation (0) and full assimilation (1). Panel (b) depicts linear predictions of SPs for recent (moved within the last 5 years) and non-recent migrants.

2.5 Results

Figure 3.1 summarizes the results. Panel (a) shows the β coefficients of the first three regressions with 95% confidence intervals. The vertical lines at 0 and 1 represent no assimilation and full assimilation, respectively (Note that for future migrants 0 represents no sorting and 1 represents positive sorting). Three findings emerge from the estimations. First, the red diamonds show strong assimilation in all preferences. In other words, an increase in one standard deviation in any of the destination country preferences is associated with an increase of 0.76 to 1.04 standard deviations in the migrant's preferences. It is noteworthy that non-social preferences have a smaller effect than SPs. Second, the green crosses show that even after controlling for country of destination fixed effects, the average preferences in the regions where migrants go has a strong and statistically significant effect on their preferences, though smaller than when using country-level variation.[5] Third, as a falsification test, we re-estimate the second specification using future migrants. If migrants are self selecting into destination countries based on SPs, we should observe a positive correlation between their preferences and their host countries' preferences.[6] The coefficients of these regressions, shown in blue squares, suggest that there is no evidence of this kind of selection.

Finally, Panel (b) of Figure 3.1 shows the linear prediction of the SPs for recent and non-recent migrants separately. We find that for each and all of the SPs, the slope is flatter (i.e., there is less assimilation) for recent migrants, though these differences are imprecisely estimated. Table 1.2 reports the corresponding coefficients.[7] In order to have a summary measure of our SPs and account for multiple hypothesis testing, we repeat the analysis using the first principal components for the group of social preferences and the group of all preferences separately. The results remain similar. Return migration could be a concern if migrants with more dissimilar SPs are leaving the country early, and hence, the longer the time since migration, the more

[5]In Table 1.A6 in the Appendix we show the results of restricting the sample to migrants that move across continents as a robustness check. The rationale is that it is less likely that these individuals are aware of the regional variation in SPs in the destination country, and hence there is less scope for sorting. With the exception of altruism, the coefficients remain the same.

[6]In the Appendix, we run a more stringent version of this test restricting the sample to those individuals whose income is above the 25th percentile of the distribution in their country. The rationale is that financially constrained individuals are less likely to migrate (Angelucci (2015), Lagakos et al. (2018)). Thus, we check whether there is evidence of sorting among the less financially constrained individuals that have stated they have intentions to migrate. Our results remain largely invariant (see Table 1.A5 in the Appendix.)

[7]Table A2 and Table A3 in the Appendix include the number of observations in each regression and the regressions without covariates. The results remain virtually unchanged.

likely that we observe similar SPs.

Variables	Before moving	After moving (Countries)	After moving (Regions)	Recent migrants (Interaction term)
Altruism	0.16	1.04	0.29	-0.21
	(0.11)	(0.11)	(0.13)	(0.27)
Trust	-0.17	0.93	0.60	-0.39
	(0.17)	(0.13)	(0.13)	(0.27)
Positive Reciprocity	-0.12	0.81	0.56	-0.10
	(0.09)	(0.08)	(0.12)	(0.21)
Negative Reciprocity	-0.19	1.03	0.62	-0.32
	(0.21)	(0.14)	(0.08)	(0.25)
Patience	-0.15	0.78	0.27	-0.16
	(0.07)	(0.07)	(0.09)	(0.16)
Risk tolerance	0.12	0.76	0.55	0.11
	(0.13)	(0.10)	(0.10)	(0.11)
Principal Component (SPs)	0.00	1.01	0.57	-0.25
	(0.10)	(0.09)	(0.13)	(0.26)
Principal Component (all preferences)	0.09	0.96	0.61	-0.29
	(0.10)	(0.10)	(0.12)	(0.26)

Table 1.2: Estimates of β from Equation 1 and its variants.
The last column presents the coefficient of the interaction term with a dummy indicating recent migrants (those who moved within the last 5 years). The last two rows repeat the analysis using the first principal component of the social preferences and of all preferences, respectively. All standard errors (in parenthesis) are clustered by country of destination.

2.6 Discussion

We show that migrants' preferences correlate strongly with the social preferences in their destination countries, but only after they migrate, which provides suggestive evidence against sorting. We further show that even after controlling for country of destination fixed effects, the effect of the average *regional* SPs remain strong and highly significant. Finally, we find that recent migrants seem to have adapted less than the migrants who spent a longer time in the destination country, though these effects are imprecisely estimated. Taken together, these results suggest that cultural assimilation -as opposed to cultural sorting- is the main mechanism shaping SPs. This supports the argument that migrants do not constitute a threat to the host country's culture (Rapoport et al. (2020)).

These results, however, should not be taken as causal but as stylized facts that need further research to be confirmed or rejected. The most important source of potential bias would arise if, among the migrants that stated that the would migrate, only those most similar (in terms of SPs) to the destination country end up effectively migrating. Similarly, selection can also occur with returning decisions, that is, if migrants who have not assimilated in their SPs are more likely to move again and hence drop out of the sample.

Further research is also needed to understand the heterogeneity and mechanisms behind assimilation. For instance, who adapts better and under what conditions? Does assimilation depend on the characteristics of the migrant, on the host population, or on the institutions? Does it depend on the cultural distance between home and host countries? It is also possible that the mechanisms driving assimilation differ by SP. Is assimilation a conscious decision? Does the effect persist even if migrants move again? We expect the growing availability of data on social preferences and mobility of people to allow researchers to answer these questions.

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2.8 Appendix

	(1)		(2)			(3)		
	Future Migrants (N=1050)		Migrants (N=3255)		(2)-(1)	Recent Migrants(N=343)		(3)-(1)
	Mean	SD	Mean	SD	Diff.	Mean	SD	Diff.
Age	30.91	11.55	45.84	17.18	14.928***	34.87	14.27	3.962***
Female	0.47	0.50	0.57	0.50	0.097***	0.55	0.50	0.078**
Income	11625	15493	34514	38190	22888***	24363	27366	12738***
Married	0.36	0.48	0.58	0.49	0.225***	0.44	0.50	0.082***
Elementary	0.22	0.42	0.16	0.36	-0.067***	0.18	0.39	-0.040
Secondary	0.63	0.48	0.56	0.50	-0.067***	0.56	0.50	-0.066**
Tertiary	0.15	0.36	0.28	0.45	0.134***	0.26	0.44	0.106***

Table 1.A1: Summary statistics for Migrants, Future migrants and Recent migrants

Income: Household annual income in US dollars. Elementary: Completed elementary education or less (up to 8 years of basic education). Secondary: Secondary to 3-year tertiary education and some education beyond secondary education (9-15 years of education). Tertiary: Completed four years of education beyond high school and/or received a 4-year college degree. Diff. stands for the simple difference between groups.

Variable	Before moving	After moving (Countries)	After moving (Regions)	Recent migrants	Before moving	After moving (Countries)	After moving (Regions)	Recent migrants
Altruism	0.16	1.04	0.29	-0.21	901	2448	2405	2371
	(0.11)	(0.11)	(0.13)	(0.27)				
Trust	-0.17	0.93	0.60	-0.39	892	2429	2386	2353
	(0.17)	(0.13)	(0.13)	(0.27)				
Positive Reciprocity	-0.12	0.81	0.56	-0.10	902	2460	2417	2383
	(0.09)	(0.08)	(0.12)	(0.21)				
Negative Reciprocity	-0.19	1.03	0.62	-0.32	893	2402	2360	2327
	(0.21)	(0.14)	(0.08)	(0.25)				
Patience	-0.15	0.78	0.27	-0.16	901	2443	2402	2368
	(0.07)	(0.07)	(0.09)	(0.16)				
Risk tolerance	0.12	0.76	0.55	0.11	898	2443	2399	2366
	(0.13)	(0.10)	(0.10)	(0.11)				
Principal Component (SPs)	0.00	1.01	0.57	-0.25	882	2368	2327	2294
	(0.10)	(0.09)	(0.13)	(0.26)				
Principal Component (all preferences)	0.09	0.96	0.61	-0.29	878	2351	2309	2277
	(0.10)	(0.10)	(0.12)	(0.26)				

Table 1.A2: Estimates of β from Equation 1 and its variants.

The fourth column presents the coefficient of the interaction term with a dummy indicating recent migrants (those that migrated within the last 5 years). The last four columns present the number of observations. The last two rows repeat the analysis using the first principal component of the social preferences and of all preferences, respectively. All standard errors (in parenthesis) are clustered by country of destination.

Variable	Before moving	After moving (Countries)	After moving (Regions)	Recent migrants	Before moving	After moving (Countries)	After moving (Regions)	Recent migrants
Altruism	0.17	1.07	0.37	-0.14	1013	2493	2405	2413
	(0.11)	(0.10)	(0.13)	(0.29)				
Trust	-0.23	0.99	0.60	-0.34	1002	2472	2386	2393
	(0.17)	(0.13)	(0.12)	(0.27)				
Positive Reciprocity	-0.14	0.84	0.60	-0.08	1014	2505	2417	2425
	(0.09)	(0.07)	(0.12)	(0.22)				
Negative Reciprocity	-0.22	1.11	0.67	-0.25	1005	2445	2360	2367
	(0.19)	(0.15)	(0.09)	(0.25)				
Patience	-0.09	0.96	0.31	-0.13	1013	2488	2402	2410
	(0.07)	(0.09)	(0.09)	(0.16)				
Risk tolerance	0.11	0.81	0.65	0.05	1010	2487	2399	2407
	(0.13)	(0.14)	(0.11)	(0.13)				
Principal Component (SPs)	-0.01	1.06	0.52	-0.17	992	2411	2285	2334
	(0.10)	(0.09)	(0.13)	(0.26)				
Principal Component (all preferences)	0.09	1.17	0.53	-0.26	988	2393	2268	2316
	(0.10)	(0.11)	(0.13)	(0.26)				

Table 1.A3: Estimates of β from Equation 1 (without covariates) and its variants.

The fourth column presents the coefficient of the interaction term with a dummy indicating recent migrants (those that migrated within the last 5 years). The last four columns present the number of observations. The last two rows repeat the analysis using the first principal component of the social preferences and of all preferences, respectively. All standard errors (in parenthesis) are clustered by country of destination.

	(1)		(2)		(3)		(4)		(2)-(1)	(3)-(1)	(1)-(4)
	Future Migrants (N=1050)		Migrants (N=3255)		Recent Migrants(N=343)		Non-Migrants(N=60771)				
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Diff.	Diff.	Diff.
Age	30.91	11.55	45.84	17.18	34.87	14.27	41.09	17.18	13.892***	3.614***	-7.614***
Female	0.47	0.50	0.57	0.50	0.55	0.50	0.55	0.50	0.095***	0.074	-0.074***
Income	11625.6	15493.61	34514.31	38190.12	24363.72	27366.38	19259.27	29228.3	10,181***	7,337***	1,569***
Married	0.36	0.48	0.58	0.49	0.44	0.50	0.52	0.50	0.137***	0.102**	-0.123***
Elementary	0.22	0.42	0.16	0.36	0.18	0.39	0.30	0.46	0.037*	0.037	-0.116***
Secondary	0.63	0.48	0.56	0.50	0.56	0.50	0.56	0.50	-0.007	-0.006	0.063***
Tertiary	0.15	0.36	0.28	0.45	0.26	0.44	0.15	0.35	-0.031	-0.031	0.054***
Altruism	0.06	1.01	-0.01	0.96	0.10	0.96	-0.05	0.99	-0.066	0.025	0.132***
Positive reciprocity	0.02	1.09	0.05	0.95	0.08	0.92	-0.02	1.01	0.067	0.162*	0.054
Negative reciprocity	0.16	1.07	0.00	1.00	0.10	1.00	-0.01	1.01	-0.226***	-0.003	0.237***
Trust	-0.12	1.12	0.13	0.98	0.06	0.99	-0.03	1.00	0.014	0.061	0.020
Patience	0.01	0.97	0.09	1.02	0.12	1.01	-0.05	0.97	0.011	0.082	0.182***
Will. to take risks	0.33	1.02	-0.05	1.01	0.15	1.00	0.01	1.00	-0.301***	-0.174*	0.283***

Table 1.A4: Summary statistics for Non-Migrants, Migrants, Future migrants and Recent migrants

Income: Household annual income in US dollars. Elementary: Completed elementary education or less (up to 8 years of basic education). Secondary: Secondary to 3-year tertiary education and some education beyond secondary education (9-15 years of education). Tertiary: Completed four years of education beyond high school and/or received a 4-year college degree. Diff. stands for the simple difference between different groups.

Variable	Coef.	Std. Err.	z	$P \geq z$	[95% Conf.	Interval]	N Obs.
Altruism	0.096	0.098	0.99	0.324	-0.095	0.289	717
Positive Reciprocity	-0.129	0.131	-0.99	0.320	-0.386	0.126	718
Negative Reciprocity	-0.290	0.207	-1.41	0.160	-0.695	0.115	710
Trust	-0.285	0.179	-1.59	0.112	-0.637	0.066	711
Patience	-0.239	0.088	-2.73	0.006	-0.411	-0.068	717
Risk tolerance	0.133	0.134	0.99	0.321	-0.130	0.397	715
Principal Component (SPs)	-0.063	0.096	-0.66	0.512	-0.251	0.125	706
Principal Component (all preferences)	-0.026	0.099	-0.27	0.789	-0.220	0.167	703

Table 1.A5: Regression coefficients for the falsification tests using non-financially constrained future migrants.

An individual is considered non-financially constrained if their income is above the 25th percentile of the income distribution of their origin country. The last two rows repeat the analysis using the first principal component of the social preferences and of all preferences, respectively. All standard errors are clustered by country of destination.

Variable	Coef.	Std. Err.	z	$P \geq z$	[95% Conf.	Interval]	N Obs.
Altruism	-0.091	0.258	-0.35	0.724	-0.596	0.415	812
Positive Reciprocity	0.499	0.205	2.44	0.015	0.097	0.900	814
Negative Reciprocity	0.683	0.127	5.39	0.000	0.435	0.932	801
Trust	0.328	0.195	1.68	0.093	-0.054	0.710	808
Patience	0.246	0.128	1.92	0.055	-0.005	0.497	811
Risk tolerance	0.857	0.148	5.79	0.000	0.567	1.147	814
Principal Component (SPs)	0.350	0.176	1.99	0.047	0.005	0.695	793
Principal Component (all preferences)	0.419	0.176	2.38	0.017	0.074	0.763	790

Table 1.A6: Regression coefficients for the estimations with country of destination fixed effects and migrants to a continent other than where they were born

The last two rows repeat the analysis using the first principal component of the social preferences and of all preferences, respectively. All standard errors are clustered by country of destination.

Chapter 3

Migration and Trust: Evidence on Assimilation from Internal Migrants

3.1 Introduction

Evidence suggest that migration has the potential to increase global efficiency and output, and decrease inequality by relaxing constraints on the optimal allocation of the labor force (Lagakos et al., 2018; Dustmann and Preston, 2019; Clemens, 2011). However, migrants differ in cultural values and beliefs from the local people and this may create frictions over cultural assimilation. These frictions could be further fueled by the media and politicians depicting immigrants as a cultural threat, who lack the capacity or the willingness to assimilate (Alesina and Tabellini, 2022). These concerns are not confined to international migration but apply to internal migration as well. The reason is that cultural differences do not necessarily coincide with country borders.[1] In fact, substantial variation in cultural traits exists within countries (Obradovich et al., 2022; Tabellini, 2010) and previous papers exploited this variation. For instance, Alesina and Fuchs-Schündeln (2007) study assimilation of migrants between the former East and West of Germany, Guiso et al. (2016) and Ichino and Maggi (2000) study internal migrants in Italy and Acharya et al. (2016) study internal migrants in the the United States.

In this paper, I study whether internal migrants assimilate culturally to the locals, where assimilation is defined as the process of becoming similar in a certain dimension such as the

[1] An extreme example is the scramble for Africa (see Michalopoulos and Papaioannou (2016)).

cultural traits. Studying this topic is conceptually challenging because migrants face a trade-off. On one hand, they might want to assimilate because of economic reasons to integrate in the labour markets (Abramitzky et al., 2020) or to conform to the prevailing social norm (Bernheim, 1994). On the other hand, they might refuse to assimilate for the social/psychological costs by the sense of identity loss (Akerlof and Kranton, 2000; Bisin and Verdier, 2000; Olcina et al., 2017). Understanding which of these effects dominates is an empirical question and motivates this paper.

Empirically, the challenge is to separate assimilation from sorting of migrants to places, i.e., migrants might move to a specific location *because* they share the same cultural traits. Disentangling assimilation from sorting requires a counterfactual of how the migrants' cultural traits would have evolved had they not migrated. Note, however, that non-migrants do not make a good counterfactual in this case because they are likely to differ from the migrants in many ways. Furthermore, studying this research question using observational data requires, at least, data on the migrants' cultural traits before migration. But, this data is typically not available.

I overcome the empirical challenge by studying assimilation of internal migrants in the context of Switzerland, which offers an ideal setting for my study for two main reasons. First, Switzerland consists of 26 sovereign cantons that, for historical reasons, have evolved in substantial institutional differences, which map on to cultural differences (Rustagi, 2022).[2] Thus, in my analysis I exploit the cultural variation at the cantonal level to study how it affects migrants' cultural traits.[3] Second, the Swiss National Science Foundation, through the Swiss Household Panel (SHP), conducts a yearly survey, following a representative sample of the population since 1999 and covering social and economic topics. In particular, the SHP follows people when they move to different places and provides one of the longest longitudinal surveys in the world (17 years) allowing to observe internal migrants (and their cultural traits) repeatedly before and after migration. Hence, it allows me to compare early and late movers in a difference-in-differences framework.

I focus on assimilation of one of the most studied cultural traits, i.e., generalized trust towards others, where "others" refers to people the respondent does not know (Alesina and Giuliano,

[2]Evidence of this are the outcomes from multiple referenda on diverse topics like restricting mass immigration (2014), joining the Schengen Area (2005) or same sex partnerships (2005).

[3]The cantons are the Swiss administrative areas and are equivalent to provinces or states.

2015; Guiso et al., 2015; Putnam, 1993). Trust is broadly defined as an individual's willingness to be vulnerable based on an expectation of cooperation (irrespective of the ability to monitor or control that other party) (Johnson and Mislin, 2008; Gambetta et al., 2000; Rousseau et al., 1998; Mayer et al., 1995).[4] This component of culture is also important because it predicts growth and other desirable economic, social and political outcomes (Guiso et al., 2015; Algan and Cahuc, 2014; Nunn and Wantchekon, 2011; Algan and Cahuc, 2010; Knack and Keefer, 1997; Putnam, 1993).

My analysis relies on two main strategies: First, an event-study approach (Callaway and Sant'Anna, 2021) allows me to test whether migrants' trust moves towards the average trust level of the host canton once they move. To illustrate the method, consider two individuals with similar characteristics who move from canton A to canton B, which has higher levels of trust than canton A. If one of them moves later for reasons that are unrelated to their trust, I could use him/her as a counterfactual for the early mover. Then, if I observe a higher trust level for the early mover, I could conclude that assimilation is taking place. Similarly, I can do the same exercise with two people migrating to lower trust cantons, which allows me to test if migrants also assimilate downwards. The validity of these two comparisons relies on the assumption that these migrants are in fact similar and the moving time is unrelated to their trust. I, thus, begin by showing that migrants moving to higher (lower) trust cantons have similar levels of trust in the years before moving (i.e., parallel trends). Reassuringly, I show that early and late migrants are also balanced in demographic characteristics.

Second, instead of exploiting the direction of move (i.e., moving to higher or lower trust cantons), I combine all migrants in a single difference-in-differences strategy with continuous treatment (see Callaway et al., 2021).[5] This allows me to exploit the large variation in trust levels in the host cantons and study the effect of the treatment intensity. Furthermore, it also allows me to hold constant all the time invariant individual factors (such as the canton of origin) via fixed effects and to control for important time-varying characteristics, such as education and

[4]In the case of trust, Butler et al. (2016) argues that there is a "right amount of trust" that balances the trade-off between a high exposure to being cheated and losing opportunities for gains. From this point of view, assimilating to the right amount of trust is economically profitable in either direction. This is especially important if we consider that people use heuristics or imitate others when information is imperfect or costly to obtain (Boyd and Richerson, 1995, 1988).

[5]Note that combining all migrants in the previous case will cancel out the effect of the assimilation to higher and lower cantons.

income. To verify that there are no composition effects, I show that migrants in the lowest and highest trust cantons, are balanced in demographic characteristics, both before and after migration (i.e., migrants leaving the lowest and highest trust cantons are similar and migrants arriving in the lowest and highest trust cantons are similar).

Using the event study approach, I find a large change in the migrants' trust, that is, migrants moving to a higher trust canton increase their trust by 0.16 standard deviations whereas migrants moving to lower trust cantons decrease their trust by 0.11 standard deviations. This assimilation can already be observed in the first few years after migration. Using the difference-in-differences approach with the continuous treatment, I find that migrants increase their trust in 0.43 standard deviations for each standard deviation increase in the trust level at the destination.

My results are robust to a battery of tests: First, I run a placebo test with non-movers, assigning a random moving year between (2003-2017) to non-movers and find no systematic change in their trust level. Second, to address concerns about the reflection problem (i.e., the fact that the migrants could simultaneously have an effect on the local peoples' trust)(Manski, 1993), I consider the level of trust in the cantons in the year 2002 (i.e., before any migration in the sample occurs) as the independent variable of interest and find that the results remain unchanged. Third, I find no assimilation for trust in the federal government, which alleviates concerns about the results being driven by mechanical aspects of the survey implementation.

I further explore heterogeneity in the assimilation by estimating sorted partial effects (Chernozhukov et al., 2018) and find that the 25% who adapted the most are more likely to be female and significantly younger, have spent more year in the host canton, are poorer and have fewer years of education but with a higher increase in income and education after migration.

This paper contributes to the literature in several ways. First, it complements the previous literature on assimilation by showing that beliefs in other's trustworthiness is also malleable. Previous studies have shown assimilation in behaviour and preferences. For instance, Ichino and Maggi (2000) shows that internal migrants shirking behavior in a bank in Italy change with the host branch peers behaviour. Alesina and Fuchs-Schündeln (2007) shows that in Germany, immigrants from the East become more similar to Western Germans in preferences for government participation. Perez-Truglia (2018) shows that internal migrants in the U.S.

change their contributions to presidential campaigns depending on the share of people in the destination supporting the party. On the other hand, Atkin (2016) shows that internal migrants in India make sub-optimal food choices due to the persistence of their cultural preferences. Moreover, the paper provides a possible explanation for the assimilation in shirking behavior found in Ichino and Maggi (2000), which might have been driven by the change in trust.

Second, previous papers in the literature have found that trust is persistent across generations (Michalopoulos and Xue, 2021; Nunn and Wantchekon, 2011; Algan and Cahuc, 2010).[6] This paper shows that there is also substantial assimilation in trust that happens in very short periods for first generation immigrants.

Third, the papers studying assimilation in trust mainly focus on second or higher generation immigrants (Giavazzi et al., 2019; Ljunge, 2014; Moschion and Tabasso, 2014).[7] Notice, however, that these people are technically not immigrants, as they were born and raised in the destination. Hence, these papers study the weights that parents and the host environment have on their cultural traits. We can also think of assimilation as a *change* in people's cultural traits when they move to a new place. A few exceptions studying first generation immigrants are Jaschke et al. (2022), Marino Fages and Morales Cerda (2022) and Cameron et al. (2015). However, none of these papers observe migrants before arriving to destination which does not allow them to quantify the change that takes place within the individual. Hence, I complement the literature by providing causal evidence of assimilation as a *change* of first generation migrants in a relatively short period of time.

Fourth, by showing that assimilation is stronger for younger immigrants, I provide support for the impressionable years hypothesis in psychology, which "proposes that individuals are highly susceptible to attitude change during late adolescence and early adulthood and that susceptibility drops precipitously immediately thereafter and remains low throughout the rest of the life cycle" (Krosnick and Alwin, 1989).

The paper is organized as follows. Section II describes the field setting and data. Section III presents the empirical strategy. Sections IV and V present the results of the event study and the difference-in-differences, respectively. Section VI presents the heterogeneity analysis and

[6]For theoretical models explaining the persistence see Tabellini (2008b) and Guiso et al. (2008).

[7]See also Fernández and Fogli (2006), Fernandez (2007) and Giuliano (2007). These papers focus on second generation immigrants and argue that the descendants are "exogenously" allocated as the location decision was made by their parents.

Section VII concludes.

3.2 Field Setting and Data

Switzerland is a federal republic founded in 1848 and composed of 26 cantons that keep strong autonomy from the central government. The country has a system of direct democracy where people's initiatives and referendums at the federal, cantonal and municipal levels give citizens the chance to influence the institutions. In particular, the cantons have the powers related to their identity—such as culture, religion, language- and public health and cross border co-operation.[8] Furthermore, the number of referendums per year and the difficulty of proposing a popular initiative also varies between cantons (Rustagi, 2022; Frey and Schaltegger, 2021; Bühlmann et al., 2014; Barankay et al., 2003). These referendums generate institutional variation between cantons that accumulate over the years.

Despite its small physical space, Switzerland is also very culturally diverse. It has four official languages (German, French, Italian and Rhaeto-Rumantsch) and two main religions (Roman Catholic and Protestant). The cultural diversity is also driven by the differences in institutions (Alesina and Giuliano, 2015). In particular, Rustagi (2022) exploits a natural experiment in the middle ages that affected institutions to show that this shock had a long lasting effects on the cantons' culture.

On top of these differences, Switzerland has one of the highest shares of international immigrants among the western countries (according to the Swiss Federal Statistical Office, 30.5% of the population were immigrants in 2019) and a significant internal mobility (6% internal movers in 2019). Combined with the differences between the cantons in terms of culture and institutions, this makes Switzerland a particularly interesting setup for answering my research question, that is, do migrants assimilate their trust level to the local average when they move places?

[8] The federal state is responsible for monetary policy, foreign affairs, social security, customs and justice; and municipalities control mostly public service delivery -such as electricity, water and gas provision. Citizenship, education and taxes are split in the three levels (see https://www.wolf-linder.ch/wp-content/uploads/2010/11/Swiss-political-system.pdf). In some municipalities, even the citizenship is only granted after a vote by the locals (Hainmueller and Hangartner, 2013).

3.2.1 Measuring trust

Since the work of La Porta (1997) and Zak and Knack (2001), the generalized trust question has become the standard measure of trust (see Nunn and Wantchekon, 2011; Algan and Cahuc, 2010), which is found in many surveys such as the World Values Survey (WVS) or the European Social Survey (ESS).[9] [10] The exact wording is as follows: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" and respondents can answer from 0 to 10 where 0 means "Can't be too careful" and 10 means "Most people can be trusted".[11] A relevant question is who are these "most people". Sturgis and Smith (2010) shows that, when answering the question, 35% of respondents in Britain think of unknown others and only 2% think of people in the local area. This is important because one might worry that respondents are just considering a different set of "most people".

3.2.2 Data

I use data from the Swiss Household Panel (SHP). This is a survey conducted yearly in Switzerland and is representative of the Swiss population aged 14 and over with respect to major demographic variables. Importantly, the survey tracks respondents when they move to different locations. Furthermore, in 2002 they introduced the generalized trust question, and hence this is our starting period. Between 2002 and 2018, a total of 31773 individuals (in 12842 households) were surveyed by computer-assisted telephone interviews. Of these individuals, 3.84% of the Swiss citizens move within Switzerland, 6.84% returned from living abroad and 13.45% are not Swiss citizens. [12]

The SHP provides a unique opportunity for my study for three reasons.[13] First, the SHP is one of the longest panels asking the generalized trust question in the world. Second, the SHP

[9]This measure is attributed to Rosenberg, see Sturgis and Smith (2010).

[10]The experimental literature has shown that generalized trust captures expected trustworthiness (beliefs) and altruism in studies with real stakes (I discuss the findings of this literature in the Appendix).

[11]See Murtin et al. (2018) and Alesina and La Ferrara (2002) for reviews of its determinants.

[12]It is worth noting that only a small fraction (2%) of them acquire Swiss citizenship, and thus, almost all the internal movers are likely to have been born in Switzerland (see https://www.swissinfo.ch/eng/naturalisation--no-thanks_why-some-residents-choose-not-to-become-swiss/35624994).

[13]The WVS, ESS and the General Social Survey (GSS) are repeated cross sections; and the Global Preferences Survey (GPS) is only one cross section, and hence, they only observe migrants after they have moved, and only once. Other panel datasets are the German Socio Economic Panel (GSOEP), but it asks the trust question in some waves only and the UK Household Longitudinal Study (UKHLS) but only asks the trust question in the first wave.

contains a comparatively large number of migrants. Third, even when different parts of the country speak different languages, the migrants are interviewed in the same language before and after moving, which eliminates language effects.

In the next subsections I show that trust varies significantly among the cantons, describe the migration patterns and the main characteristics of the migrants, and finally present some initial evidence of the effect the host canton has on the migrant's trust level.

3.2.3 Trust in the cantons

The treatment I am analyzing in this paper is the effect of moving to a canton with a different average trust level than the one at the home canton. Hence, it is important to check if there is enough variation between the cantons' trust level. Throughout the analysis I compute the average level of trust in the cantons excluding migrants. Figure 2.1 and the map in Figure 2.2 show large variation in trust across cantons, even within the same language regions. Furthermore, these differences between the cantons are economically significant. To put it into perspective, the German speaking region is similar in terms of trust to Finland while the Italian speaking regions are similar to the trust in the United States.[14]

3.2.4 Internal migrants

I define internal migrants as Swiss citizens who moved from one canton to another between 2002 and 2018.[15] In practice, I identify them as migrants when the residence changes across survey waves. In order to have a cleaner comparison group and since the assimilation might take time to take place, I focus on migrants who moved only once (this accounts for 71.5% of the migrants in the sample). Note that people who move within the canton are not considered migrants for our purposes because I am interested in the effect of the change in the culture of the host culture which varies mainly at the canton level. Migrants represent roughly 0.81% of the sample each year.

In order to understand the migration patterns of internal migrants, I divide the cantons at the median level of trust (see Figure 2.1). Table 2.1 shows the flows of migrants from the cantons

[14]For this comparison, I use the wave 5 of the WVS, which, unfortunately is not desegregated at the canton level.

[15]Note that I assume that the canton of origin is the canton where respondents are observed in year 2002.

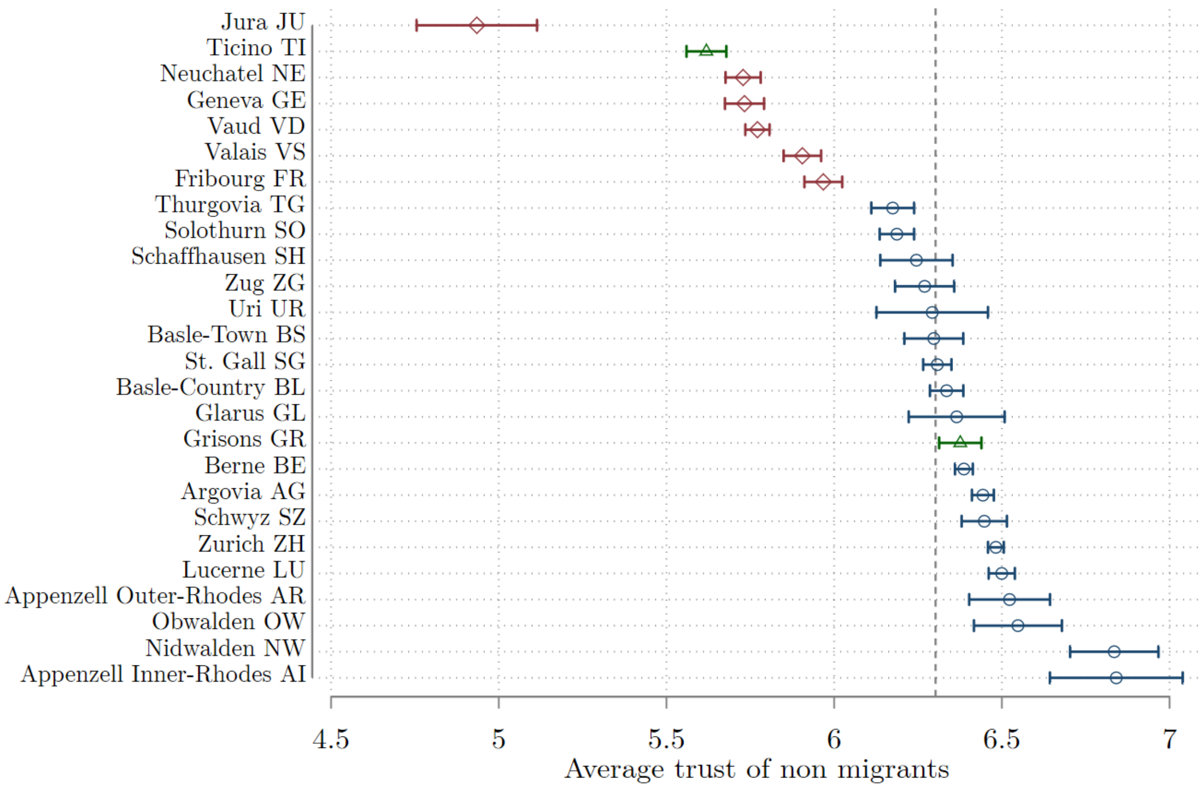

Figure 2.1: Trust in the cantons

The figure presents the average trust (individual responses range from 0 to 10) for all non-migrants in each canton over the period 2002-2018 with 95% confidence intervals. The vertical dashed line shows the median average trust among the cantons. Finally, the different colors and symbols depend on the language region.

below (low) and above (high) the median level of trust. Migrants from low trust cantons are equally split in both groups (48.7% moving to other low trust cantons and 51.30% moving to high trust cantons) but migrants moving from high trust cantons tend to go more to other high trust cantons (34.60% and 65.4%).

Table 2.1: Migration flows of internal migrants by canton trust level

		Trust in Destination		
		Low	High	Total
Trust in Origin	Low	48.7%	51.3%	100%
	High	34.6%	65.4%	100%
	Total	40.1%	59.9%	100%

The table shows the transition matrix from low/high trust canton of origin to low/high trust destination canton.

Since I am interested in the sign of the difference between the average trust at destination and average trust at the origin, I compute the percentage of people moving to a higher/lower trust canton. Table 2.2 shows that 44.65% of the migrants move to a lower trust canton and 55.35%

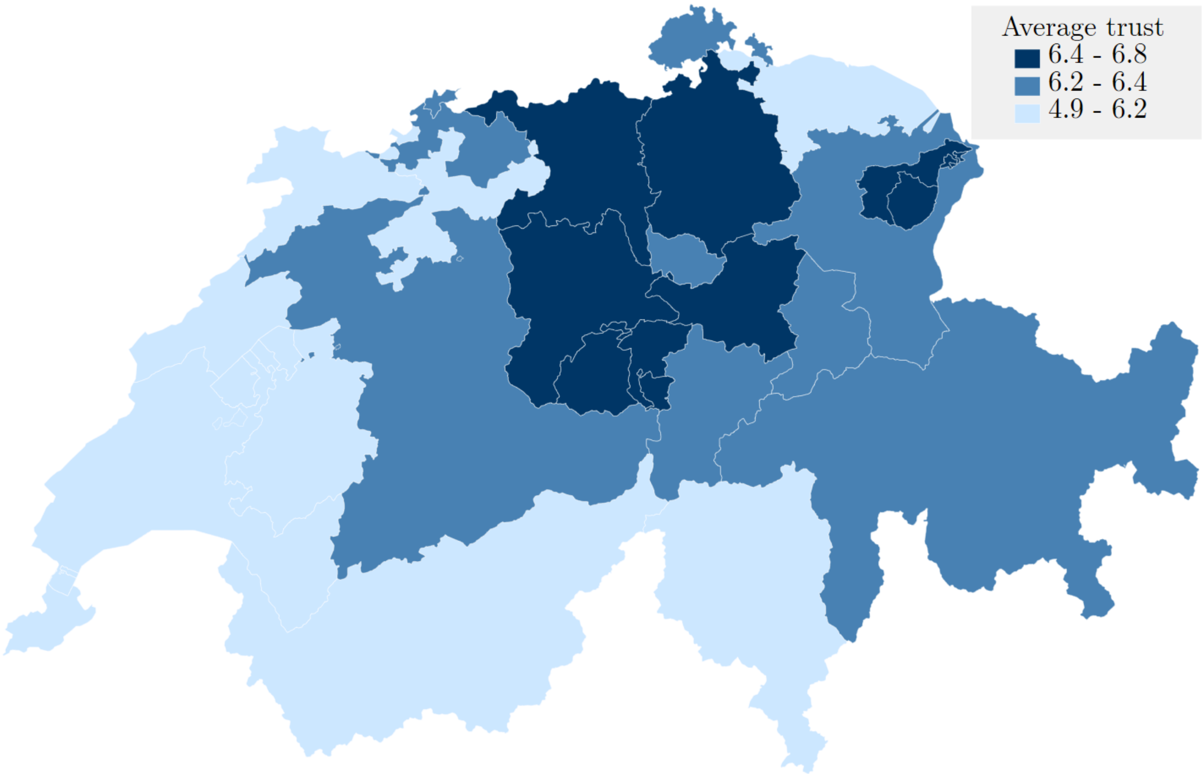

Figure 2.2: Trust in the cantons
The map presents the average of trust (individual responses range from 0 to 10), in three terciles, for all non-migrants in each canton over the period 2002-2018. White lines represent the canton borders.

move to a higher trust canton . The average size of the trust gap is similar in both groups. Finally, the last column shows the average trust level of each group in the last year before migration.

Attrition seems to be similar between migrants moving to a higher and lower trust cantons. Figure 2.A12 presents the attrition rates in both groups and Table 2.A11 in the Appendix presents a formal analysis showing that the level of trust in the destination canton has no effect on the attrition rate.

Table 2.2: Direction of the move and gap between the trust levels at origin and destination

		Percentage	Trust gap between origin and destination	Trust before migration
Moving to	lower trust canton	44.65%	-.22 (0.24)	6.32
	higher trust canton	55.35%	.22 (0.23)	5.92
	Total	100%	0.022 (0.32)	

The table shows the percent of migrants moving to higher or lower trust cantons compared to their canton of origin and the average gap between them, and the standard deviation in parenthesis. The last column presents the average trust level of each group in the last year before migration.

The left panel of Figure 2.3 shows the share of internal migrants coming from each canton while the right panel shows the share of internal migrants moving to each canton. It is clear that there is also substantial variation in the origin and destinations of the movers.

(a) Share of migrants from each origin (b) Share of migrants in each destination

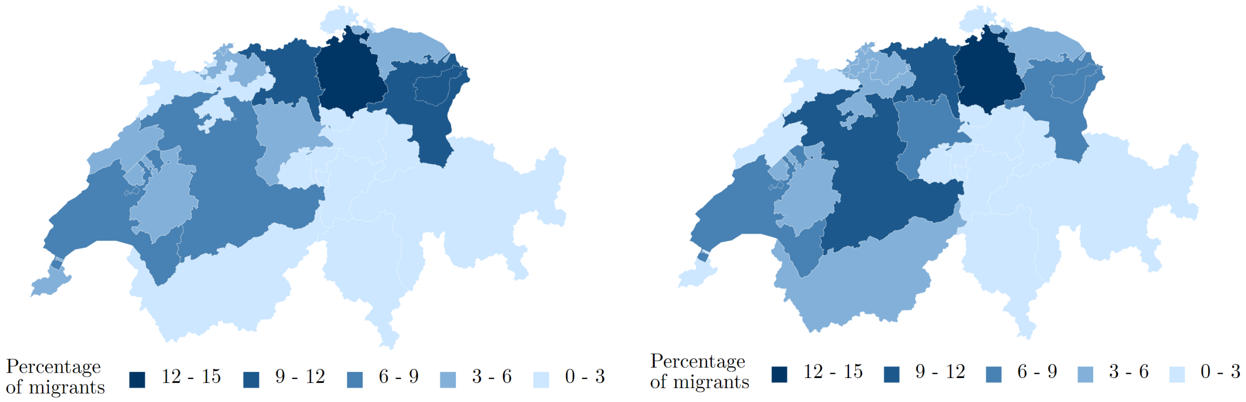

Figure 2.3: Canton of origin/destination of all migrants
The left map presents the percent of all internal migrants coming from each canton. The right map presents the percent of all internal migrants in each destination canton. White lines represent the canton borders.

3.2.5 Descriptive Evidence

Marino Fages and Morales Cerda (2022) shows that migrant's trust correlate strongly with average trust level in the host country but only after migrating (i.e., after being exposed and immersed in the country). Figure 2.4 shows similar evidence, each panel plots a binscatter of migrant's trust and average trust in the destination canton (in order to account for sorting effects, I control for canton of origin fixed effects)(see Figure 2.A1 in the Appendix for a non-parametric version of the binscatter plots). For this, I collapse all trust responses of each migrant by regressing the reported trust on calendar year dummies and average the residuals before and after migration by individual. Panel a shows the correlation for Internal migrants after migrating (controlling for canton of origin) and Panel b shows Internal migrants before migrating (controlling for canton of origin). Here I restrict to migrants moving between German cantons only to minimize the sorting effects. The pattern is clear, migrant's trust is highly correlated with the level of trust in the destination and there is no evidence of positive correlation before the migration occurs. Table 2.A7 in the Appendix shows the regression results including those for international migrants and controlling for more covariates. This pattern, however, cannot be interpreted as causal because it does not distinguish between sorting and assimilation. This is my task in the next section.

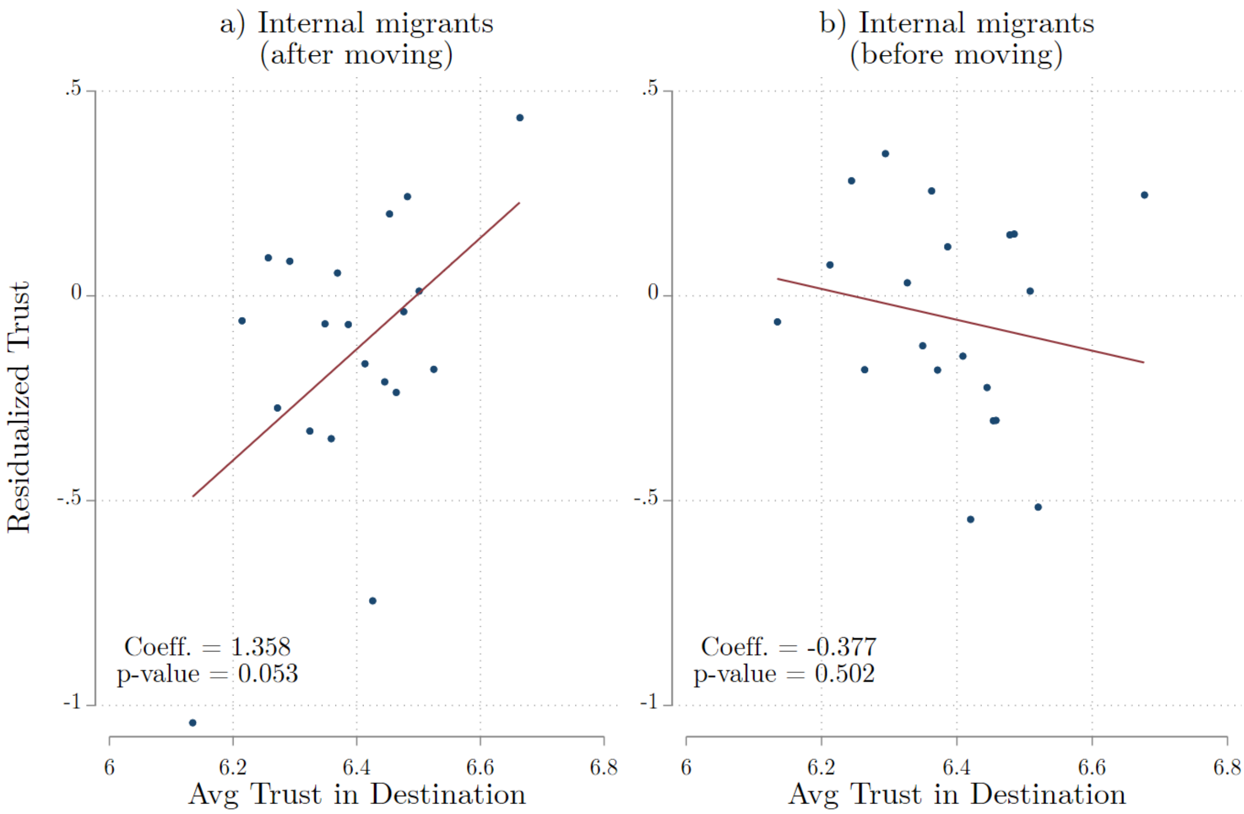

Figure 2.4: Correlation between Residualized Trust and Average Trust in the destination canton The figure presents binscatter plots of migrant's Residualized Trust and Average Trust in the destination canton (controlling for canton of origin) for internal migrants in German cantons after moving (left) and before moving (right). To compute the Residualized Trust, I first regress the Trust variable on calendar year dummies, and then average all the residuals by individual.

3.3 Empirical Strategy

I am interested in estimating the effect of the destination's trust level on migrants' trust. The main difficulty is to disentangle assimilation from sorting effects, i.e., migrants moving to specific locations *because* these locations have certain characteristics such as the trust level. This is challenging because typically there is no pre-migration data on migrants. I exploit the longitudinal feature of the SHP in two different ways. First, I perform an event-study analysis with a binary treatment (i.e., moving to higher/lower trust canton with respect to the canton of origin) (Callaway and Sant'Anna, 2021) and then a difference-in-differences approach with a continuous treatment (Callaway et al., 2021), where I exploit the full variation of trust across the cantons.

Traditionally, researchers using the event-study approach relied on static and/or dynamic two way fixed effects estimators (TWFE). However, a rapidly growing literature on difference-in-differences and event studies with variation in treatment timing has shown that one has to be careful in attaching a causal interpretation to these traditional estimators. Goodman-Bacon (2021) shows that these TWFE estimators recover a weighted average of all possible 2 x 2 difference-in-differences estimators for different group timings (this includes comparing treated units to those never treated, early treated and late treated). If the treatment evolves over time, some of those averages can take negative values because some already-treated units would act as control groups and their outcomes would also evolve over time. For this reason, I follow Callaway and Sant'Anna (2021), which solves the negative-weights issue by estimating *group-time average treatment effects* and tailoring the aggregation weights with specific purposes in mind (I return to this below). Using the potential outcomes notation, Callaway and Sant'Anna (2021) defines the group-time average treatment effect as

$$ATT(m,t) = \mathbb{E}[Y_t(m) - Y_t(0) | M_m = 1] \tag{3.1}$$

where m is defined by the time period when a migrant moves to a new canton, M_m is a binary indicator equal to 1 when a migrant moves in year m, $Y_t(m)$ are the potential outcomes (i.e., trust levels) that migrants would realize at times t, $t = 1, ..., \mathcal{T}$, had the migrant moved in year m, $Y_t(0)$ are the potential outcomes for migrants that have not yet moved by time t. In other words, $ATT(m,t)$ is the average treatment effect for the cohort that moved in year m, in year t. Then, if we fix m we can see how the average treatment effect evolves over time t.[16] As I discuss in detail below, the main assumption to estimate each $ATT(m,t)$, is that migrants who move at a later time are a good counterfactual for those migrating earlier.

In practice, the $ATT(m,t)$ parameter can be obtained by first restricting the data to only contain observations at time t and $m-1$ from units where $M_m = 1$ and those that have not-yet-moved by time t, and then, using only the observations in this subset, running the linear regression[17]

[16] Instead, one could also fix t and see whether the average treatment effect is different for different cohorts m.

[17] I omit the sub-index i to simplify notation.

$$Y_t = \alpha_1^{m,t} + \alpha_2^{m,t} \cdot M_m + \alpha_3^{m,t} \cdot 1[T = t] + \beta^{m,t} \cdot (M_m \cdot 1[T = t]) + \epsilon^{m,t} \tag{3.2}$$

where $\beta^{m,t} = ATT(m,t)$.[18] Note that this is a standard difference-in-differences estimator with two periods. $\alpha_1^{m,t}$ is the baseline average of the control group (i.e., those that have not yeat migrated by year t), $\alpha_2^{m,t}$ is the baseline difference between the treated group (i.e., the migrants that moved in year m) and the control group. $\alpha_3^{m,t}$ is the time trend. Finally, $\beta^{m,t}$ is the difference-in-differences estimator and $\epsilon^{m,t}$ is an individual-time specific error term.

In order to use an event-study design, and prevent the effect from cancelling out, I split the sample based on whether migrants move to a higher or lower trust canton and run two separate regressions. This also works as a robustness check, since there is no mechanical reason to find that the effects mirror each other in both regressions (Cullen and Perez-Truglia, 2019). Another advantage of the methodology is that it allows me to control for time-constant covariates. I run an alternative specification controlling for the trust gap (i.e., the difference in average trust level in origin and destination canton).

Four assumptions are necessary for identification of these parameters. First, irreversibility of the treatment. In my case, this means I don't have migrants returning to their home cantons (nor migrants moving to a different level of trust canton). Second, random sampling, which imposes that each migrant is randomly drawn from a large population of interest, i.e., all migrants. Third, no treatment anticipation, that is, moving has no effect on migrants' before the actual move. Fourth, unconditional parallel trends based on not-yet-treated groups (in the Appendix I repeat the analysis assuming parallel trends conditional on size of the shock, income and education). This means that the average outcome (trust in my case) for the group m follows a parallel trend with groups that are not-yet-treated (i.e., not-yet-migrated) by time t.

I am interested in how the assimilation vary with the length of stay in destination, but I would also like to know the overall assimilation in the sample. Thus, I aggregate the ATT's in two different ways that are analogous to the traditional dynamic and static TWFE estimators. Equation 3.3 presents the first measure. $\theta_{es}(e)$ is the average effect of moving to a higher/lower

[18] Alternatively, one could use the interacted TWFE regression proposed by Sun and Abraham (2021).

trust canton of all migrants that moved and lived in the host canton for exactly e years.[19] This measure consists of three parts: $1[m+e \leq \mathcal{T}]$ takes the value 1 if migrants are observed for up to e periods after migrating; $P(M=m|M+e \leq \mathcal{T})$ is the weight of each group in the subset of migrants that are observed for up to e periods after migrating; and $ATT(m, m+e)$ is the group-time average treatment effect for group m in year $m+e$.

$$\theta_{es}(e) = \sum_{m \in \mathcal{M}} 1[m+e \leq \mathcal{T}] P(M=m|M+e \leq \mathcal{T}) ATT(m, m+e) \tag{3.3}$$

The second measure is presented in Equation 3.4. θ_{sel}^{O} estimates the effect for each group m first, and then averages across all groups. This avoids putting more weight on the observations that are observed for a longer period and can be interpreted as the canonical two-period difference-in-differences setup over the entire sample. It consists of two parts. $\theta_{sel}(m) = \frac{1}{\mathcal{T}-m+1} \sum_{t=m}^{\mathcal{T}} ATT(m,t)$ is the average effect of moving for the cohort moving in period m, across all post moving periods. The other part, $P(M=m|M \leq \mathcal{T})$ are the weights applied to each cohort in the aggregation.

$$\theta_{sel}^{O} = \sum_{m \in \mathcal{M}} \theta_{sel}(m) P(M=m|M \leq \mathcal{T}) \tag{3.4}$$

where $\theta_{sel}(m)$ is the average effect of moving among units in group (m), across all their post moving periods; and $\mathcal{M}$ is the last year for which there is still a non treated group available. For inference I rely on the bootstrap method proposed in Callaway and Sant'Anna (2021), and report simultaneous confidence intervals (instead of pointwise) which do not suffer from multiple testing problems and are guaranteed to cover all ATT's with a probability at least $1-\alpha$. Due to the small number of clusters, I provide three types of standard errors. That is, robust, clustered at the canton of origin and clustered at the destination canton (see the Appendix). Since the data contains some gaps, I interpolate the trust variable linearly and perform a sensitivity analysis in the Appendix with no interpolation and other interpolation methods (nearest neighbour splines and forward).

To complement the previous analysis, I combine all migrants in one regression. For this, I follow Bertrand et al. (2004) and collapse all periods in pre- and post-move and perform a

[19] Note that these estimators may include compositional changes (see Callaway and Sant'Anna (2021)). I run robustness tests in the Appendix.

standard difference-in-differences approach with a continuous treatment (see Callaway et al., 2021; Perez-Truglia, 2018; Angrist and Imbens, 1995). I do this for several reasons. First, it allows me to directly exploit the trust variation between the host cantons in the identification. Second, it allows me to control for time varying covariates and explore heterogeneity in a simpler fashion. Third, it reduces measurement error by averaging over repeated measures of the trust responses. Fourth, it serves as a robustness check to my sample split. Formally, I regress

$$Trust_{it} = \alpha_i + \beta_1 Post_t * AvgTrust_{it} + \beta_2 Post_t + \epsilon_{it} \tag{3.5}$$

where $Trust_{it}$ is the residualized trust level for individual i at time 0 or 1, $AvgTrust_{it}$ is the average level of trust in the host canton, $Post_t$ is an indicator taking the value 1 after moving, and ϵ_{it} individual-time specific error term. α_i stands for individual fixed effects and β_1 is our coefficient of interest. I interpret this effect as the *average causal response on the treated* (ACRT) to an incremental change in the dose, where the dose is the trust level in the host canton. The main identification assumption in this case is the strong parallel trends, i.e., for all doses, the average change in outcomes over time across all migrants had they migrated to a particular dose (i.e., trust level at destination) is the same as the average change in outcomes over time for all migrants that experienced that dose, conditional on observables and time invariant characteristics (see Callaway et al., 2021).[20]

Finally, I conduct three robustness checks. First, I run a placebo using non-migrants, assigning a random moving year between (2003-2017) to nonmovers and find no systematic change in their trust level. Second, , to address concerns about the reflection problem (i.e., the fact that the migrants could simultaneously have an effect on the local peoples' trust)(Manski, 1993), I consider the level of trust in the cantons in the year 2002 (i.e., before any migration in the sample occurs) as the independent variable of interest and find that the results remain unchanged. Third, I find no assimilation for trust in the federal government, which alleviates concerns about the results being driven by mechanical aspects of the survey implementation.

[20]Formally, let d be the dose and Y_t be the potential outcome in time t. Then, strong parallel trends implies that for all d in D: $E[Y_t(d) - Y_{t-1}(0)] = E[Y_t(d) - Y_{t-1}(0)|D = d]$.

3.4 Results: Event Study

As explained in the previous section, I split the sample in migrants who moved to a higher and lower trust cantons. Panel (a) and (b) in Figure 2.5 present the event study analysis (Eq. 3.3) for each sub-sample (see tables 2.A1 and 2.A4 in the Appendix for the regression results). Both figures show parallel trends in the periods before moving as shown by the estimates being close to zero. I find that moving to a higher trust canton has a positive effect on the trust level reported by the migrant. Similarly, moving to a lower trust canton has a negative effect. The fact that both figures mirror each other gives extra credibility to my results because they are two completely disjoint tests (Cullen and Perez-Truglia, 2019). The effects seems to increase over time, supporting the use of the estimators proposed by Callaway and Sant'Anna (2021). Figure 2.A2 in the Appendix presents a placebo test where I assign random destination cantons and moving dates (2003-2017) to each non-migrant. Even with significantly smaller confidence intervals (due to the larger sample size), the figure confirms that non-migrants do not change their trust level after the randomly assigned date. Tables 2.A2, 2.A3, 2.A5, 2.A6 in the Appendix show that the results are qualitatively similar if we aggregate by migration cohort or calendar year. The Appendix, also presents the event study graphs clustering standard errors at the canton of origin and destination, without interpolating the data (and using other interpolation methods), and controlling for the difference in trust between the canton of origin and destination. In all cases, the graphs look remarkably similar.

Since I am also interested in the overall effect, I aggregate the ATTs in one estimate following Eq. 3.4. The overall effect of moving to a higher trust canton is 0.323 (p-value=0.035) and to a lower trust canton is -.223 (p-value=0.059). In terms of standard deviations this means an increase (decrease) in trust of 0.16 standard deviations (0.11 standard deviations). This is a large effect if we consider that the point estimates are larger than the average gap between the canton of origin and destination (see Table 2.2). This assimilation takes place in an average of 5 years.

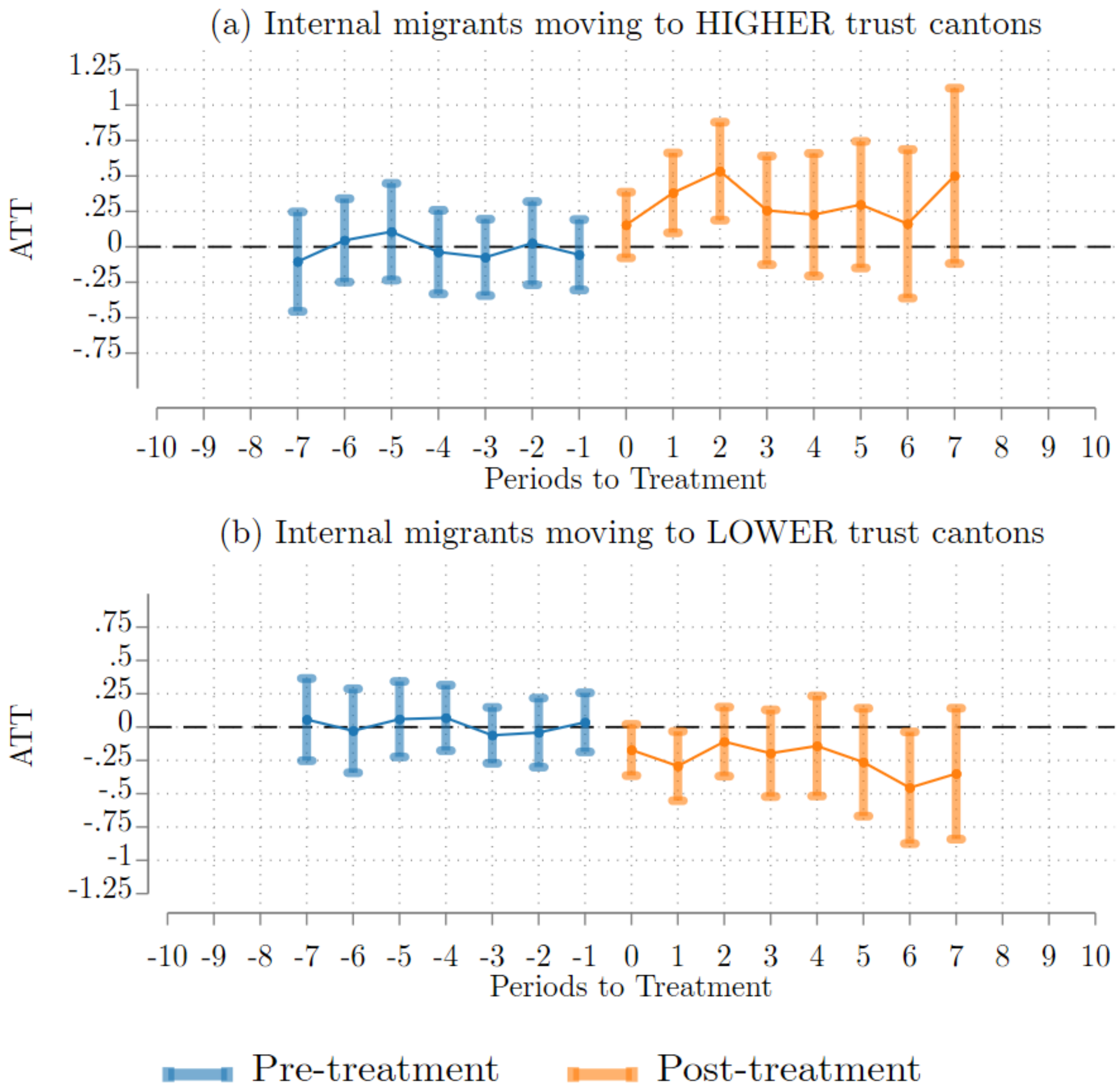

Figure 2.5: Event study

Panel (a) and (b) present the event study results of each ATT on trust for the migrants moving to a HIGHER and LOWER cantons. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors. I fill the gaps in trust in the survey by interpolating from the nearest neighbour. Results remain similar with clustered standard errors, with no interpolation and using other interpolation methods (forward, linear, splines), and controlling for the size of the shock (See Appendix). The analysis was performed using the Stata command csdid (Rios-Avila et al., 2021).

3.4.1 Robustness

In the previous subsection, I have shown graphically that the parallel trends condition is satisfied (i.e., the $\theta_{es}(e)$ estimates from the pre migration periods are indistinguishable from zero for both, migrants going to higher or lower trust cantons). In Table 2.3, I check whether early and late migrants are also similar before migration in terms of observable characteristics. I define late migrants as those who migrate on or after 2011. The top (bottom) panel compares early and late migrants going to higher (lower) trust cantons. None of the differences are economically nor statistically significant at the conventional levels, which reassures the validity of our counterfactual group.

Table 2.3: Early vs late migrants

	Early Movers		Late Movers			
	N	Mean (s.d.)	N	Mean (s.d.)	Coeff.	p-value
Moving to HIGHER trust canton						
Age	189	37.89	280	35.45	-2.445	0.10
		(15.07)		(17.16)		
Female	189	0.53	280	0.50	-0.038	0.42
		(0.50)		(0.50)		
Married	189	0.33	280	0.28	-0.050	0.23
		(0.46)		(0.43)		
Income (CHF)	158	51818.99	233	47152.29	-4,666.697	0.29
		(35288.32)		(51305.36)		
Education (years)	188	13.38	260	13.37	-0.009	0.97
		(2.84)		(3.07)		
HH Size	125	2.26	146	2.12	-0.144	0.33
		(1.32)		(1.08)		
Moving to LOWER trust canton						
Age	157	37.14	273	37.09	-0.053	0.97
		(16.13)		(15.96)		
Female	157	0.55	273	0.52	-0.037	0.46
		(0.50)		(0.50)		
Married	157	0.38	273	0.33	-0.053	0.25
		(0.47)		(0.45)		
Income (CHF)	124	52000.03	223	49254.88	-2,745.147	0.46
		(33289.02)		(33455.39)		
Education (years)	155	13.13	248	13.60	0.465	0.12
		(2.75)		(3.24)		
HH Size	93	2.26	153	2.27	0.012	0.94
		(1.27)		(1.31)		

The table shows the number of observations, means, standard deviations, coefficients and p-values of regressing each variable on an indicator that takes the value 1 for late migrants and 0 for early migrants. Late migrants are migrants who moved on or after 2011. The top (bottom) of the table describes internal migrants moving to HIGHER (LOWER) trust cantons.

3.5 Results: Difference in Differences

Another standard approach is to collapse all the data in periods before and after the migration occurs and perform a standard difference-in-differences analysis with two periods and a continuous treatment. In particular, I follow Bertrand et al. (2004) and regress the trust variable on interview year dummies and take the average of the residuals as my new outcome variable. I do this separately for periods before and after migration. This approach has several advantages. First, I avoid splitting the sample and exploit the intensity of the treatment directly in the identification. Second, it allows me to control for two important time varying covariates, i.e., income and education (two of the most important determinants of individual trust according to Alesina and La Ferrara (2002)). Third, it is easy to interpret and study heterogeneity. Finally, the method accounts for serial correlation and I reduce measurement error by keep migrants with 3 or more observations before and after moving.

3.5.1 Balance tests

In the previous section, I have shown that there are no pre-trends in trust within migrants going to higher or lower trust cantons than their origins. But migrants moving to higher and lower trust cantons may differ in many ways that might confound the analysis. For instance, if trust increases with income (or education) and migrants that get richer (more educated) when they move to higher trust cantons, I might mistakenly conclude that moving to such cantons has a positive effect on trust. For this reason, I start by testing the difference in important observable characteristics across the sets of migrants (i.e., age, gender, civil status, years of education, income, number of people in the household). Table 2.4 (top) shows that, before moving, internal migrants in the high and low trust cantons are very similar. The only statistically significant variables are education and household size. Table 2.4 (bottom) compares internal migrants in high and low trust destination cantons. None of the variables is statistically significant, including years of education and size of the household which balanced out after migration.

Table 2.4: Balance tests for Internal migrants

	Low Trust		High Trust			
	N	Mean (s.d.)	N	Mean (s.d.)	Coeff.	p-value
Before moving						
Age	444	35.44	767	34.89	-0.550	0.57
		(15.82)		(16.49)		
Female	444	0.53	767	0.53	0.009	0.76
		(0.50)		(0.50)		
Married	444	0.30	767	0.29	-0.012	0.64
		(0.44)		(0.44)		
Income (CHF)	368	48,845	633	46,080	-2,765	0.30
		(42,910)		(36,780)		
Education (years)	422	13.50	737	12.80	-0.698	0.00
		(3.56)		(3.12)		
HH Size	261	2.10	406	2.30	0.200	0.03
		(1.10)		(1.31)		
After moving						
Age	522	41.14	810	40.65	-0.496	0.58
		(15.49)		(16.73)		
Female	522	0.53	810	0.54	0.010	0.72
		(0.50)		(0.50)		
Married	522	0.39	810	0.37	-0.013	0.61
		(0.46)		(0.46)		
Income (CHF)	452	61,044	706	61,988	944	0.70
		(39,163)		(41,348)		
Education (years)	522	14.53	810	14.40	-0.125	0.48
		(3.21)		(3.07)		
HH Size	434	2.10	694	2.13	0.030	0.63
		(1.02)		(1.05)		

The table shows the number of observations, means, standard deviations, coefficients and p-values of regressing each variable on an indicator that takes the value 1 for respondents in cantons with trust above the median and 0 for respondents in cantons with trust below the median. The top (bottom) of the table describes internal migrants before (after) moving.

3.5.2 Results

Table 2.5 presents the results of the difference in differences regressions (Eq. 3.5). Column 1 shows the results with no covariates. Column 2 controls for income, education and age (which are arguably the main time varying confounders). Note that age is the average age in all the periods in which the migrant is observed either before or after migration, hence, the difference is also a proxy for the time gap between the periods. The results are in line with the event study, an increase in one standard deviation in the canton's average trust increases individual trust of the migrant by 0.43 standard deviations, the result is virtually unchanged when adding the controls. Table 2.A9 in the Appendix shows that the effect almost identical for men for women in split regressions. I also note that there is no effect of migration itself, captured in the "Post move" variable.

Table 2.5: Difference in differences results

VARIABLES	(1) Trust	(2) Trust	(3) Trust	(4) Trust	(5) TrustFed	(6) TrustFed
Avg trust in canton X Post move	0.489	0.432				
	(0.204)	(0.212)				
Avg trust in canton (2002) X Post move			0.408	0.428		
			(0.152)	(0.169)		
Avg fed trust in canton X Post move					0.004	0.016
					(0.442)	(0.465)
Post move	-0.005	-0.063	0.107	0.048	0.032	0.118
	(0.030)	(0.139)	(0.046)	(0.136)	(0.034)	(0.178)
Age		0.014		0.015		-0.006
		(0.019)		(0.019)		(0.023)
Education (years)		0.008		0.007		-0.025
		(0.018)		(0.018)		(0.021)
Log(income)		-0.085		-0.088		-0.035
		(0.045)		(0.044)		(0.048)
Constant	-0.046	0.237	-0.046	0.253	-0.037	0.882
	(0.015)	(0.792)	(0.015)	(0.781)	(0.017)	(1.016)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	726	676	726	676	624	612
R-squared	0.890	0.883	0.891	0.885	0.873	0.874

The table presents OLS estimates of regressing migrants Trust (FedTrust) on the average trust in the canton (Equation 3.5). Trust (FedTrust) is the individual average of the residuals of regressing individual trust in strangers (trust in the federal government) on year dummies. The main independent variable is the average trust in strangers (trust in the federal government) in the host canton either measured over the period 2002-2017 or 2002 only. Columns 1 and 2 present the main specification. Columns 3 and 4 use the average trust in the canton as measured in 2002 only. Columns 5 and 6 use the trust in the federal government instead of trust in strangers. All regressions include individual fixed effects. Standard errors (in parentheses) clustered at the individual level. Income is measured in Swiss Francs.

A pervasive issue in the literature of endogenous social effects is that of the reflection problem that arises when one wants to infer whether the average behavior in some group influences the behavior of the individuals that are part of it (Manski, 1993). In my case, it is possible that the migrants are also affecting the local people trust level, making both variables to move together. To explore this possibility, I compute the average trust in the cantons using responses from the year 2002 only (i.e., before any of the migrants in the sample move). The idea is that the trust level in a canton should not be affected by the migrants before they arrive. [21] Columns 3 and 4 show an effect of identical size and statistically more precise.

Finally, since I am worried that the response to trust is capturing anything mechanical of how people respond to questions in different locations (although the interview language do not change regardless of the canton the respondent is living at the time), I repeat the analysis for trust in the federal government (columns 5 and 6).[22] I find that migrants do not adapt their responses regarding their trust in the federal government, which alleviates my concern. One possible interpretation of these results is that the views about the federal government are not affected as much as the generalized trust because it relates to others' *beliefs* as opposed to others' *behavior* and these political beliefs might be more difficult to transmit and learn.

3.6 Heterogeneity

In previous sections I showed that *on average* internal migrants assimilate their trust level towards the local level (i.e., $\beta_1 > 0$ in Eq. 3.5). However, underlying this average treatment effect there might be some variation in how individuals respond to the shock caused by migrating to a place with a different level of general trust (i.e., different βs for different individuals). I am interested in the following questions: a) Do all immigrants assimilate? b) Do some migrants assimilate more than others? c) What are the main characteristics explaining these differences? Exploring this is important for at least three reasons. First, it can provide insights on the mechanisms by which the assimilation occurs. Second, it can be useful to assess the generalizability of the results to other contexts (e.g., predicting assimilation of international migrants). Third, it can provide insights to design and target policies efficiently to either facilitate assimilation of the least affected groups or consolidate the most affected groups.

To explore these questions I compute the Sorted Partial Effects (SPEs) proposed by Cher-

[21]Of course, they might be affected by migrants who moved on or before 2002 that I cannot observe.

[22]I show the variation of trust in the federal government in the Appendix.

nozhukov et al. (2018).[23] In my difference-in-differences analysis, the coefficient $\beta_1 = \frac{\delta Trust}{\delta(Post*AvgTrust)}$ represents the average partial effect (APE) (also known as average treatment effect). Instead, the sorted partial effects method reports the entire range of conditional average treatment effects (CATEs) sorted in increasing order and indexed by a ranking $u =\in [0, 1]$ with respect to the population of interest.

Since the method is designed for cross-sectional data, I regress

$$\Delta Trust_i = \gamma_0 + \gamma_1 AvgTrustDest_i + \gamma_2 AvgTrustOrig_i + \gamma_3 \Delta X_i + \\ + \gamma_4 AvgTrustDest_i * \Delta X_i + \gamma_5 AvgTrustOrig_i * \Delta X_i + \mu_i \quad (3.6)$$

where $\Delta Trust_i$ is the first difference of the residualized trust level for individual i, $AvgTrustDest_i$ is the average level of trust in the host canton, $AvgTrustOrig_i$ is the average level of trust in the canton of origin, ΔX_i is a vector of first differences of time varying characteristics (i.e., age, education and log of income), and μ_i is an individual specific error term.

Figure 2.6 presents the average treatment effect (black line) and the SPEs (blue line) with 90% bootstrap uniform confidence intervals. Although these intervals are very broad, we see that all point estimates are positive. The SPE crosses the APE at the 70th percentile, which presents some evidence of heterogeneity. Following Chernozhukov et al. (2018), Table 2.6 compares the 25% that assimilated the most with the 25% that assimilated the least. Again, the standard errors are very large but the estimates are economically significant. For instance, the 25% who adapted the most are more likely to be female and 24 years younger which is consistent with the impressionable years hypothesis which "proposes that individuals are highly susceptible to attitude change during late adolescence and early adulthood and that susceptibility drops precipitously immediately thereafter and remains low throughout the rest of the life cycle" (Krosnick and Alwin, 1989) (I explore this further below). The 25% who adapted the most also have a larger difference between the average age before and after migration which is a proxy for time of exposure to the new environment. This is consistent with Marino Fages and Morales Cerda (2022) and reassures the assimilation argument. Furthermore, a novel result is that these 25% seem to be also poorer and have less years of education but with a higher

[23]For this I use the R package SortedEffects (Chen et al., 2019).

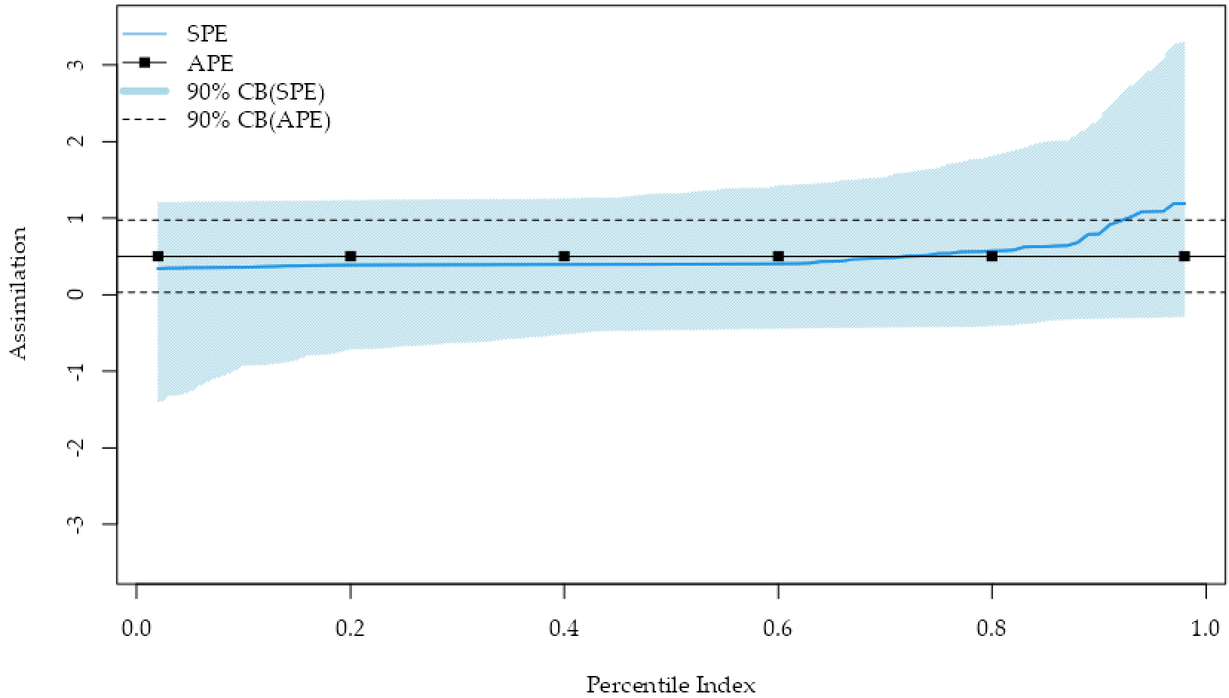

Figure 2.6: APE and SPE of host canton average level of trust on migrants' trust
The figure shows the average partial effect (APE) and sorted partial effects (SPEs) from Chernozhukov et al. (2018). Estimates and 90% bootstrap uniform confidence intervals based on Eq. 3.5 controlling for age, education, log of income and individual fixed effects (as in column 2 of Table 2.5); and interactions of the treatment variable with gender, average time between the measures, age of moving, and the level of education and log of income before migratin three forms: the value pre move, after move and the difference. The plot was made using the R package SortedEffects (Chen et al., 2019).

increase in income and education after migration. This is partially in contrast with Jaschke et al. (2022), which finds that refugees who assimilate the most culturally do not exhibit faster economic convergence. Finally, there does not seem to be a difference between the trust at the canton of origin or destination.

The previous analysis serves as a data driven approach to identify the most relevant characteristics of those who adapt the most *versus* those that adapt the least. I now look at this from a different angle by splitting the sample according to pre move income and age at moving (Table 2.A9 in the Appendix shows no clear difference by gender). First, I run the regression from Eq. 3.5 for three different migration age groups, i.e., 14-31, 32-49 and 50-90 years old. Figure 2.7 shows clear results. The effect is strongest for the youngest migratns. This is important because, in most contexts, the vast majority of migrants move between the ages of 15 and 29

Table 2.6: Bias corrected mean characteristics of the 25% who assimilated the most and the least

Variables	Most	Least	Difference	JP-value	P-value
Trust	-0.04	0.13	-0.16	0.89	0.14
	(0.09)	(0.10)	(0.15)		
Female	0.68	0.56	0.13	0.86	0.12
	(0.19)	(0.24)	(0.43)		
Age when moved	22.85	45.11	-24.26	0.61	0.04
	(5.64)	(6.95)	(12.21)		
Year difference	7.31	4.44	2.87	0.94	0.18
	(0.70)	(1.20)	(1.74)		
Log(income) before moving	8.80	11.27	-2.48	0.30	0.01
	(0.51)	(0.32)	(0.80)		
Difference in log(income)	1.95	-0.62	2.57	0.53	0.03
	(0.55)	(0.34)	(0.87)		
Education (years) before moving	11.23	14.59	-3.36	0.14	0.00
	(1.08)	(1.44)	(2.39)		
Difference in education years	5.11	-0.52	5.63	0.10	0.00
	(0.99)	(0.52)	(1.38)		
Avg trust in origin	6.27	6.22	0.06	0.99	0.28
	(0.02)	(0.01)	(0.02)		
Avg trust in destination	6.27	6.30	-0.03	0.99	0.28
	(0.01)	(0.01)	(0.01)		

The table presents the estimates, differences and bootstrap standard errors (in parenthesis) for the most and least assimilated migrants. The last two columns present the JP-value, which accounts for simultaneous inference of all variables; and the P-value, which stands for pointwise p-values. Trust is the individual average of the residuals of regressing trust in strangers on year dummies before and after migration. Year difference is the difference between the average year before and after migration.

years old (Milasi, 2020). Second, I rank the pre move income levels and split it in three equal group sizes. Figure 2.8 shows that the effect is driven by the poorer group. Note, however, that income and age are highly correlated and, thus, the results should be interpreted with care.

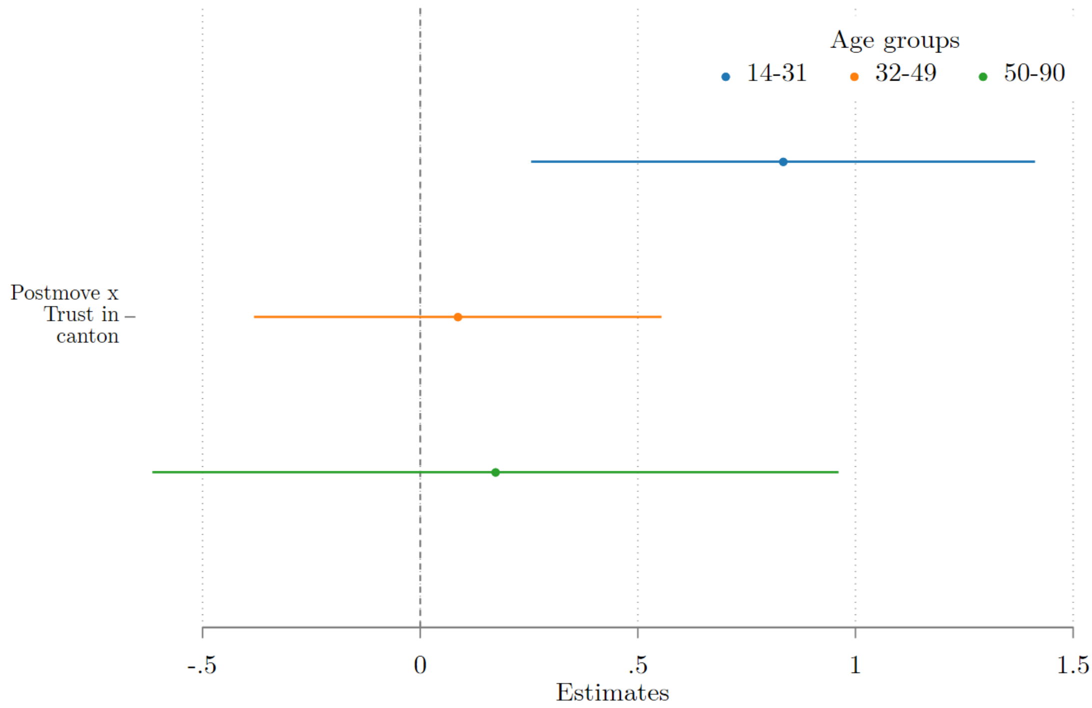

Figure 2.7: Assimilation effects for different moving age groups
The figure shows the coefficients of Equation 3.5 for different samples. The dependent variable is the individual average of the residuals of regressing trust on year dummies. The independent variable is the average trust level in the host canton. 95% confidence intervals computed using clustered standard errors at the individual level.

3.7 Conclusion

When migrants arrive in a new country, they face the challenge of inserting themselves into society. This implies joining the labour market, learning the language and culture, marrying, making friends, and so on. At the same time, trust, as a component of culture, has been shown be a predictor of many desirable social, political and economic outcomes. In this paper, I study how first generation internal migrants in Switzerland assimilate in their trust levels towards the average trust of the locals. The main challenge in this kind of research lies in disentangling assimilation from sorting. In general, it is hard to find longitudinal datasets following first generation immigrants over time (Abramitzky et al., 2020), especially if we are interested in

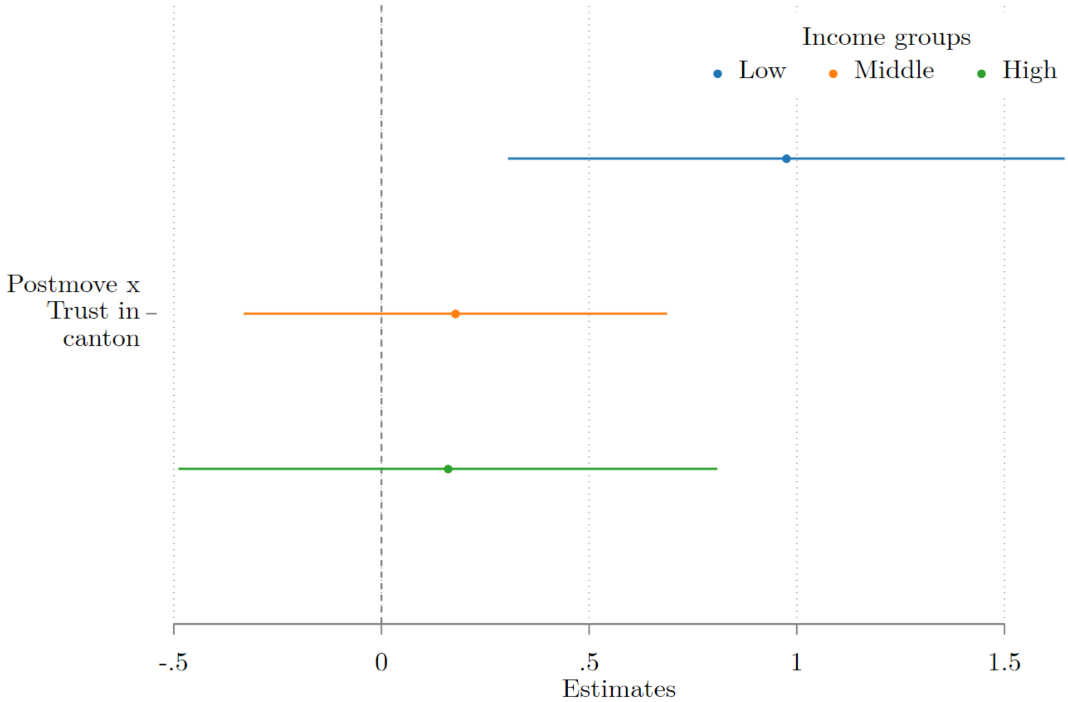

Figure 2.8: Assimilation effects for different pre move income groups
The figure shows the coefficients of Equation 3.5 for different samples. The dependent variable is the individual average of the residuals of regressing trust on year dummies. The independent variable is the average trust level in the host canton. 95% confidence intervals computed using clustered standard errors at the individual level.

observing pre-migration information. In fact, even for non migrants, it is uncommon for surveys to ask the generalized trust question more than once to the same individual.

The unique panel characteristic of the Swiss Household Panel allows me to provide *causal* evidence on migrants' assimilation in their trust level towards the local level. This is because I can combine the 17-year-panel with people moving between places with large cultural differences in a difference-in-difference approach. Migrants moving to higher (lower) trust cantons have parallel trends in trust and balance in other demographics before moving. Furthermore, early and late migrants are also balanced in demographics. These evidence allows me to identify a causal effect of moving to a canton with a different level of trust.

I find a large change in the migrants' trust, that is, migrants moving to a higher trust canton increase their trust by 0.16 standard deviations whereas migrants moving to lower trust cantons decrease their trust by 0.11 standard deviations. This assimilation takes place in an average of 5 years. Using the difference-in-differences approach with the continuous treatment, I find that, migrants increase their trust in 0.43 standard deviations for each standard deviation increase in the trust level at the destination. The results are unchanged if I consider the level of trust in the cantons in the year 2002 (i.e., before any migration in the sample occurs), which eases concerns about the reflection problem. I also show that the results are not driven by differential attrition, as the attrition rate is similar for migrants in higher and lower trust cantons. On the other hand, I find no assimilation for trust in the federal government, confirming that my results are not driven by aspects of the survey implementation.

I further explore heterogeneity in the assimilation using the data driven method by Chernozhukov et al. (2018) and find that the 25% who adapted the most are more likely to be female and 24 years younger (supporting the impressionable years hypothesis in psychology (Krosnick and Alwin, 1989)), have spent more year in the host canton, are poorer and have fewer years of education but with a higher increase in income and education after migration. Finding more robust evidence on these heterogeneities in assimilation not only would be helpful to inform international migration policy but also to correct native's missperceptions about immigrants' assimilation (Alesina and Tabellini, 2022).

Lastly, it is noteworthy to mention that, the setting does not allow me to understand whether migrants' assimilation is due to the locals' trust or the locals' trustworthiness. Since, in general, both characteristics have a positive correlation, it would be interesting to explore their relative weights. Kim et al. (2022) studied this in an experimental setting and found that people make the same inferences from the trusting as from the trustworthiness of others. Further research should study this in a real world setting.

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3.9 Appendix

3.9.1 Event study results: Moving to higher trust cantons

Table 2.A1: Results from event study analysis with migrants moving to higher trust cantons

	Coef.	s.e.	P-value	C.I. low	C.I. high
Pre migration average	-0.013	0.025	0.592	-0.062	0.035
Post migration average	0.314	0.165	0.057	-0.010	0.639
Tm7	-0.104	0.179	0.560	-0.455	0.246
Tm6	0.046	0.150	0.760	-0.248	0.340
Tm5	0.107	0.174	0.540	-0.235	0.448
Tm4	-0.037	0.150	0.807	-0.332	0.258
Tm3	-0.074	0.137	0.589	-0.344	0.195
Tm2	0.026	0.150	0.862	-0.267	0.319
Tm1	-0.056	0.127	0.659	-0.304	0.192
Tp0	0.154	0.118	0.192	-0.077	0.386
Tp1	0.381	0.144	0.008	0.099	0.663
Tp2	0.534	0.176	0.002	0.189	0.880
Tp3	0.257	0.196	0.188	-0.126	0.641
Tp4	0.227	0.221	0.303	-0.205	0.659
Tp5	0.298	0.228	0.191	-0.149	0.744
Tp6	0.163	0.267	0.543	-0.362	0.687
Tp7	0.501	0.316	0.112	-0.118	1.120

	Coef.	s.e.	P-value	C.I. low	C.I. high
ATT	0.323	0.153	0.035	0.022	0.623

The table presents the $\theta_{es}(e)$ for each year relative to the year of migration, and the average before and after. At the bottom, the table presents the overall average of the ATT estimates for all cohorts across all periods.

Table 2.A2: Results from event study analysis with migrants moving to higher trust cantons, by cohort

	Coef.	s.e.	P-value	C.I. low	C.I. high
GAverage	0.193	0.141	0.173	-0.084	0.469
G2003	0.524	0.396	0.186	-0.252	1.301
G2004	0.598	0.502	0.233	-0.386	1.581
G2005	0.575	0.387	0.138	-0.184	1.333
G2006	-0.003	0.422	0.995	-0.831	0.825
G2007	-0.441	0.439	0.315	-1.301	0.419
G2008	0.339	0.377	0.369	-0.401	1.078
G2009	0.030	0.387	0.939	-0.730	0.789
G2010	1.508	0.845	0.074	-0.148	3.164
G2011	0.005	0.350	0.988	-0.681	0.692
G2012	0.533	0.403	0.186	-0.257	1.323
G2013	1.913	0.605	0.002	0.728	3.099
G2014	-0.320	0.262	0.223	-0.833	0.194
G2015	0.163	0.352	0.644	-0.527	0.853
G2016	-0.045	0.326	0.891	-0.684	0.595
G2017	-0.530	0.444	0.232	-1.401	0.340

The table presents the aggregate estimates of the ATTs for each cohort (G), across all years, and the grand average of all of them. Bootstrap standard errors (in parentheses).

Table 2.A3: Results from event study analysis with migrants moving to higher trust cantons, by year

	Coef.	s.e.	P-value	C.I. low	C.I. high
CAverage	0.292	0.150	0.052	-0.002	0.585
T2003	-0.533	0.585	0.363	-1.680	0.614
T2004	0.372	0.389	0.339	-0.391	1.135
T2005	0.439	0.368	0.233	-0.282	1.161
T2006	0.411	0.273	0.132	-0.123	0.946
T2007	0.240	0.277	0.386	-0.303	0.784
T2008	0.268	0.237	0.258	-0.197	0.733
T2009	0.469	0.249	0.059	-0.019	0.956
T2010	0.608	0.266	0.022	0.086	1.129
T2011	0.291	0.237	0.221	-0.175	0.756
T2012	0.326	0.256	0.204	-0.177	0.828
T2013	0.210	0.265	0.428	-0.309	0.728
T2014	0.671	0.244	0.006	0.193	1.149
T2015	0.004	0.237	0.985	-0.461	0.470
T2016	0.173	0.262	0.508	-0.340	0.686
T2017	0.424	0.298	0.155	-0.160	1.008

The table presents the aggregate estimates of the ATTs for each calendar year (T), across all cohorts, and the grand average of all of them. Bootstrap standard errors (in parentheses).

3.9.2 Event study results: Moving to lower trust cantons

Table 2.A4: Results from event study analysis with migrants moving to lower trust cantons

	Coef.	s.e.	P-value	C.I. low	C.I. high
Pre migration average	0.013	0.021	0.532	-0.028	0.054
Post migration average	-0.247	0.127	0.052	-0.497	0.002
Tm7	0.056	0.158	0.720	-0.252	0.365
Tm6	-0.028	0.161	0.864	-0.343	0.287
Tm5	0.060	0.145	0.681	-0.224	0.343
Tm4	0.069	0.125	0.581	-0.176	0.315
Tm3	-0.061	0.107	0.566	-0.271	0.148
Tm2	-0.041	0.132	0.755	-0.300	0.218
Tm1	0.036	0.113	0.752	-0.186	0.258
Tp0	-0.172	0.098	0.080	-0.364	0.021
Tp1	-0.292	0.133	0.028	-0.552	-0.032
Tp2	-0.109	0.132	0.409	-0.368	0.150
Tp3	-0.196	0.166	0.237	-0.522	0.129
Tp4	-0.142	0.192	0.459	-0.517	0.234
Tp5	-0.263	0.206	0.202	-0.668	0.141
Tp6	-0.455	0.214	0.033	-0.874	-0.036
Tp7	-0.350	0.251	0.163	-0.841	0.142

	Coef.	s.e.	P-value	C.I. low	C.I. high
ATT	-0.223	0.118	0.059	-0.455	0.008

The table presents the $\theta_{es}(e)$ for each year relative to the year of migration, and the average before and after. At the bottom, the table presents the overall average of the ATT estimates for all cohorts across all periods.

Table 2.A5: Results from event study analysis with migrants moving to lower trust cantons, by cohort

	Coef.	s.e.	P-value	C.I. low	C.I. high
GAverage	-0.291	0.113	0.010	-0.512	-0.069
G2003	-0.170	0.434	0.695	-1.022	0.681
G2004	-0.273	0.309	0.377	-0.879	0.333
G2005	0.320	0.387	0.408	-0.438	1.078
G2006	-0.396	0.323	0.220	-1.030	0.238
G2007	-0.818	0.345	0.018	-1.495	-0.142
G2008	-0.625	0.287	0.029	-1.187	-0.063
G2009	-0.575	0.632	0.363	-1.814	0.664
G2010	-0.432	0.323	0.180	-1.065	0.200
G2011	0.167	0.363	0.646	-0.545	0.879
G2012	-0.108	0.602	0.858	-1.287	1.071
G2013	0.271	0.289	0.348	-0.295	0.838
G2014	-0.263	0.229	0.250	-0.712	0.186
G2015	-0.141	0.240	0.556	-0.611	0.329
G2016	-0.372	0.319	0.244	-0.998	0.254
G2017	-0.911	0.453	0.044	-1.798	-0.024

The table presents the aggregate estimates of the ATTs for each cohort (G), across all years, and the grand average of all of them. Bootstrap standard errors (in parentheses).

Table 2.A6: Results from event study analysis with migrants moving to lower trust cantons, by year

	Coef.	s.e.	P-value	C.I. low	C.I. high
CAverage	-0.200	0.126	0.112	-0.448	0.047
T2003	-0.617	0.573	0.281	-1.739	0.505
T2004	-0.250	0.378	0.509	-0.991	0.492
T2005	0.103	0.263	0.695	-0.413	0.620
T2006	-0.399	0.249	0.109	-0.887	0.090
T2007	0.339	0.274	0.216	-0.198	0.877
T2008	0.166	0.200	0.408	-0.226	0.558
T2009	-0.162	0.229	0.479	-0.611	0.287
T2010	-0.243	0.196	0.214	-0.628	0.141
T2011	-0.295	0.201	0.142	-0.688	0.098
T2012	-0.425	0.210	0.044	-0.837	-0.012
T2013	-0.125	0.212	0.554	-0.541	0.290
T2014	-0.418	0.189	0.028	-0.789	-0.046
T2015	-0.155	0.183	0.398	-0.514	0.204
T2016	-0.144	0.235	0.540	-0.604	0.316
T2017	-0.384	0.233	0.099	-0.840	0.073

The table presents the aggregate estimates of the ATTs for each calendar year (T), across all cohorts, and the grand average of all of them. Bootstrap standard errors (in parentheses).

3.9.3 Measuring trust: Experimental literature

Some early papers, comparing self reported trust with experimental measures found mixed results.[24] Glaeser et al. (2000); Lazzarini et al. (2005); Ermisch et al. (2009) found no correlation with the sending decision in the trust game but a strong and significant correlation with the return decision (i.e., trustworthiness). Both of these papers, however, were based on small and unrepresentative samples (Murtin et al., 2018). Fehr et al. (2003) used a large representative sample in Germany and found no correlations between self-reported trust in others and experimental measures of either one's own's trust or trustworthiness.

On the other hand, in a meta-analysis of experiments run in 35 countries, Johnson and Mislin (2012) finds a strong positive correlation with the experimental measure. Similarly, Murtin et al. (2018) finds a positive correlation between our generalized trust question and the experimental measures using representative samples from France, Germany, Italy, Korea, Slovenia and the United States.

Sapienza et al. (2013) reconciles these findings by separating the preferences and beliefs components in the senders decision in the trust game. They conclude that self-reported trust mainly captures beliefs while the amount sent in an experiment is confounding the two components.[25] Partially confirming this, Murtin et al. (2018) finds experimental measures of expected trustworthiness (i.e., beliefs) and altruism (i.e., preferences) to be the strongest predictors of self-reported trust. Furthermore, Fehr (2009) shows that self reported trust is also driven by risk and betrayal aversion.

In sum, by capturing expected trustworthiness and altruism, self-reported trust is a good predictor of many desirable social, political and economics outcomes (Nunn and Wantchekon, 2011; Algan and Cahuc, 2010) and, thus, understanding how migrants develop this is important. Although disentangling assimilation in beliefs from assimilation in preferences would be a difficult task with non experimental data, one can expect that both components (beliefs and preferences)

[24]Experimental measures operationalize trust as the amount sent and trustworthiness as the money returned in a Berg-Dickhaut-McCabe Investment Game (commonly known as the Trust Game)(Berg et al., 1995).

[25]Interestingly, the papers finding no correlation with trust but with trustworthiness did not endow the trustee. According to Aksoy et al. (2018), this induces more altruism from the part of the trustor, which worsens the confounding between beliefs and preferences (see also Ashraf et al. (2006) and Cox (2004)). They replicate the experiment endowing both parties and find a significant correlation between the self-reported and experimental measure.

affect behavior in the same direction (Alesina and Giuliano, 2015; Tabellini, 2008a).[26]

3.9.4 Full regressions from the descriptive evidence section

The large majority of the literature on cultural assimilation (mostly in adjacent fields) have relied on the epidemiological approach(See Fernández and Fogli, 2006; Fernandez, 2007; Giuliano, 2007) sometimes exploiting the time spent in the destination (Marino Fages and Morales Cerda, 2022; Helliwell et al., 2016; Wu, 2020, 2021; Cameron et al., 2015; Dinesen and Hooghe, 2010; Dinesen, 2013, 2012; Nannestad et al., 2014; Kim, 2021). The approach involves studying individuals from different backgrounds in one specific location (holding culture and institutions at the destination constant). I do the opposite analysis, by controlling for origin fixed effects and observing the effect of the destination on the migrants' trust level. Formally, I run the following equation:

$$Trust_{irh} = \alpha + \beta_1 \overline{Trust}_r + \beta_2 X_i + Origin_h + \epsilon_{irh} \tag{3.7}$$

where, $Trust_{irh}$ is individual i level of trust in canton r from canton h, $\overline{Trust}_r$ is the average trust level in the residence canton r, $Origin_h$ are canton(country) of origin h fixed effects, X_i is a vector of control variables and ϵ_{irh} is the individual specific error term. β_1 is the coefficient of interest. I run three separate regressions: 1) International migrants, 2) Internal migrants in the destination, and 3) Internal migrants before they move as a falsification test. For this analysis I restrict the sample to the german regions only and report bootstrapped standard errors.

Table 2.A7 presents the results. The first two columns show that the average trust in the destination canton is a significant predictor of the individual trust for both internal and international migrants. The coefficient of interest for internal and international migrants are both positive and significant at conventional levels. A standard deviation increase in the average cantonal trust is associated with a 2.49 (1.35) standard deviation increase in the residualized trust of the internal (international) migrant.

The assumption needed to interpret these results as causal is that, conditional on observables,

[26]One could potentially argue, as Fehr (2009) conjectures, that the speed of assimilation can give some evidence since beliefs are likely to be more malleable and change more quickly in response variations in the prevailing conditions.

migrants' destinations are as good as random. For the internal migrants I also have data on their pre-move trust level. This allows us to check whether internal migrants look similar in terms of trust to the destination cantons, even before moving to those cantons. Column 3 shows that, a negative and non-significant effect of the destination canton on migrants before they migrate which provides evidence against a selection mechanism.

Table 2.A7: Effect of average trust in the canton on individual trust of migrants

VARIABLES	(1) Trust International	(2) Trust Internal	(3) Trust Internal (premove)
Avg trust in the canton	1.590	2.492	-0.160
	(0.631)	(1.353)	(1.223)
Age	0.004	-0.002	-0.011
	(0.006)	(0.006)	(0.006)
Female	-0.016	0.243	0.189
	(0.126)	(0.160)	(0.161)
Married	0.268	0.265	-0.174
	(0.158)	(0.189)	(0.228)
Years of Education	0.114	0.122	0.091
	(0.022)	(0.030)	(0.038)
Log(income)	-0.097	-0.011	-0.134
	(0.078)	(0.132)	(0.089)
time_here	0.001		
	(0.006)		
Constant	-1.073	-2.615	0.183
	(0.821)	(1.340)	(0.839)
Observations	1,097	530	508
R-squared	0.133	0.094	0.096

The dependent variable is the individual average of the residuals of regressing trust on year dummies. The independent variable is the average trust level in the host canton. All regressions control for age, gender, civil status, years of education, income (in logs) is measured in Swiss Francs. The first column also includes years since arriving in Switzerland. All regression control for either country of origin or canton of origin fixed effects. Bootstrap standard errors in parentheses.

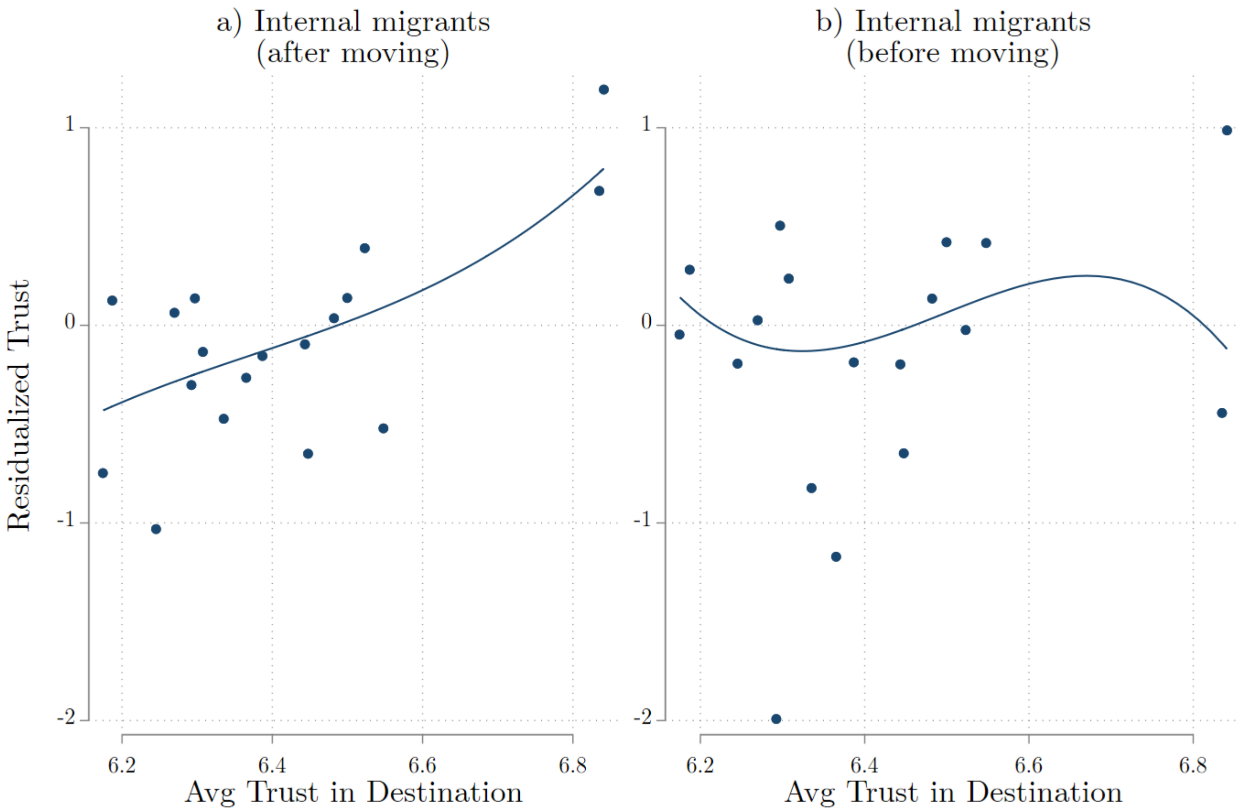


Figure 2.A1: Correlation between Residualized Trust and Average Trust in the destination canton

The figure presents binsreg plots with cubic polynomial (Cattaneo et al., 2019) of migrant's trust and average trust in the destination canton (controlling for canton of origin) for internal migrants in German cantons before and after moving. To compute the Residualized Trust, I first regress the Trust variable on calendar year dummies, and then average all the residuals by individual.

3.9.5 Balance check international

Table 2.A8 shows that international migrants going to higher and lower trust cantons are very similar in terms of age, gender, civil status, years of education, income and time spent in the country. If anything I can observe a lower income and time spent in the country, but all variables are statistically insignificant.

It is also important to note that, in terms of these observable characteristics, international migrants seem to be younger, less educated, earning less; and less likely to be female and more likely to be married than internal migrants.

Table 2.A8: Balance tests for International migrants

	Low Trust		High Trust			
	N	Mean (s.d.)	N	Mean (s.d.)	Coeff.	p-value
After moving						
Age	2,211	37.39	2153	37.21	-0.175	0.77
		(19.66)		(19.06)		
Female	2,211	0.48	2153	0.48	-0.000	0.98
		(0.50)		(0.50)		
Married	2,211	0.47	2153	0.48	0.011	0.45
		(0.49)		(0.49)		
Income (CHF)	1,130	53,563	1,070	52,196	-1,366	0.59
		(74,743)		(39,747)		
Years since arrival	1,592	19.73	1582	18.94	-0.798	0.13
		(15.02)		(14.34)		
Education (years)	1,987	11.26	1939	11.13	-0.122	0.43
		(4.97)		(4.76)		
HH Size	1,071	2.68	1017	2.70	0.026	0.64
		(1.23)		(1.28)		

The table shows the number of observations, means, standard deviations, coefficients and p-values of regressing each variable on an indicator that takes the value 1 for international migrants in cantons with trust above the median and 0 otherwise.

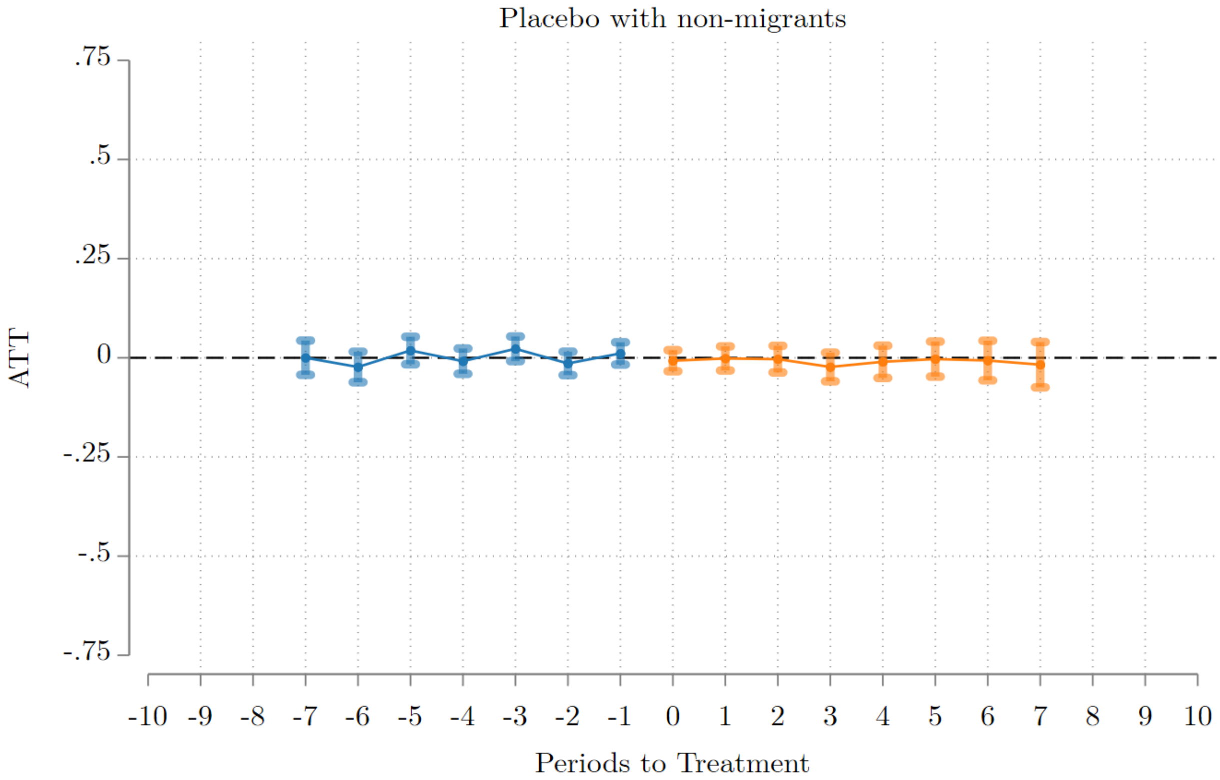


Figure 2.A2: Placebo

The figure presents a placebo test where I assign random destination and moving dates to non-migrants. The horizontal dashed line represents the last period before the assigned moving time and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors. I fill the gaps in trust in the survey by linear interpolation. The analysis was performed using the Stata command csdid (Rios-Avila et al., 2021).

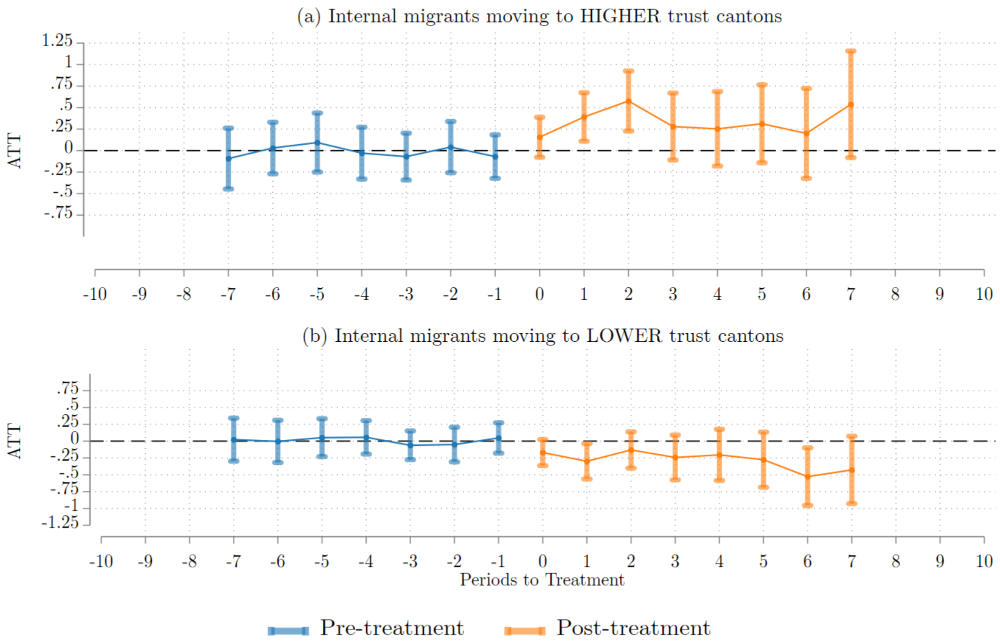


Figure 2.A3: Event study: Controlling for the trust gap between the cantons
Panel (a) and (b) present the event study results of each ATT of migrants moving to a HIGHER and LOWER cantons controlling for the trust gap between the canton of origin and destination. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors. I fill the gaps in trust in the survey by interpolating from the nearest neighbour.

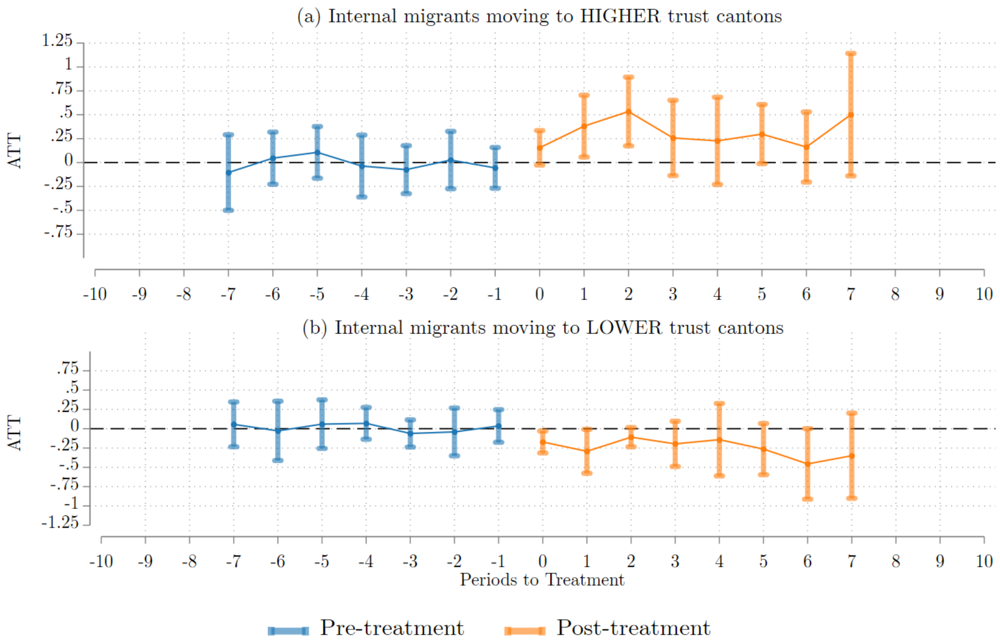


Figure 2.A4: Event study: Canton of origin clusters

Panel (a) and (b) present the event study results of each ATT of migrants moving to a HIGHER and LOWER cantons. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors clustered at the canton of origin. I fill the gaps in trust in the survey by interpolating from the nearest neighbour.

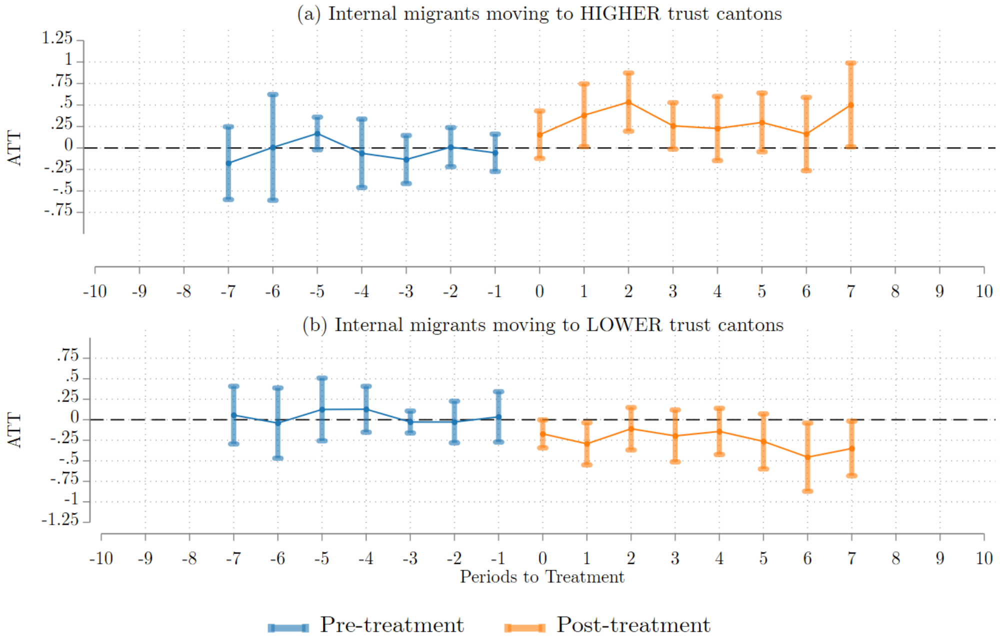


Figure 2.A5: Event study: Canton of destination cluster

Panel (a) and (b) present the event study results of each ATT of migrants moving to a HIGHER and LOWER cantons. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors clustered at the canton of destination. I fill the gaps in trust in the survey by interpolating from the nearest neighbour.

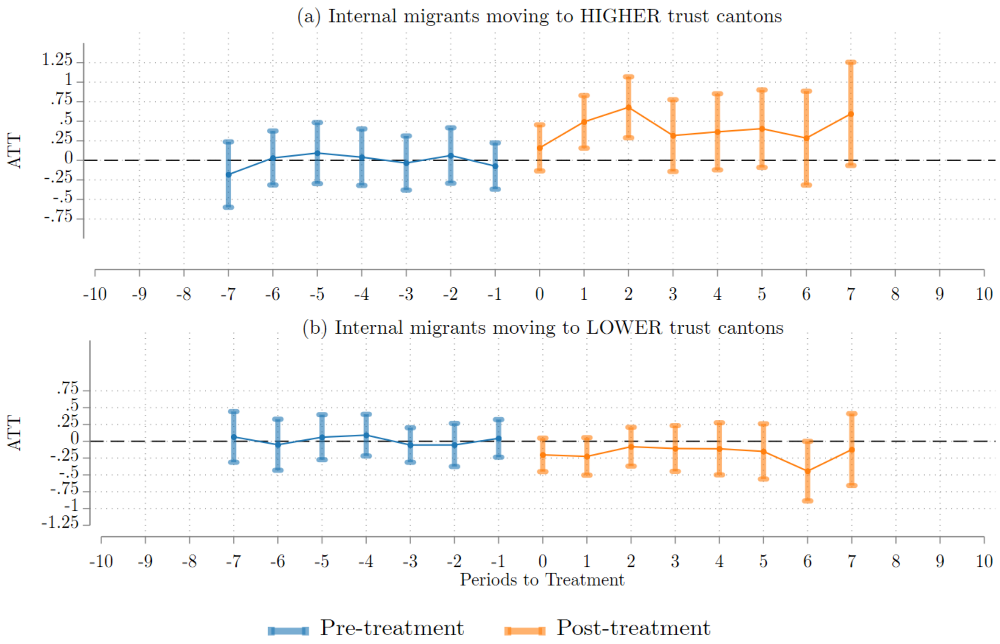


Figure 2.A6: Event study: no interpolation

Panel (a) and (b) present the event study results of each ATT of migrants moving to a HIGHER and LOWER cantons. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors.

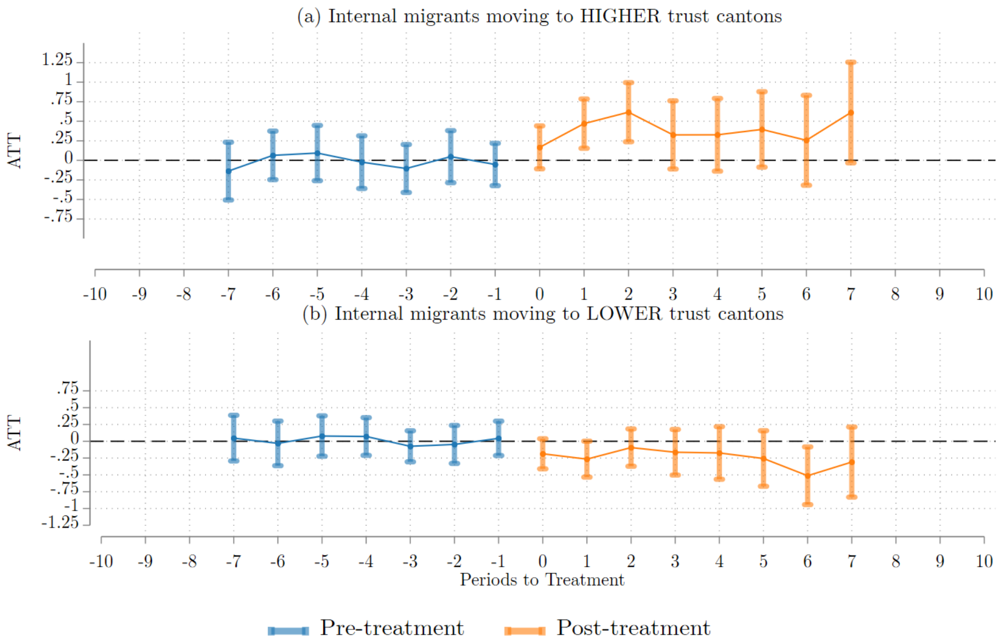


Figure 2.A7: Event study: linear interpolation

Panel (a) and (b) present the event study results of each ATT of migrants moving to a HIGHER and LOWER cantons. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors. I fill the gaps in trust in the survey by linear interpolation.

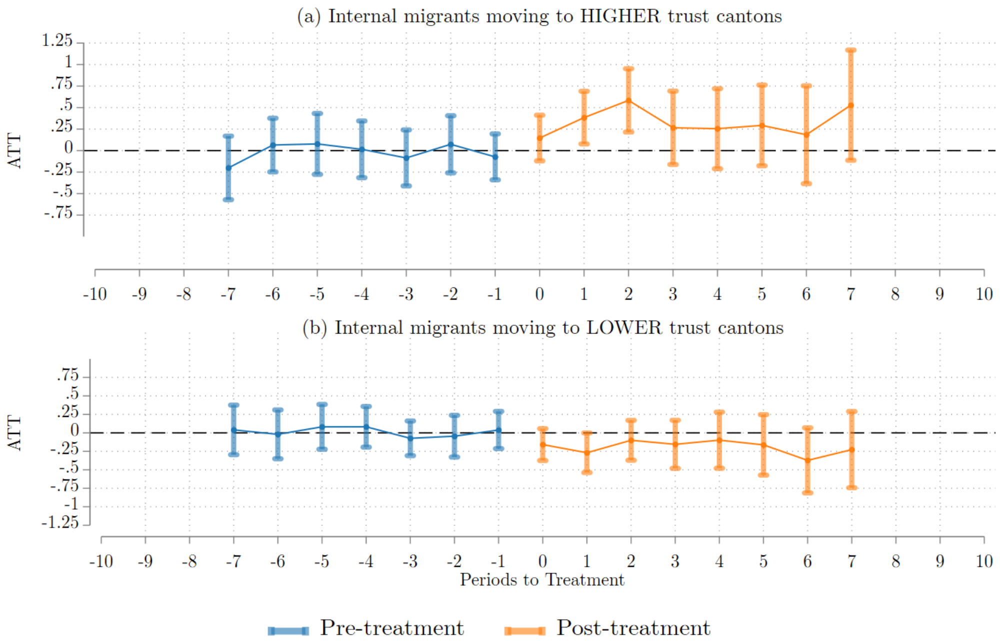


Figure 2.A8: Event study: forward interpolation

Panel (a) and (b) present the event study results of each ATT of migrants moving to a HIGHER and LOWER cantons. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors. I fill the gaps in trust in the survey by forward interpolation.

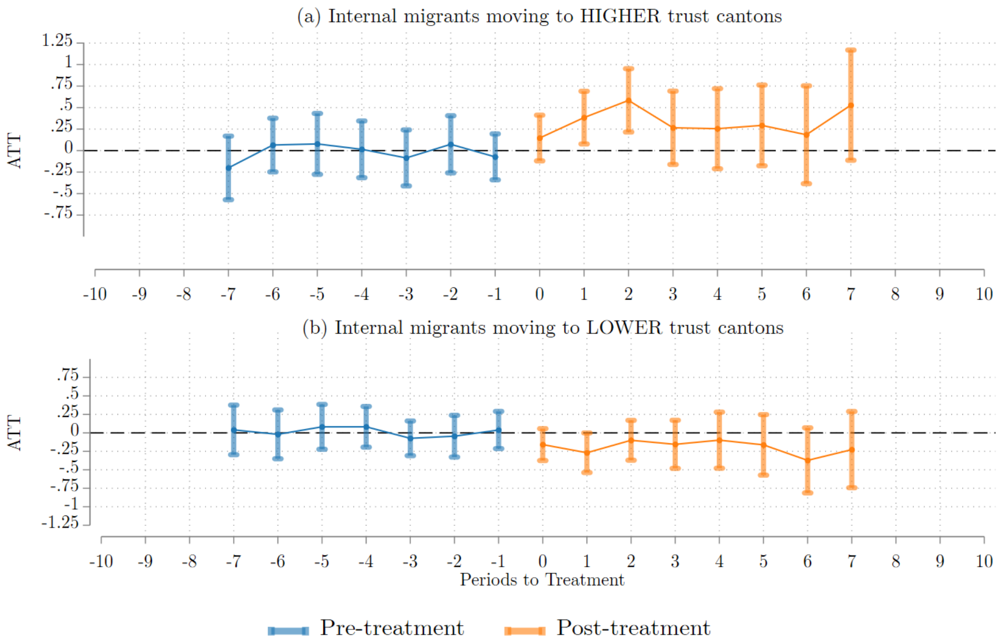


Figure 2.A9: Event study: splines interpolation

Panel (a) and (b) present the event study results of each ATT of migrants moving to a HIGHER and LOWER cantons. In both cases, the base period (i.e., the last period before moving) is represented by the horizontal dashed line and the spikes show the 95% simultaneous confidence intervals around each ATT using wild bootstrap standard errors. I fill the gaps in trust in the survey by splines interpolation.

Table 2.A9: Difference in differences results by gender

VARIABLES	(1) Trust All	(2) Trust All	(3) Trust Males	(4) Trust Females
Avg trust in the canton X Post move	0.489	0.432	0.419	0.431
	(0.204)	(0.212)	(0.323)	(0.288)
Post move	-0.005	-0.063	0.092	-0.241
	(0.030)	(0.139)	(0.177)	(0.214)
Log(income)		-0.085	-0.044	-0.096
		(0.045)	(0.064)	(0.057)
Age		0.014	-0.007	0.037
		(0.019)	(0.025)	(0.028)
Education (years)		0.008	-0.021	0.023
		(0.018)	(0.026)	(0.024)
Constant	-0.046	0.237	1.036	-0.674
	(0.015)	(0.792)	(1.095)	(1.131)
Individual FE	Yes	Yes	Yes	Yes
Observations	726	676	302	374
R-squared	0.890	0.883	0.895	0.878

The table presents difference-in-differences regressions (Equation 3.5) for trust in strangers (Trust) in columns 1 and 2. Separate regression for each gender are presented in Columns 3 and 4 . The dependent variable is the individual average of the residuals of regressing Trust on year dummies. The main independent variable is the average Trust level in the host canton. All regressions include individual fixed effects. Standard errors (in parentheses) clustered at the individual level. Income is measured in Swiss Francs.

Table 2.A10: Summary statistics of trust by canton in the full sample and year 2002

Canton	Trust (all years)		Trust (2002)	
	Mean	s.d.	Mean	s.d.
Jura JU	4.93	2.61	3.33	4.16
Ticino TI	5.62	2.49	4.99	2.79
Neuchatel NE	5.73	2.37	5.09	2.76
Geneva GE	5.73	2.48	4.86	3.00
Vaud VD	5.77	2.42	5.12	2.71
Valais VS	5.91	2.37	5.00	3.03
Fribourg FR	5.97	2.39	5.26	2.97
Thurgovia TG	6.17	2.18	5.55	1.99
Solothurn SO	6.19	2.08	5.82	2.05
Schaffhausen SH	6.25	2.07	5.67	1.72
Zug ZG	6.27	2.05	5.5	2.13
Uri UR	6.29	2.29	6.29	2.97
Basle-Town BS	6.3	2.41	5.97	2.36
St. Gall SG	6.31	2.17	5.71	2.34
Basle-Country BL	6.34	2.06	5.83	2.17
Glarus GL	6.37	2.28	5.77	2.12
Grisons GR	6.38	2.08	5.81	2.12
Berne BE	6.39	2.13	5.8	2.25
Argovia AG	6.44	2.05	5.76	2.17
Schwyz SZ	6.45	1.99	6.05	2.09
Zurich ZH	6.48	2.07	5.94	2.35
Lucerne LU	6.5	2.00	5.91	2.22
Appenzell Outer-Rhodes AR	6.52	2.14	6.68	2.19
Obwalden OW	6.55	1.96	5.83	2.42
Nidwalden NW	6.84	2.04	6.05	2.27
Appenzell Inner-Rhodes AI	6.84	1.83	5.67	2.08

The table presents the mean and standard deviation of the trust variable for the Swiss population that are not moving internally in the full sample and for the year 2002 separately. The Pearson correlation coefficient between both means is 0.88.

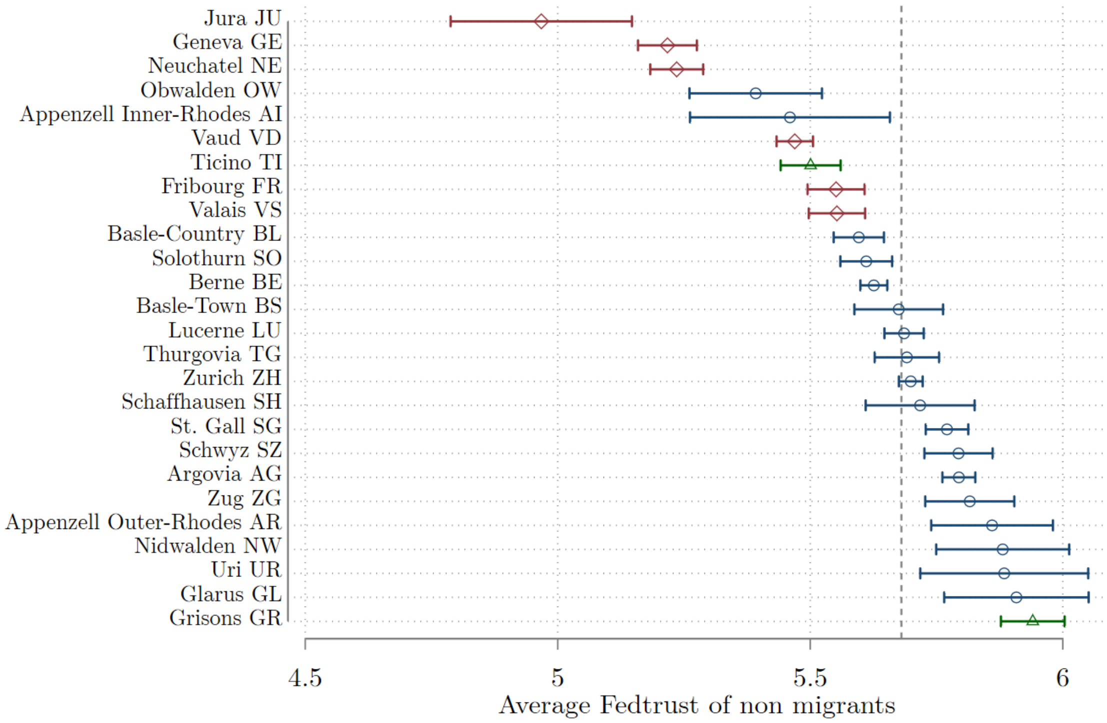


Figure 2.A10: FedTrust in the cantons

The figure presents the average trust in the federal government (ranging from 0 to 10) for all non-migrants in each canton over the period 2002-2018 with 95% confidence intervals. The vertical dashed line shows the median average trust in the federal government among the cantons. Finally, the different colors and symbols depend on the language region.

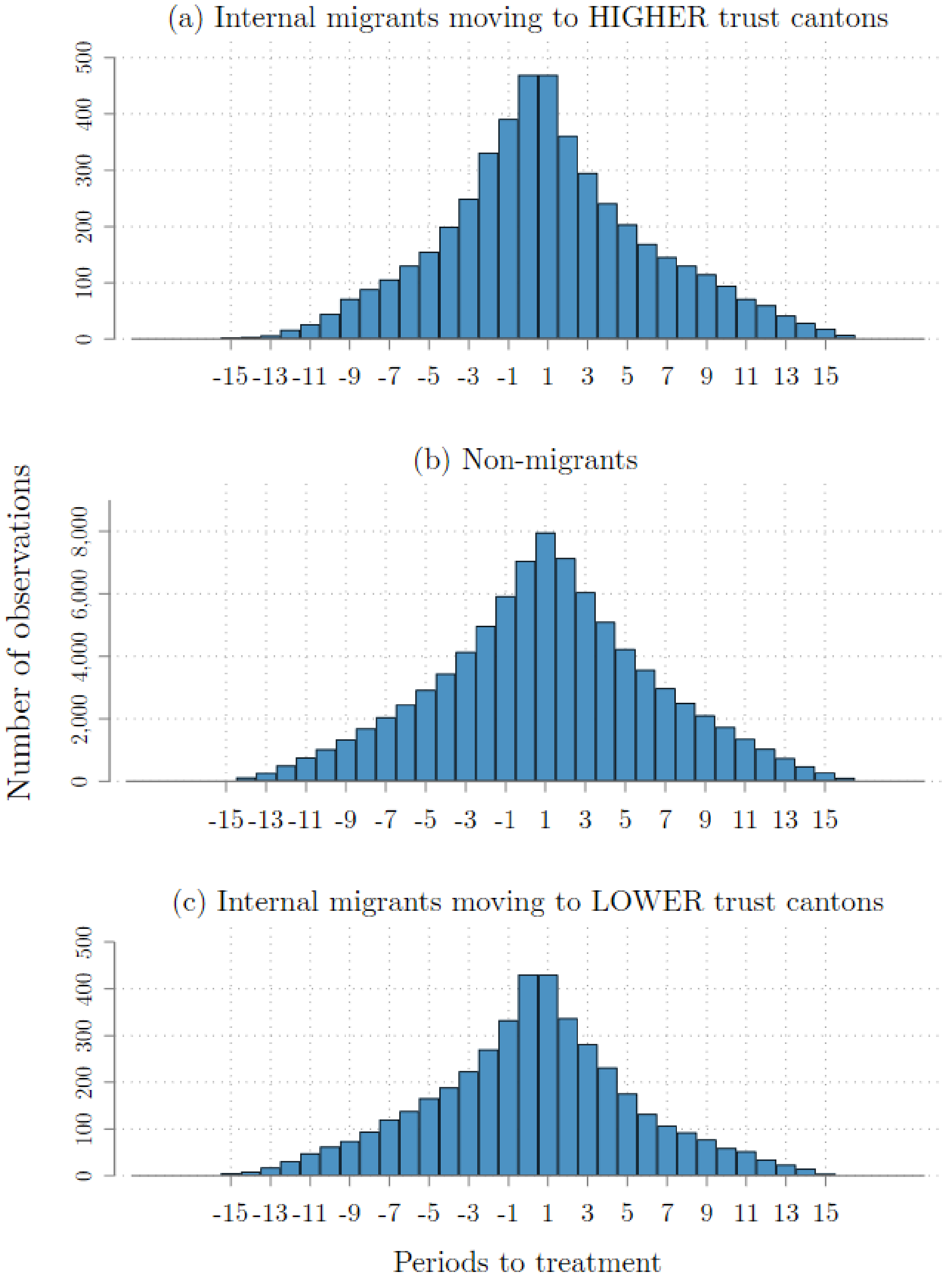


Figure 2.A11: Number of observation per period

Panel (a) and (c) present the number of observations per period (relative to the moving period) for migrants moving to a HIGHER and LOWER cantons. Panel (b) shows the number of observations per period in the sample of non-migrants where the moving period is randomly assigned.

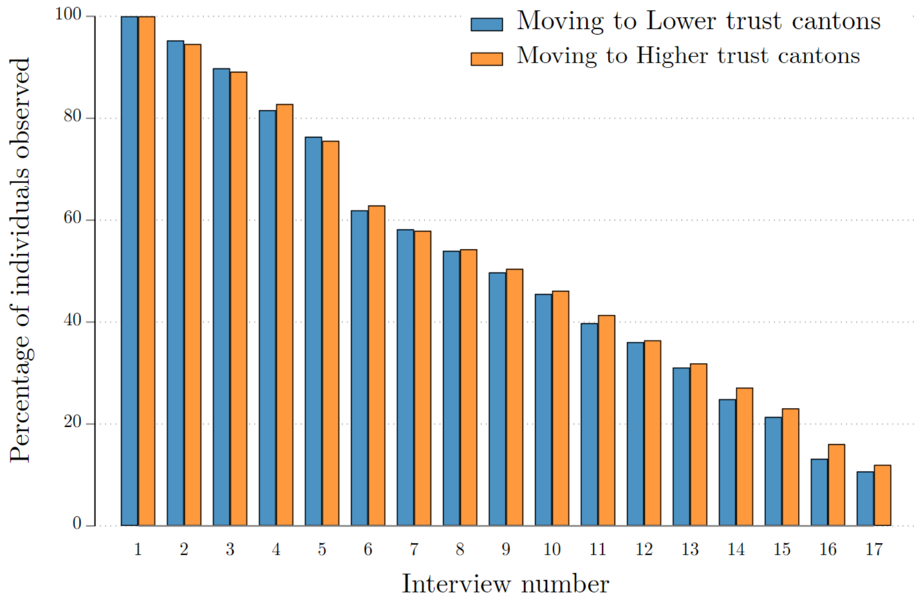


Figure 2.A12: Attrition for migrants moving to higher and lower trust cantons
The figure presents the percentage of respondents observed in each interview number relative to the first interview. E.g., roughly 81% of the respondents (moving to higher and lower trust cantons) are observed at least four times, and roughly 40% are observed 11 times.

Table 2.A11: Effect of average trust in the host canton on attrition

	Dep. variable: Prob. of non response				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Coef.	s.e.	P-value	C.I. low	C.I. high
Avg trust in the canton X Post move	0.040	(0.056)	0.476	-0.070	0.150
Avg trust in the canton	-0.062	(0.053)	0.235	-0.166	0.041
Post move	0.002	(0.009)	0.819	-0.016	0.020
Interview year:					
2003	-0.050	(0.029)	0.081	-0.107	0.006
2004	-0.014	(0.022)	0.529	-0.056	0.029
2005	0.033	(0.026)	0.202	-0.018	0.084
2006	-0.001	(0.025)	0.954	-0.050	0.047
2007	-0.003	(0.024)	0.898	-0.049	0.043
2008	0.008	(0.025)	0.741	-0.040	0.056
2009	0.010	(0.024)	0.683	-0.037	0.057
2010	0.010	(0.025)	0.691	-0.039	0.058
2011	0.001	(0.025)	0.964	-0.048	0.050
2012	0.028	(0.025)	0.267	-0.022	0.078
2013	0.064	(0.026)	0.014	0.013	0.114
2014	0.075	(0.026)	0.003	0.025	0.125
2015	0.088	(0.027)	0.001	0.036	0.141
2016	0.112	(0.027)	0.000	0.060	0.164
2017	0.104	(0.030)	0.000	0.046	0.162
2018	0.110	(0.023)	0.000	0.064	0.155
Interview number:					
2	0.096	(0.021)	0.000	0.054	0.138
3	0.113	(0.017)	0.000	0.078	0.147
4	0.090	(0.019)	0.000	0.052	0.128
5	0.094	(0.019)	0.000	0.057	0.132
6	0.087	(0.018)	0.000	0.052	0.121
7	0.090	(0.020)	0.000	0.051	0.128
8	0.090	(0.019)	0.000	0.052	0.128
9	0.064	(0.020)	0.001	0.025	0.103
10	0.068	(0.020)	0.001	0.028	0.107
11	0.038	(0.021)	0.071	-0.003	0.079
12	0.014	(0.021)	0.502	-0.028	0.056
13	0.025	(0.022)	0.248	-0.018	0.069
14	-0.027	(0.023)	0.241	-0.073	0.018
15	-0.018	(0.021)	0.389	-0.060	0.023
16	0.009	(0.028)	0.757	-0.046	0.064
Constant	-0.021	(0.015)	0.165	-0.050	0.008
Individual FE	Yes				
Observations	8,280				
R-squared	0.344				

The table presents the regression of the probability of non response on the average trust level in the current canton (postmove takes the value 1 after moving and zero otherwise) controlling for interview year, interview number and individual fixed effects. Bootstrap standard errors in parentheses. I report 95% confidence intervals.

Chapter 4

Using the Strategy Method and Beliefs to Explain Group Size and MPCR Effects in Public Good Experiments

4.1 Introduction

Public good games (PGGs) are one of the classic games to study cooperation in social dilemmas. PGGs have been used to investigate many aspects of voluntary cooperation (for surveys see Chaudhuri (2011); Fehr and Schurtenberger (2018); Gächter and Herrmann (2009); Ledyard (1995); Zelmer (2003); Drouvelis (2021)). In this paper, we revisit a classic question in PGG research by separately measuring preferences and beliefs: the role of group size and the marginal per capita return (MPCR) for cooperation.

One important insight that will be crucial for our analysis of MPCR and group size effects, is that contributions are correlated with beliefs about others' contributions (e.g., Croson (2007); Fischbacher and Gächter (2010); Dufwenberg et al. (2011); Gächter and Renner (2018)). To go beyond mere correlations, Fischbacher et al. (2001) (henceforth FGF) introduced a tool based on the strategy method that measures the causal influence of beliefs about others' contributions on own contribution. The FGF method measures people's preferences for cooperation by eliciting contributions conditional on how much others contribute to the public good, which fixes beliefs. FGF also allows classifying people into preference types as conditional cooperators, free riders, and others.

FGF find that most people are conditional cooperators or free rider types. The distribution of types (in particular conditional cooperators) has been shown to be similar across comparable studies (Thöni and Volk, 2018); mostly robust to the (mis-)understanding of incentives (Gächter et al., 2022; Fosgaard et al., 2017); stable over time (Gächter et al., 2022; Volk et al., 2012); mostly similar across different cooperation games (Mullett et al., 2020; Eichenseer and Moser, 2020) and similar across different cultures (Weber et al., 2021). Moreover, the ABC approach - using people's conditional preferences (also called *a*ttitudes, dispositions) together with their *b*eliefs - can explain individual *c*ontributions to public goods fairly well (Fischbacher and Gächter, 2010; Fischbacher et al., 2012; Gächter et al., 2017, 2022; Isler et al., 2021; Weber et al., 2021), which makes the ABC approach a promising methodology for analyzing MPCR and group size effects in cooperation.

A limitation of the existing evidence on the distribution of conditionally cooperative attitudes (preference types) as well as on the predictive power of the ABC approach to explain contributions is, however, that it mostly comes from very similar group sizes of 3 and 4 members, with one exception (Mill and Theelen, 2019) who also studied group sizes of 5 and 7.[1] As far as we are aware, there is no evidence on the distribution of cooperative types across substantially different group sizes. Similarly, not much is known about how the MPCR affects conditionally cooperative preferences because most studies use MPCRs of 0.4 or 0.5. Finally, to our knowledge, there is no evidence on how well the ABC approach predicts cooperation in larger groups. Hence, two main goals of our paper are, first, to measure how group size and MPCR affect attitudes, beliefs, and contributions; and, second, to apply the ABC approach for analyzing MPCR and group size effects in cooperation.

We present two studies based on one-shot games. In Study 1 (n=936), we use the strategy method and the ABC approach to study group sizes of 3 and 9 and MPCRs of 0.4 and 0.8, in a factorial design. In Study 2 (n=1200) we extend group size to 30 members. We use the ABC approach to be able to disentangle preference and belief effects: if we observe different contributions across different group sizes or different MPCRs, it could be because (i) cooperative

[1] Relatedly, in the Cooperation Databank (a recent effort by Spadaro et al. (2022) to collect papers on cooperation in order to facilitate meta-analyses) only 8 out of 137 published papers related to continuous PGGs (with no deception) mention group size as a treatment variable.

attitudes vary with group size (or MPCR) or (ii) because individuals respond to beliefs that change with group size (or MPCR) or (iii) both cooperative attitudes and beliefs are affected by group size (or MPCR).

Using the strategy method as developed by FGF to measure cooperative attitudes in different group sizes is not straightforward. The reason is as follows: The FGF method elicits cooperative attitudes incentive-compatibly. To achieve incentive compatibility, FGF asks for conditional and unconditional contributions from all participants and randomly selects one of the participants to have their conditional responses as payoff relevant; for the others in the group the unconditional contribution is used to calculate payoffs. Therefore, the probability of having the conditional response – in which we are most interested in – selected as payoff relevant is $1/n$ for each subject. This is less problematic if all groups are of the same size. However, as group size increases, the incentives of the strategy method decisions change (since n increases) confounding the effect of the group size with the weights of the incentives, which become approximately hypothetical as n grows.

To overcome the problem of vanishing incentive compatibility as group size grows, we propose a new incentive-compatible strategy method to elicit conditionally cooperative preferences where the incentives for the conditional responses are independent of group size and hence scalable to any group size. The essential idea of the scalable strategy method (henceforth, SSM) is to select the unconditional and the conditional strategies with equal probability. SSM ensures incentive scalability but might be conceptually problematic because the public good is not well defined. We describe the pros and cons in more detail in Section 3 (and the Appendix). By comparing FGF and SSM we treat the role of incentive scalability of FGF and the conceptual weakness of SSM for eliciting conditional contributions as empirical questions.

In Study 1, in a $2\times2\times2$ design, we compare (i) groups sizes of 3 and 9; (ii) MPCRs of 0.4 and 0.8; and (iii) we elicit conditional preferences using either FGF or SSM.

In Study 2, we also run a $2\times2\times2$ design: we compare groups of 3 and 30 members, with MPCRs of 0.04, 0.08, 0.4 and 0.8 (yielding two levels of marginal social return, 1.2 and 2.4), and we again use either FGF or SSM. Notice that with groups of 30, under FGF elicited conditional preferences become approximately hypothetical because the likelihood of the elicited conditional contribution to be payoff relevant reduces to 1/30. Thus, comparing FGF and SSM in groups of 30 reveals how important incentive scalability is for eliciting conditional preferences.

In both studies, our experiments have two phases: In Phase 1, we elicit people's conditionally cooperative preferences (either using FGF or SSM) in one of the four MPCR×GroupSize parameterizations. This is followed, in Phase 2, by a one-shot direct response PGG (with beliefs) keeping the same parameterization. As we will explain in more detail in Section 2.3, this setting allows us to apply the ABC method, i.e., using the elicited attitudes from Phase 1 and the beliefs from Phase 2 to predict contributions in Phase 2. We then compare these predictions to the actual contributions in Phase 2.

Our main results are as follows. Consistent with previous literature (see next section) we find in both studies that beliefs and contributions increase in MPCR but not in group size. By contrast, the distribution of elicited types of cooperative preferences in Phase 1 are very similar across MPCR and group sizes and in the two methods of how to elicit them (FGF or SSM). This is the case in both studies. We show that the ABC framework explains the observed contribution levels under both strategy methods. According to the ABC approach, the MPCR effect is driven by increased beliefs, and not cooperative preferences because preferences are not much affected by game parameters. Finally, we find evidence that the effect of beliefs on contributions interacts with group size and MPCRs.

This paper is organized as follows. Section 2 describes the standard PGG and the related literature on group size, MPCR effects and the ABC of cooperation. Section 3 describes the FGF and our new scalable strategy method, SSM. Section 4 contains the details of the experimental design of Study 1. Section 5 presents the main results of Study 1. Section 6 describes the design details of Study 2 and Section 7 presents its results. Section 8 investigates the role of beliefs in more detail. Section 9 concludes.

4.2 Related literature, and the ABC of cooperation

4.2.1 The public goods game

In the linear public goods game (PGG) we use, each of n group members receives an equal endowment, e tokens. Participants decide how to allocate the endowment between a private $(e - c_i)$ and a public account (c_i). The private account has a return of 1 whereas all the money allocated to the public account (by all participants) gets multiplied by $\alpha > 1$ and the resulting amount is split equally among the n participants so that each subject gets a return of α/n, also known as MPCR, from her investment in the public account. Formally, the material payoff function for subject i is the following:

$$U_i = e - c_i + \frac{\alpha}{n} \sum_{j=1}^{n} c_j, \tag{4.1}$$

where $e = 10$ and $\frac{\alpha}{n} < 1$ in all our experiments, which will vary α and n. Assuming monetary payoff maximization, the Nash equilibrium in all games states that all participants should contribute zero to the public account. However, the efficient allocation is achieved when all participants contribute $c_i = e = 10$ to the public account. The standard result in the experimental literature is that people contribute some amounts in between those extremes (e.g., Ledyard (1995); Zelmer (2003); Gächter and Herrmann (2009)). There are different theories for why this is the case, including altruism and warm glow (Croson, 2007; Palfrey and Prisbrey, 1997; Andreoni, 1995b); confusion (Andreoni, 1995a; Houser and Kurzban, 2002; Burton-Chellew et al., 2016; Bayer et al., 2013); reciprocity (Sugden, 1984; Weber et al., 2018; Isler et al., 2021); matching behavior (Guttman, 1986); inequality aversion (Fehr and Schmidt, 1999); and guilt aversion (Chang et al., 2011; Dufwenberg et al., 2011). See also Katuščák and Miklánek (2022) for a recent comparative analysis. In the following, we review the most relevant literature for our purposes, that is, the role of MPCR and group size for cooperation and the ABC approach to explaining cooperation.

4.2.2 MPCR and group size effects

MPCR effects - the higher the marginal per capita return in a public goods game, the higher the level of cooperation - have long been observed in the literature (see, e.g., Ledyard (1995); Palfrey and Prisbrey (1997); Brandts and Schram (2001); Goeree et al. (2002) and Zelmer (2003)). MPCR effects are also closely linked to the question of how group size affects voluntary cooperation. As can be seen from the payoff function shown in Eq. 4.1, if n increases, the MPCR (α/n) also diminishes. To isolate a pure group size effect therefore requires controlling for MPCR, which is what Isaac and Walker (1988) achieved in their seminal experiments.

Isaac and Walker (1988) found that group size increased cooperation but only if the MPCR changed with group size. When the MPCR was held constant they found no group size effects. Since then, a number of papers have studied the effect of group size on contributions to PGGs.[2] For instance, Pereda et al. (2019a) found that groups of 100 and 1000 are not significantly different in terms of cooperation. This suggests that extrapolating conclusions from smaller group sizes might be reasonable. In a within-subjects design, with group sizes of 5, 10, ..., 40, Pereda et al. (2019b) observed a monotonic increase of the cooperation rate as a function of group size.

Diederich et al. (2016) also found a positive group size effect and concluded that the effect was driven by the intensive margin (i.e., those who contribute contributed more in larger group sizes). This is consistent with the beliefs of the subjects. They also show that the share of free riders remains constant in spite of the beliefs of the participants showing a larger share of free riders in larger groups. An older study (Kerr, 1989) argued that beliefs are also affected by an efficiency illusion (i.e., a diminished sense of self-efficacy in larger groups) even when the self-efficiency was kept constant.

Nosenzo et al. (2015) and Weimann et al. (2019) showed that the effect of group size depends on the MPCR level. When the MPCR is low, the effect of group size on contributions is positive, but the effect disappears or becomes negative when the MPCR is high. Weimann et al. (2019) argue that the reason is due to beliefs, which in turn are affected by the saliency of the advantages of cooperation. They propose a measure of this saliency and show the change in this measure with respect to group size is higher in PGGs with low MPCRs.

In summary, beliefs take a central role in most recent studies, but how conditionally cooperative preferences are influenced by group size and MPCR remains unexplored. Moreover, it is unknown whether the ABC approach works for larger group sizes and high MPCRs. The aim of this paper is to provide the missing evidence.

[2] Further experiments on MPCR and group size include Marwell and Ames (1979); Isaac et al. (1994); Goeree et al. (2002); Carpenter (2007); see also Zelmer (2003) and Ledyard (1995) for overviews.

4.2.3 The ABC of cooperation

Our ambition in this paper is not only to provide evidence on conditionally cooperative preferences as a function of group size and MPCR but also to explore the explanatory power of conditionally cooperative preferences jointly with beliefs to explain cooperation levels across a variety of PGG parameter sets. The basic idea was provided by Fischbacher and Gächter (2010) who used the strategy method to explain the decline of cooperation in repeated public goods games. They elicited people's preferences for conditional cooperation (details follow in the next section) and had subjects play ten rounds of a repeated public goods game played in the Stranger matching protocol (that is, group composition is changed at random in each round). In each round, players made a contribution decision and reported their beliefs about how much their current group members contribute in the next round. Fischbacher and Gächter (2010) then showed that the elicited cooperative preferences evaluated at the beliefs of a given period predicted actual contributions round by round. Fischbacher et al. (2012) further showed that this method also predicts contributions well in one-shot public goods games.

Gächter et al. (2017) named this method the ABC approach to cooperation. It measures individual *a*ttitudes (a_i) to cooperation as a function of all possible rounded average contributions of other group members (sometimes the function a_i is also called dispositions or preferences), *b*eliefs (b_i) about others' contributions average contributions and actual *c*ontributions (c_i) separately and explains cooperation as $a_i(b_i) \rightarrow c_i$, that is, the function a_i evaluated at player $i's$ belief b_i predicts player $i's$ contribution c_i. Gächter et al. (2017) found that the ABC approach explains contributions in maintenance and provision versions of public goods (see also Gächter et al. (2022) for a related result).

Interestingly, Gächter et al. (2017) and Gächter et al. (2022) observed that the share of conditional cooperators was higher (and the share of free riders lower) in the provision version of the public good game than in the maintenance version, which suggests that attitudes to cooperation are influenced by the context of the game. Isler et al. (2021) replicated these findings and present a framework that generalizes the ABC approach to what they call the Contextualized Strong Reciprocity Approach (CSR).[3] CSR is a version of the ABC approach that allows for

[3]Conditional cooperation is one important instance of "strong reciprocity". See Weber et al. (2018) and Isler et al. (2021) for discussions and analyses.

context effects: CSR explains cooperation as $a_i(f, b_i(f)) \to c_i$, where both a_i and b_i are potentially functions of the contextual features (f) of a given public goods game. In this paper, f is the MPCR or the group size, both of which were very similar in all previous studies that used the ABC approach (in Isler et al. (2021), f referred to maintenance or provision public good). Our goal in this paper is to provide evidence on all elements of $a_i(f, b_i(f)) \to c_i$ where the experiments will manipulate f as group size and MPCR.

4.3 Strategy methods

The strategy method was introduced by Selten (1967) in the context of an oligopoly game but has now been used in all kinds of games (Brandts and Charness (2011); Keser and Kliemt (2021)). Here we focus on the application of the strategy method to PGG, where participants make contingent decisions for each possible average contribution of other members in the group (for a review, see Thöni and Volk (2018)). By eliciting a complete contribution profile, we get data on all possible situations including those that are only rarely reached (e.g., everyone in the group contributing zero or fully). We will first review the standard method by Fischbacher et al. (2001) and present its problems in the context of our research questions in Section 3.1 and then introduce our new version, called the scalable strategy method, in Section 3.2.

4.3.1 Fischbacher, Gächter and Fehr (2001; FGF)

The first application of the strategy method in the one-shot public goods game is due to Fischbacher et al. (2001) (FGF). In the FGF method, participants are asked to make two decisions: (i) an unconditional contribution and, (ii) a contribution table (that is, a_i). The unconditional contribution is the amount they would like to contribute without any information on the contribution of the other group members. For the contribution table, participants need to answer how much they would like to contribute for each possible average contribution of the other group members (i.e., the contributions they would like to make conditional on the other group member's contributions as if they were last movers in a sequential game). Participants are told that after the decisions are made, $n - 1$ of them will be selected randomly to have the unconditional contribution used as their payoff relevant decision and the remaining group member will have their contribution table used as their payoff relevant decision (computed by imputing the average of the other $n-1$ members in their contribution table). See the Online Appendix for the instructions.

The FGF method is an incentive-compatible way to elicit the conditional contribution decisions a_i (since all the choices are potentially payoff relevant). For our research purposes, it is important to note that the probability of a participant having their contribution table selected as payoff relevant depends on the number of participants in the group (i.e., $\frac{1}{n}\%$). Therefore, the larger the group, the more hypothetical the contribution table becomes. This posits a problem if we want to incentive-compatibly elicit cooperative dispositions as a function of group size. In the following subsection, we introduce a method that solves this problem.

4.3.2 A scalable strategy method (SSM)

Our research questions demand an incentive-compatible method that also keeps the probability of the contribution table being payoff relevant constant across group sizes ("scalable"). We achieve these goals by giving the contribution table and the unconditional contribution equal weights (50% each). So, instead of randomly selecting *one* group member (with probability $1/n$) for whom the contribution table is payoff relevant (like in FGF), SSM randomizes with equal probability for *each* group member whether their unconditional contribution or their contribution table is selected as payoff relevant. This feature achieves incentive scalability.

The SSM procedure involves two steps: First, we calculate the *computed conditional contribution* for group member i by plugging the average contribution of the remaining group members (rounded to the nearest integer) into group member i's contribution table. Second, for each group member i, we randomly select either their unconditional contribution or their contribution table with 50% probability each. If for i the unconditional contribution is selected, we use all other group members' computed conditional contributions to determine i's individual payoff; otherwise, if for i the contribution table is selected, we use the computed conditional contribution for player i and all other player's unconditional contributions to determine i's individual payoff (see the Appendix of this paper for further details and a concrete example of the procedure).

Notice that it is possible to have groups where either the unconditional contribution or the contribution table is selected for all players. The reason is that under SSM payoffs are independent between group members. By contrast, because FGF only selects one group member's contribution table to determine his/her contribution, whereas all other group members contribute their unconditional contribution, payoffs are interdependent like in any standard public good game. Hence, SSM gives up FGF's payoff interdependence to achieve the scalability that FGF lacks. Put differently, SSM has an undesirable feature: the size of the public good is individual-specific, as opposed to the standard PGG where the same size of the public good applies to everyone in the group.

However, there are several reasons why SSM's conceptual downside is not a major concern. First, we are still studying a social dilemma (i.e., the Nash equilibrium is to contribute zero, and efficiency demands to contribute everything). Second, this problem is independent of group size or MPCR. Third, and most importantly, we are only interested in the elicited conditional preferences and not the unconditional contributions. The conditional preferences are elicited incentive-compatibly and the incentives for their truthful revelation are independent of group size. The empirical comparison of the elicited a_i and the ABC predictions derived from them will reveal how important the respective disadvantages of FGF and SSM are.

4.4 Study 1: Design

The experiments consisted of a 2×2×2 between-subjects design varying the strategy method (FGF and SSM), group size (small=3 and large=9) and MPCR (low=0.4 and high=0.8). Participants (n=936) were randomized into one of the eight conditions (Table 3.1). Each group member was endowed with $e = 10$ tokens to either keep or invest into the public good (Section 2.1). The strategy methods therefore elicited conditional contributions a_i for each of the eleven (0 to 10) possible average contributions of other group members.

All experiments had two phases. In Phase 1, participants played the PGG in either the FGF or SSM strategy method. In Phase 2, they played the PGG in the direct-response mode. Apart from different parameters in the respective condition (see Table 3.1) the Phase 2 PGGs were the same regardless of the strategy method used in Phase 1.

After explaining the game, we used three incentivized control questions: two questions about the

Condition	Phase 1 Strat. method	MPCR	Group size (n)	Social return (α)	N
1	FGF	0.4	3	1.2	117
2	FGF	0.4	9	3.6	117
3	FGF	0.8	3	2.4	117
4	FGF	0.8	9	7.2	117
5	SSM	0.4	3	1.2	117
6	SSM	0.4	9	3.6	117
7	SSM	0.8	3	2.4	117
8	SSM	0.8	9	7.2	117

Table 3.1: Study 1 experimental conditions (between-subjects)

PGG and one regarding the probability of having the contribution table as the payoff relevant decision (see the Online Appendix for instructions and control questions). Participants who responded incorrectly in the first attempt had to keep trying until they got it right before proceeding (but only those responding correctly in the first attempt were compensated for their correct answers). Participants then completed the respective strategy method task (FGF or SSM, depending on the condition they were randomly selected into). This completed Phase 1 of the experiment.

In Phase 2, participants made a contribution decision in a one-shot direct response PGG with the same parameters as relevant in the respective condition (see Table 3.1). We also elicited the beliefs (first and second order). We incentivized the belief elicitation by rewarding subjects if their prediction was exactly right. We will use these games to test for the predictions made by the ABC approach (see Section 2.3).

The experiment was programmed in Qualtrics and conducted online using the platform Prolific (Palan and Schitter (2018)) with participants from the UK in the 18-25 years old range (average age 21.8 years; 67.4% females; 60.0% students).[4] We restricted participation by age in order to minimize confounds caused by age and cohort effects.[5] Study 1 was run in early 2021. Participants were paid £12.71 per hour on average. The average participant took 8 minutes to complete the experiment.

[4]See Hergueux and Jacquemet (2015) for the reliability of the online elicitation of social preferences and Arechar et al. (2018) for a methodologial discussion of online experiments.

[5]Age is known to influence cooperation positively, see, e.g., List (2004); Gächter and Herrmann (2011); Arechar et al. (2018). To maximize statistical power, we kept the age of our participants constant and similar to the vast majority of studies on MPCR and group size effects.

4.5 Study 1: Results

4.5.1 Attitudes

Both strategy methods allow us to classify participants into types according to their cooperative preferences ("attitudes" a_i). Here we follow Thöni and Volk (2018) and classify the attitude types as Conditional Cooperators, Triangle Cooperators, Unconditional Cooperators and Free Riders.[6]

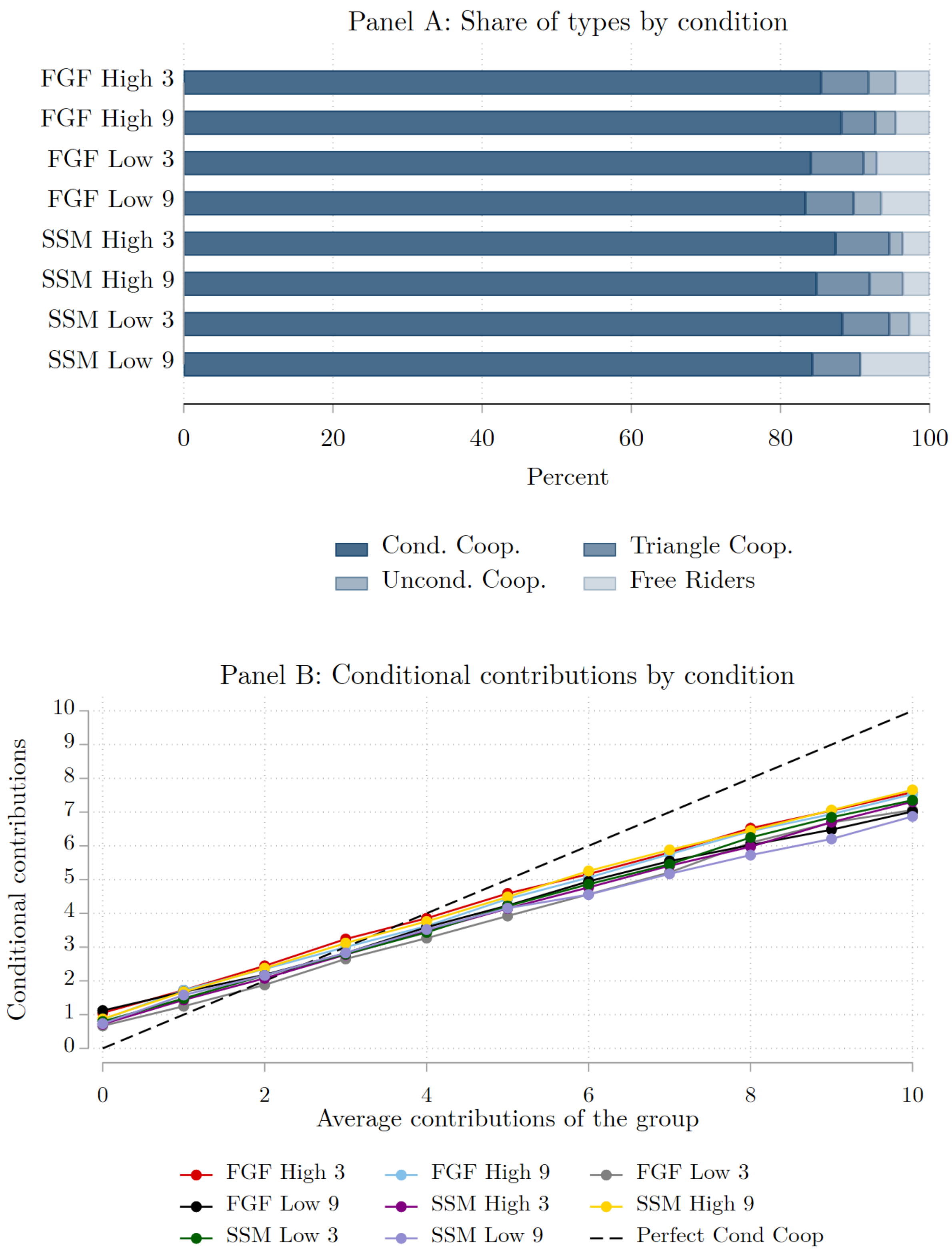
Figure 3.1A shows that the distribution of types is remarkably similar in all eight conditions. Conditional Cooperators is the main category, which accounts for 80.9% of the subjects, followed by the Triangle Cooperators 6.1% and Free Riders with 4.9%. We also compare the attitude type distributions between FGF and SSM for each of the four parameterizations using Chi-squared tests and find that none of the pairwise comparisons is significant (smallest p-value = 0.338). This suggests that compared to FGF, SSM is equally good in identifying attitude types.

Figure 3.1B shows the average of the responses in the contribution tables (i.e., the average conditional contributions $\bar{a}_i$). As a benchmark, we also plot the line for perfect conditional cooperation (the diagonal). Average conditional cooperation $\bar{a}_i$ is almost the same in all conditions (i.e., by method, MPCR, and group size).

To test the link between game parameters and conditional cooperation formally, we averaged the conditional contributions for each subject and regress them on dummies for high MPCR, large group and their interaction. The results are shown in Table 3.2.[7] Although the results are, with one exception, not statistically significant, we see differences between the methods. In Column 1 (SSM), average conditional contributions are insignificantly lower in the large group and in MPCR, but the effect reverses insignificantly when the MPCR is high. In Column 2 (FGF), average conditional contributions increase insignificantly with group size and significantly with MPCR but decreases insignificantly with the interaction of the two.

[6] For this classification we used the Stata command "cctype" provided in Thöni and Volk (2018). In words, Conditional Cooperators increase their cooperation with the cooperation of others; Free Riders contribute zero for any contribution of others; Triangle Cooperators increase their contributions up to a certain point and then decrease with the contribution of others; Unconditional Cooperators contribute a non-zero constant value for any contribution of others.

[7] The results are virtually unchanged if we use a participant $i's$ 11 responses in their vector a_i (rather than the average of the 11 responses a_i as in Table 2) and cluster the standard errors by participant.



Panel A: Distribution of conditionally cooperative types. Panel B: Average conditional contribution $\bar{a}_i$ across all preference types. High (Low) refers to an MPCR of 0.8 (0.4). Large (Small) refers to a group size of 9 (3).

Figure 3.1: Cooperative attitudes a_i as elicited in Phase 1 in Study 1

	(1)	(2)
	SSM	FGF
	Av. cond. contrib.	Av cond. contrib.
large	-0.193	0.216
	(0.232)	(0.252)
high MPCR	-0.078	0.524**
	(0.226)	(0.244)
large x high MPCR	0.540	-0.336
	(0.333)	(0.351)
_cons	4.149***	3.932***
	(0.160)	(0.176)
R^2	0.009	0.011
N	468	468

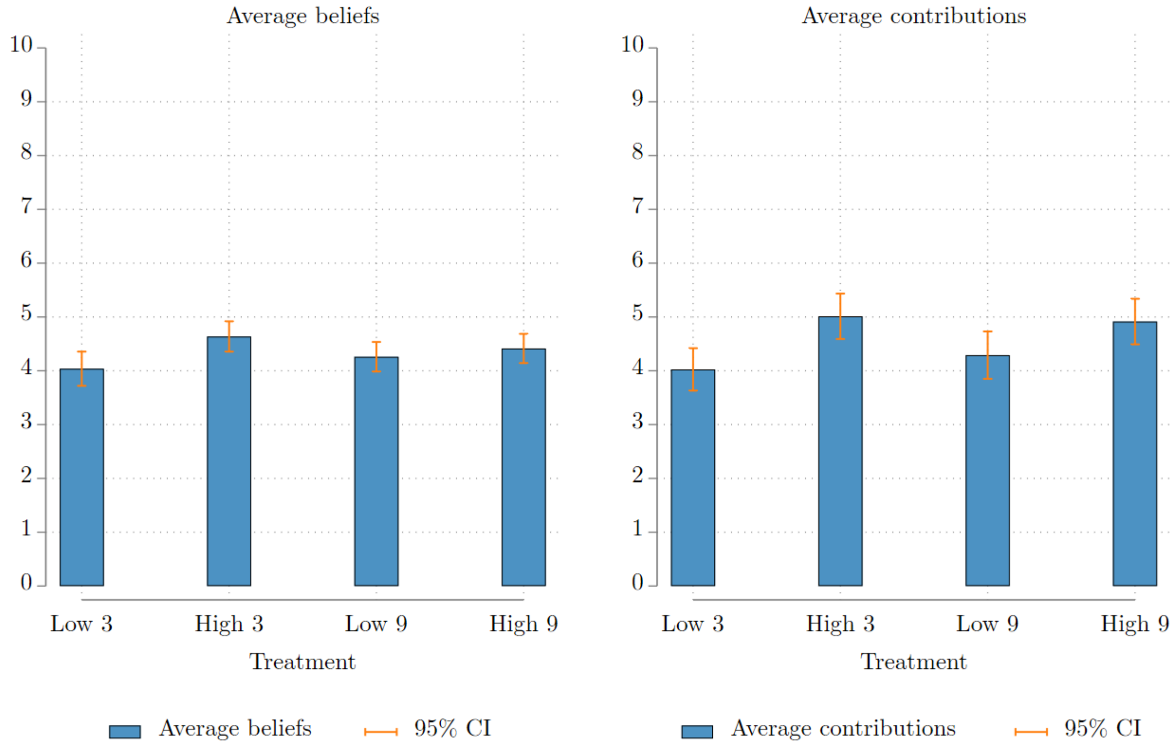
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
OLS estimates. The dependent variable is the average of all 11 conditional contributions a_i in either FGF or SSM. *large* is an indicator that takes the value 1 for groups of 9 and 0 for groups of 3. *high MPCR* is an indicator that takes the value 1 for MPCR=0.8 and 0 for MPCR=0.4. Robust standard errors in parentheses.

Table 3.2: Average conditional contributions a_i as elicited in Phase 1 by SSM and FGF in Study 1 as a function of group size and MPCR

4.5.2 Beliefs and contributions

After the strategy method PGG experiment in Phase 1, participants in Phase 2 took part in a one-shot direct-response PGG where we observed c_i and where we also elicited beliefs b_i. Recall that these one-shot PGG games in Phase 2 had the same parameter conditions as in Phase 1, regardless of whether we used FGF or SSM in Phase 1. Figure 3.2 shows the averages of beliefs and contributions by treatment and suggests a positive MPCR effect in both beliefs and contributions, but no group size effect.

To study the differences between the treatments formally, we regress beliefs and contributions on dummy variables for large group ($n = 9$) and high MPCR (0.8). For this, we pool the observations from both strategy methods since, for given game parameters, the direct response one-shot PGG in Phase 2 is the same regardless of the strategy method used in Phase 1. Table 3.3 presents the results. We find positive and significant effects of the MPCR on beliefs and contributions. These results confirm the MPCR effects reported in previous literature (see Section 2.2). Regarding group size, we find a positive effect but it is not statistically significant.



High (Low) refers to an MPCR of 0.8 (0.4). Large (small) refers to group size of 9 (3).

Figure 3.2: Average of beliefs b_i and contributions c_i by treatment in Phase 2 of Study 1

Figure A.1 in the Online Appendix presents the full distributions.[8]

4.5.3 Testing the accuracy of ABC predictions

Having shown the descriptive evidence, we proceed by testing the predictive accuracy of the ABC approach. We start by using the elicited beliefs b_i and check how well they can predict actual contributions c_i by using the attitudes a_i as described in subsection 2.3. We compute the prediction error as the difference between the actual contributions and the contributions predicted by the ABC approach.

Formally, the predicted contribution of individual i is calculated as $\hat{c}_i = a_i(b_i)$; the prediction error therefore is $\hat{c}_i - c_i$. Individual $i's$ $\hat{c}_i$ can be derived non-parametrically (by taking $i's$ contribution c_i as indicated in $i's$ table of conditional contributions a_i at the belief b_i) or parametrically (by estimating the slope of the conditional contributions $\hat{a}_i$ from all 11 entries

[8]For completeness, Fig.A.2 (Online Appendix) presents the distributions of second-order beliefs. However, for the ABC approach only first-order beliefs matter, which is why we focus on them here.

	(1)	(2)
	Pooled beliefs	Pooled contrib.
large	0.222	0.265
	(0.213)	(0.300)
high MPCR	0.598***	0.987***
	(0.215)	(0.293)
large x high MPCR	-0.444	-0.363
	(0.291)	(0.426)
_cons	4.038***	4.026***
	(0.161)	(0.200)
R^2	0.010	0.016
N	936	936

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
OLS estimates. The dependent variables are the *beliefs* (column 1) and *contributions* (column 2) reported in the Phase 2 PGG. *large* is an indicator that takes the value 1 for groups of 9 and 0 for groups of 3. *high MPCR* is an indicator that takes the value 1 for MPCR=0.8 and 0 for MPCR=0.4. Robust standard errors in parentheses.

Table 3.3: Beliefs and contributions in Phase 2 of Study 1 as a function of group size and MPCR

in individual $i's$ vector a_i and using these parameters and the beliefs to calculate $\hat{c}_i = \hat{a}_i(b_i)$). Since most subjects are (imperfect) conditional cooperators, we follow the second approach to obtain smoother estimates, but the results are similar if we follow the non-parametric approach (see Online Appendix Section B).

Figure 3.3 shows that in all conditions the mode of the $\hat{c}_i - c_i$ distributions is at zero, which means actual contributions coincide with the contributions predicted by the ABC approach. Figure 3.3 also suggests that the distributions are similar across conditions. Note, however, that the distributions in different treatments overlap slightly more under SSM. Kolmogorov-Smirnoff tests comparing the prediction errors under FGF and SSM in each treatment only reject the null hypothesis of equal distributions in the High 9 condition (p-value=0.046), but this does not survive a Bonferroni correction for multiple comparisons (see the Online Appendix Figure A.4 for treatment-specific graphs).

Table 3.4 shows the regressions of the ABC model adapted from Fischbacher and Gächter (2010)

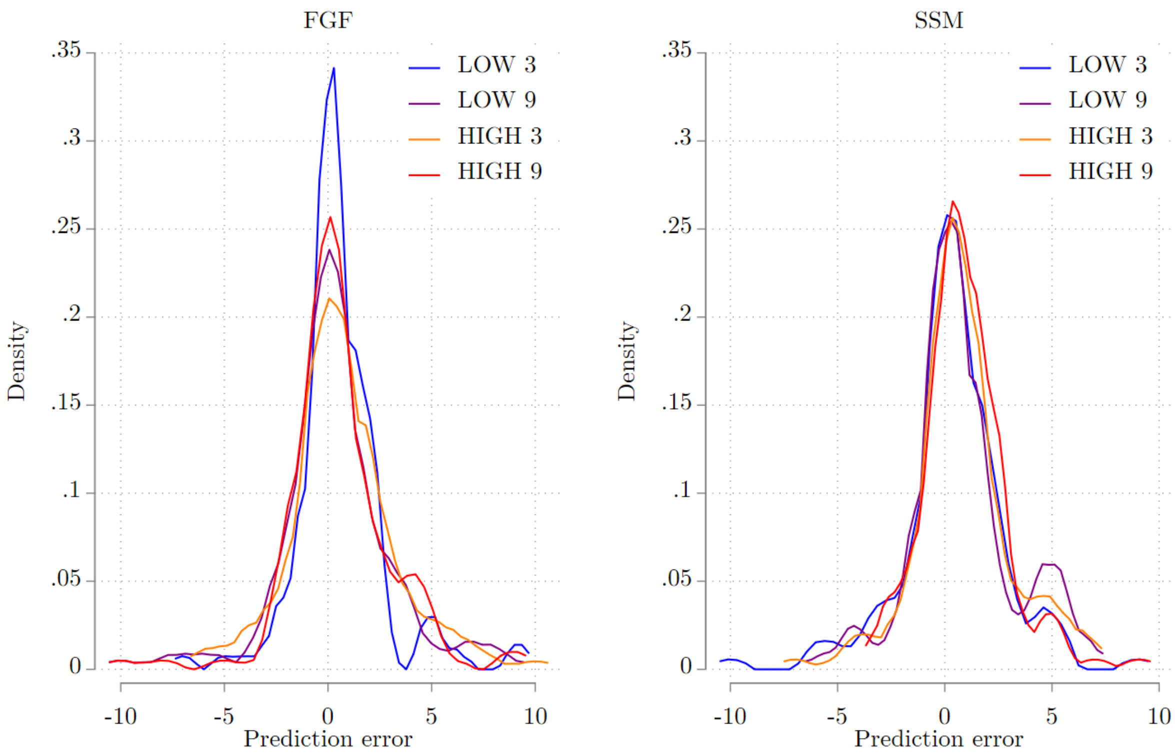


Figure 3.3: Distribution of ABC prediction errors ($\hat{c}_i - c_i$) in Study 1

with the contributions c_i in the Phase 2 one-shot PGG as dependent variable. This approach includes predicted contributions $\hat{c}_i$ and beliefs b_i as additional regressors because Fischbacher and Gächter (2010) have shown that $c_i = \beta\hat{c}_i + (1-\beta)b_i$, that is, actual conntributions are a weighted average of predicted contributions and beliefs. In other words, beliefs matter on top of predicted contributions (presumably because of the enhanced saliency of a specific belief in a direct response PGG). We also add a dummy for high MPCR and a dummy for large group size (in the pooled models of Columns 1 and 2). Columns 1, 3 and 5 show the results for FGF and columns 2, 4 and 6 for SSM for different samples.

The estimation results confirm that both beliefs and predicted contributions are highly significantly positively correlated with contributions in all models. High MPCR does not contribute significantly on top of beliefs and predicted contributions (except in Columns 2 and 6 where we find a weakly significantly positive effect).

Our next step is to compare the two methods in terms of in-sample and out-of-sample prediction power (as in, e.g., Andreoni et al. (2015)). The cross-validated Mean Squared Error (CVMSE) is a measure of out-of-sample prediction, in other words, how well the estimated model predicts

	(1) Pooled FGF	(2) Pooled SSM	(3) Large (9) FGF	(4) Large (9) SSM	(5) Small FGF	(6) Small SSM
predicted	0.555***	0.615***	0.521***	0.670***	0.578***	0.560***
	(0.0919)	(0.0676)	(0.140)	(0.0911)	(0.124)	(0.101)
beliefs	0.405***	0.407***	0.467**	0.486***	0.362**	0.344***
	(0.118)	(0.0807)	(0.193)	(0.0996)	(0.152)	(0.124)
high MPCR	0.222	0.393*	0.223	0.268	0.233	0.510*
	(0.226)	(0.209)	(0.331)	(0.283)	(0.305)	(0.302)
large	-0.174	0.269				
	(0.220)	(0.202)				
_cons	0.528*	0.127	0.222	-0.108	0.614**	0.567
	(0.279)	(0.250)	(0.455)	(0.269)	(0.308)	(0.367)
R^2	0.489	0.547	0.454	0.615	0.528	0.484
$CVMSE$	5.938	4.807	6.650	4.306	5.482	5.303
N	468	468	234	234	234	234

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
OLS estimates. The dependent variable are the contributions c_i in the Phase 2 one-shot PGG. *beliefs* are the b_i elicted in Phase 2 and *predicted* is the ABC prediction using either FGF or SSM. *large* is an indicator that takes the value 1 for groups of 9 and 0 for groups of 3. *high MPCR* is an indicator that takes the value 1 for MPCR=0.8 and 0 for MPCR=0.4. Robust standard errors in parentheses.

Table 3.4: Regressions explaining contributions in Study 1 using the ABC method

the contributions of new observations. To compute this, we split the sample randomly in five sub-samples and train the data (i.e., estimate the parameters) using four of them to predict the remaining one.[9] After that, we compute the mean squared error of these predictions.

For the full sample comparison, we find that the SSM outperforms FGF because the CVMSE is smaller in SSM than in FGF (4.807 vs. 5.938). We should also expect this relative increase in performance to be higher when group size is larger. This is because the probability of the contribution table being payoff relevant changes with group size in FGF but not in the SSM: The probabilities are 0.33 (FGF) vs. 0.50 (SSM) in groups of 3 members and 0.11 (FGF) vs. 0.50 (SSM) in groups of 9 members (see Section 4.3.1). To see this, we split the data by group sizes in columns 3 to 6. The CVMSE in the large groups is 6.650 in FGF and 4.306 in SSM. Even in the small groups, SSM slightly outperforms FGF in out-of-sample predictions (5.303 vs. 5.482). Similarly, the R-squared (in-sample prediction) is 35% higher in the large group

[9]We used the Stata command "crossvalidate" (Schonlau, 2020).

and 12% higher in the full sample, but 8% lower in the small group.[10] The main results are also robust to restricting the sample to conditional cooperator types only.

In summary, we find that neither MPCR nor group size affect conditional contributions a_i. By contrast, beliefs b_i and contributions c_i do significantly increase in MPCR but not group size, confirming previous literature (Section 2.2). Because attitudes are not affected by game parameters, but a high MPCR increases beliefs, the ABC approach predicts higher contributions when the MPCR is high, and our experiments confirm this prediction.

While our results are reassuring, some caution is warranted: although our large group was three times larger than the small group, we are still in a relatively small group size context. Next, we therefore explore significantly larger group sizes.

4.6 Study 2: Design

For Study 2, we compare group sizes of 3 and 30 (a ten-fold increase). This poses a new problem. Keeping the MPCR constant would imply a huge social return α. Thus, instead of holding the MPCR (α/n) constant, we hold α constant across group sizes but vary its level. The parameters are shown in Table 3.5.

In summary, the experiment in Study 2 consisted of a 2×2×2 between-subjects design using the SSM and FGF, varying group size (small = 3 and large = 30) and α (low = 1.2 and high = 2.4). Apart from these differences, the Study 2 experiment was very similar to the Study 1 experiment: like Study 1, Study 2 had two phases. In Phase 1 we elicited attitudes to cooperation using the SSM method, and in Phase 2 participants played a direct response PGG (with the parameterization of the respective condition). We also elicited first- and second-order beliefs.

Note that some of the conditions in Study 2 are exactly the same as in Study 1. In the Online Appendix we show that the results are replicated.

Study 2 was run on Prolific with 1200 participants (average age 21.6 years; 57.8% females; 64.8% students). Participants were paid the equivalent to £13.72 per hour on average. The

[10] It is also possible that the SSM outperforms FGF because it is simpler to understand (i.e. 50% probability of each decision being payoff relevant as opposed to picking a participant at random with an ad-hoc probability). However, why this is the case is beyond the scope of this paper.

average subject took around 8 minutes to complete the experiment. Study 1 participants could not take part in Study 2.

Condition	Phase 1 Strat. method	MPCR	Group size (n)	Social return (α)	N
1	FGF	0.4	3	1.2	150
2	FGF	0.04	30	1.2	150
3	FGF	0.8	3	2.4	150
4	FGF	0.08	30	2.4	150
5	SSM	0.4	3	1.2	150
6	SSM	0.04	30	1.2	150
7	SSM	0.8	3	2.4	150
8	SSM	0.08	30	2.4	150

Table 3.5: Study 2 experimental conditions (between-subjects)

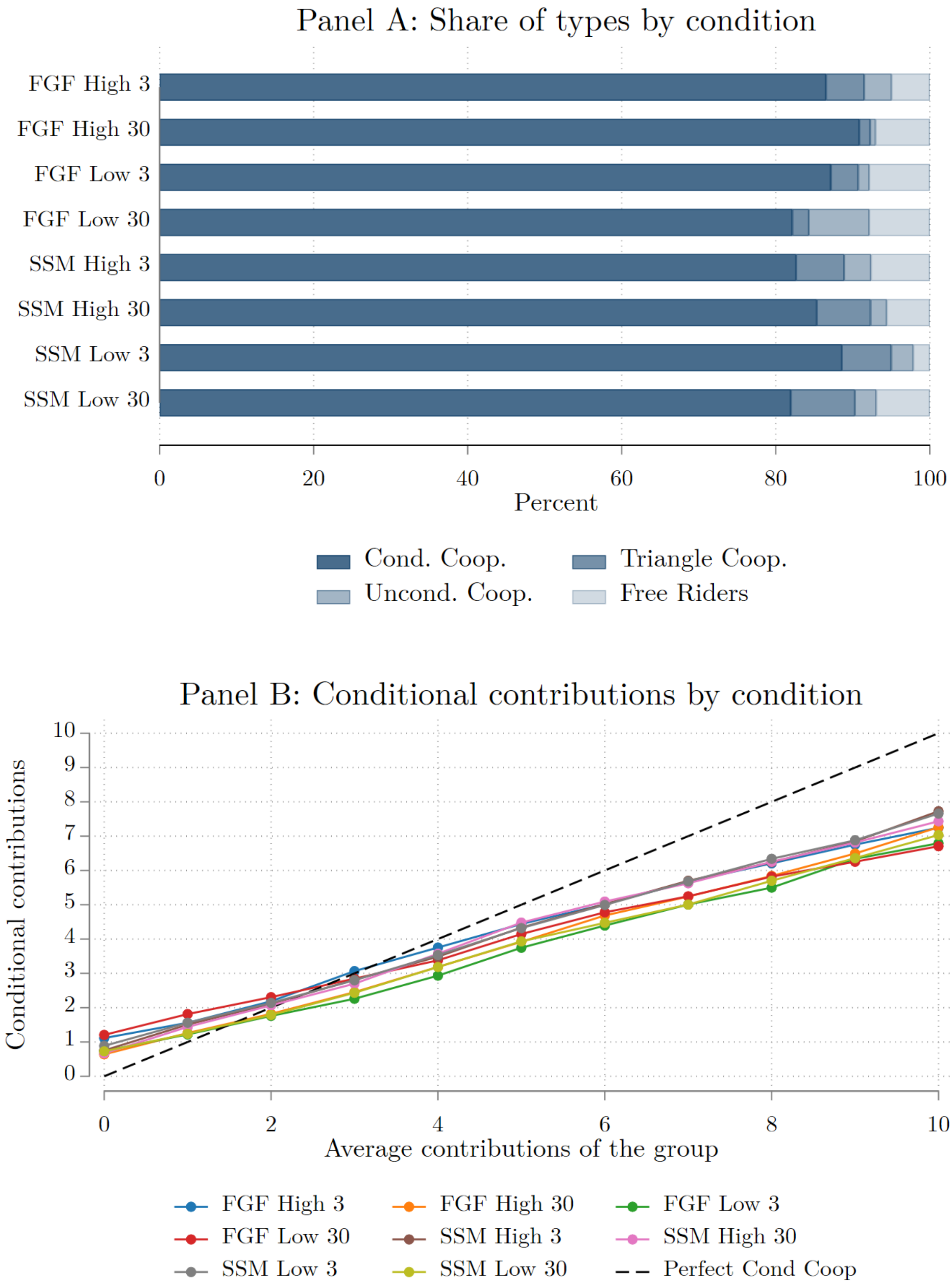
4.7 Study 2: Results

4.7.1 Attitudes

Figure 3.4A reveals that the share of types is very similar in all conditions. In the low α treatments (with SSM), nonetheless, there is some evidence that the number of free riders increases (from 2% to 6.7%) and the number of conditional cooperators decreases (from 82.7% to 78.7%) with group size. This also happened in Study 1 (SSM) for the Low MPCR treatments, the number of free riders increases (from 2.6% to 8.6%) and the number of conditional cooperators decreases (from 83.8% to 77.8%) with group size.

Nosenzo et al. (2015) and Weimann et al. (2019) found that, in low MPCR treatments, cooperation increases with group size, but they do not disentangle the role of conditional preferences and beliefs for cooperation. Our results would be consistent with theirs if conditional cooperators in larger groups had a slope high enough to compensate for the increase in free riders and the reduction in conditional cooperators. This argument is consistent with Diederich et al. (2016), who found a positive group size effect driven by the intensive margin (see Section 4.2.2).

Figure 3.4B shows the average of the responses in the contribution tables by condition (with the dashed black line representing a hypothetical perfect conditional cooperator). Again, the slopes are similar in all eight conditions.



Panel A: Distribution of conditionally cooperative types. Panel B: Average conditional contributions $\bar{a}_i$ across all preference types. High (Low) refers to a social return of 2.4 (1.2). Large (small) refers to group size of 30 (3).

Figure 3.4: Cooperative attitudes a_i as elicited in Phase 1 of Study 2

	(1) SSM Av. cond. contrib.	(2) FGF Av. cond. contrib.	(3) Pooled beliefs	(4) Pooled contrib.
large	-0.447**	0.347	-0.367	-0.190
	(0.211)	(0.247)	(0.170)	(0.260)
high α	-0.023	0.575**	0.883***	0.917***
	(0.205)	(0.223)	(0.187)	(0.261)
large x high α	0.411	-0.730**	-0.587**	-0.447
	(0.299)	(0.327)	(0.252)	(0.378)
_cons	4.254***	3.699***	3.847***	3.797***
	(0.134)	(0.155)	(0.134)	(0.175)
R^2	0.010	0.011	0.028	0.012
N	600	600	1200	1200

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

OLS estimates. The dependent variable is the average of all 11 *conditional contributions* a_i as elicited in Phase 1 of Study 2 (model 1); the *beliefs* b_i (model 2); and *contributions* c_i (model 3) as elicited in the direct-response one-shot PGG in Phase 2 of Study 2. *large* is an indicator that takes the value 1 for groups of 30 and 0 for groups of 3. *high* α is an indicator that takes the value 1 when the social return = 2.4 and 0 when the social return = 1.2. Robust standard errors in parentheses.

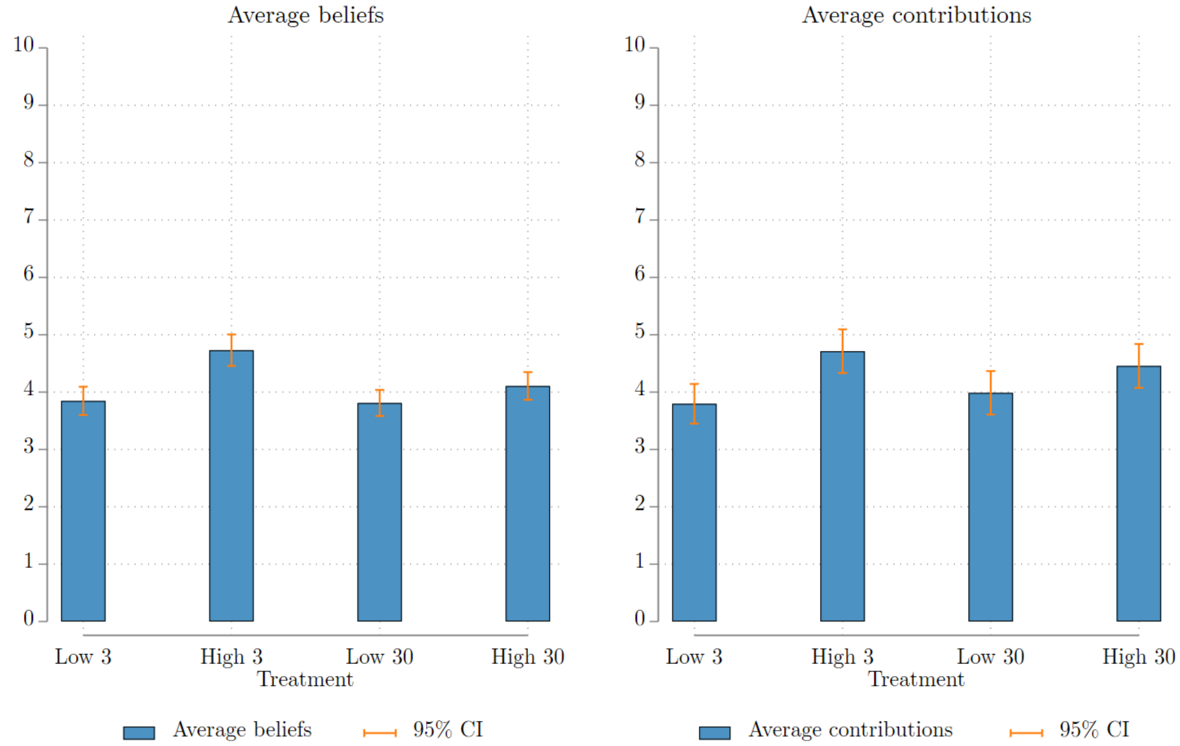
Table 3.6: Average conditional contribution a_i; beliefs b_i; and contributions c_i, all as a function of group size, MPCR, and their interaction in Study 2

In the first two columns of Table 3.6 we test formally how game parameters affect the attitudes to cooperation. Column 1 shows that (in SSM) preferences for cooperation are lower in the large groups, but the interaction term with high α is positive and of the same magnitude, meaning that only large groups with low α have significantly lower preferences for cooperation. Column 2 shows (in FGF) a positive (but not statistically significant) effect of large groups with a negative interaction with α, meaning that large groups with high α have significantly lower preferences for cooperation. These differences between SSM and FGF are similar to the differences found in Study 1.

4.7.2 Beliefs, contributions, and ABC prediction errors

Figure 3.5 presents the average beliefs b_i (left) and contributions c_i (right) in each treatment of Study 2. Consistent with the results from Study 1 (see Fig. 2), beliefs and contributions increase in the social return (α) and suggest no group size effect.

The formal analysis is presented in Columns 3 and 4 of Table 3.6, which shows the regressions of



High (Low) refers to social returns of 2.4 (1.2). Large (small) refers to group size of 30 (3).

Figure 3.5: Average of beliefs b_i and contributions c_i by treatment in Phase 2 of Study 2

beliefs and contributions on dummy variables for groups of 30 and $\alpha = 2.4$. We find a positive and statistically significant effect and similar in magnitude for α in both cases. The coefficients for group size (*large*) are negative for beliefs and contributions but not statistically significant. In both cases, the interaction term (*large x high* α)is negative but only statistically significant for beliefs.[11] Like in Study 1, the prediction errors are similar across conditions, as shown in Figure 3.6. Overall, the results are consistent with Study 1.

Finally, Table 3.7 shows the regressions of the basic ABC model. Although we are holding α instead of the MPCR constant, the results are similar to Study 1, the coefficients of *beliefs* and *predicted* are economically and statistically significant and the coefficients of large and high α moderate and not statistically significant.

[11] Online Appendix Fig. A.5 separately presents the distributions of beliefs and contributions holding group size or MPCR constant. Fig. A.6 presents the distributions of second-order beliefs.

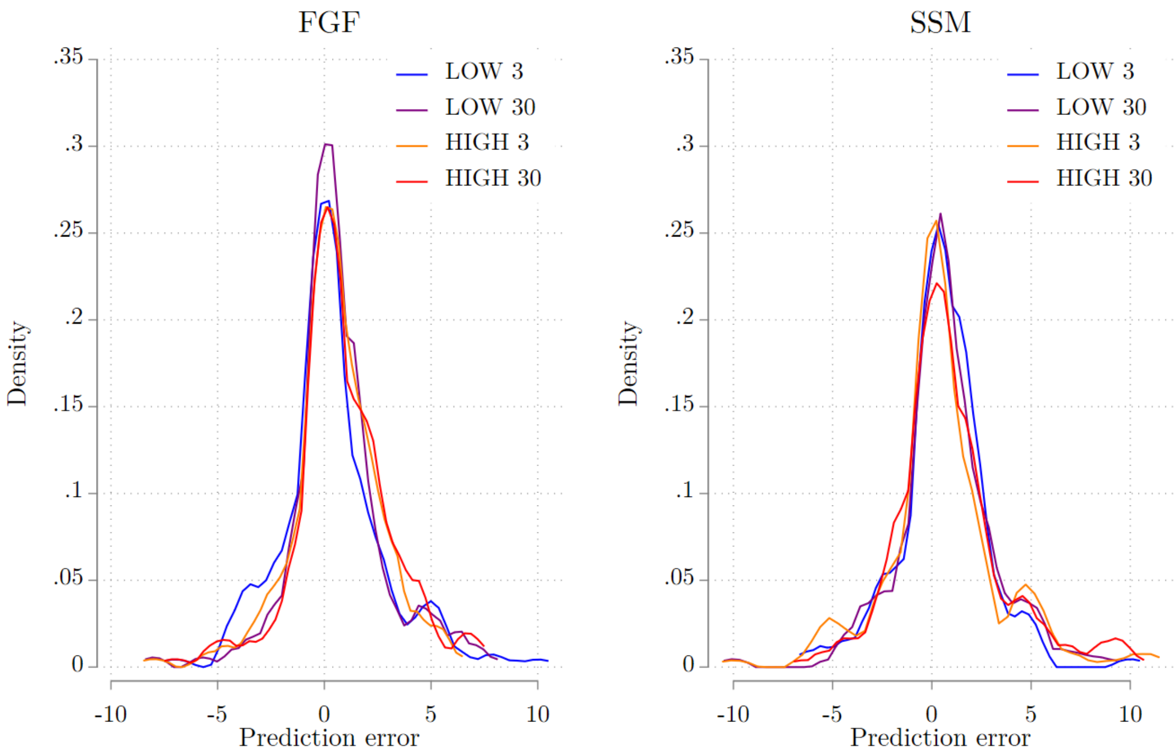


Figure 3.6: Distribution of ABC prediction errors ($\hat{c}_i - c_i$) in Study 2

4.8 MPCR, group size, and the role of beliefs for cooperation

Confirming previous results in the literature (see Section 2.2), we find that, on average, MPCR (and α) has a positive effect on contributions (Figures 3.2 and 3.5, and Tables 3.3 and 3.6). Regarding group size the data show no clear pattern of the average effect on contributions (positive in Study 1 and negative in Study 2).

The CSR approach (see Section 2.3) proposes that a_i and b_i can be functions of contextual features f (i.e., MPCR and group size). We found that f does not affect a_i but MPCR does affect beliefs b_i and contributions c_i. In theory, the CSR approach should internalize f in *predicted* (that is, $\hat{c}_i$), but, like Fischbacher and Gächter (2010), we found in both studies that *beliefs* matter on top of *predicted* to explain contributions (Tables 3.4 and 3.7). Although with large standard errors, Table 3.4 and Table 3.7 also show large coefficients for MPCR and group size. Here we explore whether f governs the effect of beliefs on contributions (e.g., beliefs might become a more important component in the ABC regressions as MPCR or group size increases).

	(1) Pooled FGF	(2) Pooled SSM	(3) Large (30) FGF	(4) Large (30) SSM	(5) Small FGF	(6) Small SSM
predicted	0.784***	0.571***	0.902***	0.586***	0.671***	0.552***
	(0.0550)	(0.0801)	(0.0615)	(0.106)	(0.0836)	(0.121)
beliefs	0.180***	0.329***	0.111	0.379***	0.243**	0.297**
	(0.0689)	(0.101)	(0.0870)	(0.139)	(0.0987)	(0.146)
high α	0.190	0.147	0.190	0.244	0.258	0.0522
	(0.183)	(0.204)	(0.259)	(0.300)	(0.257)	(0.276)
large	0.301	0.217				
	(0.183)	(0.203)				
_cons	0.394*	0.713***	0.567**	0.627*	0.495*	0.977***
	(0.216)	(0.267)	(0.259)	(0.342)	(0.259)	(0.359)
R^2	0.551	0.421	0.571	0.429	0.537	0.415
$CVMSE$	5.158	6.524	5.603	6.460	4.865	6.441
N	600	600	300	300	300	300

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
OLS estimates. The dependent variable are the *contributions* c_i in the Phase 2 one-shot direct-response PGG. *predicted* are the ABC predictions using either FGF or SSM. *beliefs* are the b_i elicited in the Phase 2 PGG. *large* is an indicator that takes the value 1 for groups of 30 and 0 for groups of 3. *high* α is an indicator that takes the value 1 when the social return = 2.4 and 0 when the social return = 1.2. Column 1 uses the full sample and columns 2 and 3 split the sample by group size. CVMSE is the cross validated mean square error. Robust standard errors in parentheses.

Table 3.7: Regressions explaining Phase 2 contributions in Study 2 using the ABC approach

To test this formally, we re-run, for each study, the ABC regressions including beliefs interacted with group size and MPCR (or α).

Table 3.8 presents the results. Column 1 shows the results for Study 1 using the SSM. We find a strong negative effect of group size on contributions. The interaction of *beliefs* x *large* indicates that the effect size depends on the level of beliefs. Mathematically, $\frac{\partial c}{\partial \text{large}} = -0.803 + 0.245 * \textit{beliefs}$. The direct negative effect gets reversed if *beliefs* are high enough, that is, if $b_i > 0.803/0.245 = 3.28$ in our sample. These results are not replicated in the FGF sample (Column 2) but they are qualitatively similar in the pooled sample (Column 3).

Regarding MPCR, we find a strong negative effect but with large standard errors. The interaction term *beliefs* x *MPCR* is positive, statistically significant and similar in magnitude to the

	(1) Study 1 SSM contrib.	(2) Study 1 FGF contrib.	(3) Study 1 Pooled contrib.	(4) Study 2 SSM contrib.	(5) Study 2 FGF contrib.	(6) Study 2 Pooled contrib.
predicted	0.601***	0.550***	0.570***	0.571***	0.783***	0.684***
	(0.069)	(0.092)	(0.0582)	(0.080)	(0.056)	(0.049)
beliefs	0.189*	0.364***	0.288***	0.263**	0.127	0.191**
	(0.114)	(0.126)	(0.0851)	(0.116)	(0.099)	(0.076)
large	-0.803**	-0.345	-0.542	-0.286	-0.025	-0.146
	(0.420)	(0.523)	(0.338)	(0.474)	(0.328)	(0.287)
beliefs x large	0.245***	0.043	0.139*	0.119	0.084	0.102
	(0.093)	(0.122)	(0.0776)	(0.112)	(0.082)	(0.070)
high MPCR	-0.636	-0.036	-0.316			
	(0.433)	(0.523)	(0.342)			
beliefs x high MPCR	0.236**	0.062	0.147*			
	(0.099)	(0.121)	(0.0786)			
high α				0.049	0.086	0.069
				(0.478)	(0.330)	(0.288)
beliefs x high α				0.024	0.030	0.027
				(0.110)	(0.084)	(0.070)
_cons	1.123	0.706	0.872***	0.996***	0.597*	0.775***
	(0.426)	(0.347)	(0.270)	(0.380)	(0.303)	(0.240)
R^2	0.560	0.490	0.520	0.422	0.551	0.486
N	468	468	936	600	600	1200

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
OLS estimates. The dependent variables are the *contributions* c_i in the Phase 2 one-shot PGG. *beliefs* are the b_i elicited in Phase 2. *predicted* is the ABC prediction using either FGF or SSM. *large* is an indicator that takes the value 1 for groups of 9 or 30 and 0 for groups of 3. *high MPCR* is an indicator that takes the value 1 for MPCR=0.8 and 0 for MPCR=0.4. *high α* is an indicator that takes the value 1 when the social return = 2.4 and 0 when the social return = 1.2. Robust standard errors in parentheses.

Table 3.8: The role of beliefs in explaining cooperation, controlling for ABC predictions, group size, and MPCR

interaction with group size. Mathematically, $\frac{\partial c}{\partial \text{MPCR}} = -0.636 + 0.236 * \textit{high MPCR}$. As in the group size case, the negative effect gets reversed if *beliefs* are high enough; here the threshold is $0.636/0.236 = 2.69$. Again, we do not reject any of these hypotheses in the FGF method but the results survive in the pooled sample.

Interestingly, we find that the beliefs threshold to make the overall group size effect positive (3.28) is higher than the beliefs threshold to make the overall MPCR effect positive (2.69).

This could explain why there is more consensus in the effect of MPCR than on the group size effects in the literature.

Columns 4, 5 and 6 show the regression results for Study 2. Although the group size effect is not statistically significant, the results are qualitatively similar. We conjecture that this is due to the MPCR adjustment (i.e., holding the α constant instead of the MPCR) offsetting the group size effect. Our interpretation is that group size (as well as MPCR effects) operate by affecting the weight of beliefs in the decision to contribute which is consistent with previous literature (e.g., Weimann et al. (2019); Kerr (1989)).

4.9 Summary

In this paper we revisited a classic question in the experimental economics literature on public goods games: the role of group size and MPCR for voluntary cooperation. Our starting point was the observation that many people have a preference for conditional cooperation (Fischbacher et al., 2001; Fischbacher and Gächter, 2010; Chaudhuri, 2011; Thöni and Volk, 2018), which renders the beliefs about others' cooperation important. The specific question we addressed in this paper was how group size and MPCR affect preferences (that is, attitudes to cooperation) and beliefs, and how preferences and beliefs jointly explain cooperation.

For our analysis we used the ABC approach which measures an individual i's attitudes to cooperation (a_i) and beliefs (b_i) to explain i's cooperation (c_i): $a_i(b_i) \rightarrow c_i$, which has proven to be a good framework to explain, quantitatively, the level of cooperation we see in small-group experimental public goods games. The ABC approach we used in this paper $[a_i(f, b_i(f)) \rightarrow c_i]$ allows to go beyond simply observing resulting levels of cooperation as a function of the contextual features of the public good game: the contextual features f (group size and MPCR parameters in our case) might affect a_i or b_i or both, and it is their interactions $a_i(b_i)$ that explains the cooperation levels c_i we observe.

The ABC approach requires measuring the attitudes to cooperation a_i, for which (Fischbacher et al., 2001) (FGF) introduced an incentive-compatible method. The ABC approach has been successfully used in small groups of four players with very similar MPCR parameters (Fischbacher and Gächter, 2010; Fischbacher et al., 2012; Gächter et al., 2017, 2022; Isler et al., 2021). Until this paper, there has been no evidence on how the ABC approach fares in larger groups and with different MPCR parameters. Moreover, the FGF method to measure attitudes to cooperation might loses its incentive-compatibility as group size increases. We therefore also introduced a new incentive-compatible version of the strategy method, which is scalable to any group size but has the downside that incentivization implies that the public good is not well defined (see Section 3.2 and Appendix). However, despite this theoretical weakness, SSM returns the same type distribution (and average conditional cooperation schedules) as FGF. It also works similarly as FGF in the ABC predictions.

We conducted two studies. In Study 1 we applied the SSM and compared it with the traditional FGF method with group sizes 3 and 9 and MPCRs of 0.4 and 0.8. We found that the ABC approach on average correctly predicted actual contribution levels in all conditions. In terms of predictive success and using cross-validated mean squared error and R^2 as criteria, the SSM method did at least as well as FGF, in particular in large groups. In Study 2, however, with group sizes of 3 and 30, and MPCRs of 0.04, 0.08, 0.4 and 0.8, FGF performed better in terms of R^2 and cross-validated mean squared error (possibly due to the composition of the sample).Again, the ABC approach predicts contribution levels in all conditions.

Our results are striking: none of the game parameters in both studies, nor the elicitation method of cooperative attitudes (FGF or SSM) affects attitudes to cooperation (a_i) in a significant way, with the exception of groups of 30 and low MPCR, where we find a_i to be slightly flatter than in other conditions. In terms of cooperation behavior, we find that higher MPCRs lead to higher beliefs and higher cooperation, confirming previous evidence. Holding MPCR constant, we find no statistically significant evidence for group size effects: group size neither affects a_i, nor b_i, nor c_i. However, group size magnifies the effects of beliefs on cooperation. Similarly, we conclude that MPCR effects work via increased beliefs about others' cooperativeness and not via changed attitudes to cooperation.

On a methodological note, our results on the two strategy methods show that the lack of incentive scalability of FGF does not matter much empirically. This holds when comparing the elicited a_i under FGF and under SSM (see Figs. 3.1 and 3.4) and also for the ABC predictions (Figs. 3.3 and 3.6 and Tables 3.4 and 3.7). However, while SSM is incentive scalable by design it has the conceptual problem that the public good is not well defined but the fact that the elicited a_i are similar also shows that this conceptual problem is empirically not very important. Thus, it is up to the taste of researchers which method to use when studying group size effects in future research.

In summary, we conclude that the ABC approach works well to explain cooperation for a wide range of parameter sets and for either strategy method we use. Future research should therefore explore the applicability of the ABC approach in further public goods settings of economic interest.

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4.11 Appendix: The Scalable Strategy Method (SSM)

Here we describe some further technical details of how SSM works and illustrate with an example. The instructions are available in the Online Appendix and a Qualtrics version (Qualtrics *qsf* format) is available at https://osf.io/7psud/.

Procedure

Consider a group of three people playing a PGG. Table 3.A.1 displays sample responses to the unconditional contribution and the contribution table (i.e., first 11 rows). For illustrative purposes, let's say we have a conditional cooperator, a free rider and a triangle cooperator. Each group member's payoff is randomly determined from either their unconditional contribution or from their contribution table, with 50% probability each. Since this is true for any group size, SSM guarantees the incentive scalability of the strategy method. Because both the unconditional contribution and the contribution table are potentially payoff relevant, participants have an incentive to take both the unconditional and the conditional contribution seriously.

The steps for calculating individual payoffs are the following:

- First: Calculate the *computed conditional contribution* for i by plugging in the average contribution of the remaining players into player i's contribution table. The contribution table is a function that depends on the average unconditional contributions (rounded to the nearest integer) of the other players. Example: Player 1 will have a computed conditional contribution of 2 because the average of the other two players' unconditional contributions is $(0 + 4)/2 = 2$. Then if we plug in 2 in Player 1's contribution table we get a computed conditional contribution of 2 (because Player 1 indicates in their contribution table that they will contribute 2 if others contribute 2 on average). With the same reasoning, Player 2's and Player 3's computed conditional contribution will be 0 and 2, respectively.

- Second: We proceed to compute the individual payoff for each player independently. For each player i, we randomize to use either their unconditional contribution or their contribution table (each with 50% probability).

– If player i's *unconditional contribution* is randomly selected, we use all other player's computed conditional contributions to determine i's individual payoff (but not necessarily for the payoffs of the other players, as those are computed independently using the same procedure). Example: If Player 1 is assigned to the unconditional contribution, he/she would contribute 5. To compute player i's payoff, we also need the contributions of the other group members. For those we will use their computed conditional contributions. Example of Player 1's payoff: $10-5+\frac{\alpha(5+0+2)}{3}$. Note that player 1's payoff is not affected by the outcomes of the randomization for players 2 and 3.

– If player i's *contribution table* is randomly selected, we use player i's computed conditional contribution and all other player's unconditional contributions to determine i's individual payoff (but not necessarily for the payoffs of the other players, as those are computed independently using the same procedure). Example: Player 1 contributes 2. To compute player i's payoff we also need the contributions of the other players. For those, we will use the unconditional contributions. Example of Player 1's payoff: $10-2+\frac{\alpha(2+0+4)}{3}$. Note again that player 1's payoff is not affected by the outcomes of the randomization for players 2 and 3.

Type examples	Player 1 Conditional Cooperator	Player 2 Free Rider	Player 3 Triangle Cooperator
Unconditional cont.	5	0	4
Conditional table			
0	0	0	0
1	1	0	1
2	2	0	1
3	3	0	2
4	4	0	3
5	4	0	4
6	5	0	3
7	5	0	3
8	6	0	2
9	6	0	2
10	7	0	1
Computed conditional cont.	(2)	(0)	(2)

The parenthesis in the last row indicate that the numbers are computed by the researcher using the other rows as explained in the procedure.

Table 3.A.1: Example of responses

Remarks

- For each player, the probability that his/her contribution is determined from the unconditional contribution or the contribution table is guaranteed to be 50% each. This is a result of the randomization in the first step of the procedure. Participants are told about this in the instructions (see Online Appendix).

- Incentive scalability (keeping incentive compatibility constant across group sizes) requires that the probability of selecting the unconditional contribution and the contribution table remains constant for any group size. We can only achieve incentive scalability by changing at what level the randomization happens:

  – FGF randomizes at the level of the group and randomly selects *one* group member to determine their contribution from their contribution table, while all other group members' contribute their unconditional contribution. Payoffs are therefore interdependent like in any standard public good game (e.g., if player 1's contribution is derived from player 1's contribution table, the others players automatically contribute their unconditional contribution). This feature of payoff interdependence renders FGF not scalable (see Section 3.1).

  – By contrast, SSM randomizes at the level of individual group members, that is, for *each* group member i, i's unconditional contribution or their contribution table is randomly selected. Hence, the outcome of the randomization for player i has no payoff consequences for the other players. Therefore, because the randomization between unconditional contribution and contribution table affects individual i only, payoffs under SSM are not interdependent but individual-specific (see section 4.3.2).