The impact of refugees on natives' trust in political institutions – Evidence from Germany

Module: Causal Inference (7SSPP124)
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Content

Introduction

In this research essay, I explore the causal effect of refugees on natives' **T**rust in **P**olitical **I**nstitutions (TPI) in Germany. Therefore, my research contributes to the broader literature on the effects of (humanitarian) migration on the host country. While the economic dimensions of these effects have been researched quite comprehensively (See Orrenius & Zavodny (2012) for a slightly outdated meta-study on this subject), the literature on the effect of refugees on natives' political believes and their trust in political institutions remains dispersed. Many studies have focussed on the relationship between refugees and the rise of right-wing populist parties but the broader effect on trust in political institutions has not been explored yet. Using the exogenous treatment of refugee allocation in Germany to different federal states based on a centralized allocation mechanism ("Königssteiner key") allows me to estimate the causal effect of refugees on TPI through a fixed-effect model using both state- and time-fixed effects. I find robust evidence that a higher refugee-per-population ratio per state is associated with a higher level of trust in political institutions. This effect seems to be driven by a sharp divide between relatively high levels of TPI in the old states of Germany[1], and relatively low levels of TPI in the new states of Germany[2]. Therefore, it is likely that the historical trajectory of the former divided Germany still shapes the levels of TPI.

This essay proceeds as follows: First, I review the contemporary literature on the effects of humanitarian migration on political beliefs of the host country. Second, I describe my sample data, show my methodological approach, and explain all the relevant variables in my model. Third, I discuss my results, state the limitations of my research, and review further research questions.

Contextual analysis of the relevant literature

The impact of refugees on natives' political beliefs is part of the broader literature of the effects of (humanitarian) migration on the host country population. Even though refugees lack the citizenship of their host country that forbids them to vote in elections, they still exert influence on political institutions mostly by influencing the political attitudes of natives (Foner, 2008). However, the empirical evidence assessing the direction and strength of these effects yields conflicting results.

On the one hand, many studies have found a strong relationship between higher numbers of refugees and migrants and an increased likelihood to vote for a right-wing party (Otto & Steinhardt, 2014;

[1] The old states include Baden-Württemberg, Bavaria, Bremen, Hamburg, Saarland, Schleswig-Holstein, Hesse, Lower Saxony, North Rhine-Westphalia and Rhineland-Palatia.
[2] The new states include Saxony, Thuringia, Brandenburg, Mecklenburg-Vorpommern, Saxony-Anhalt.

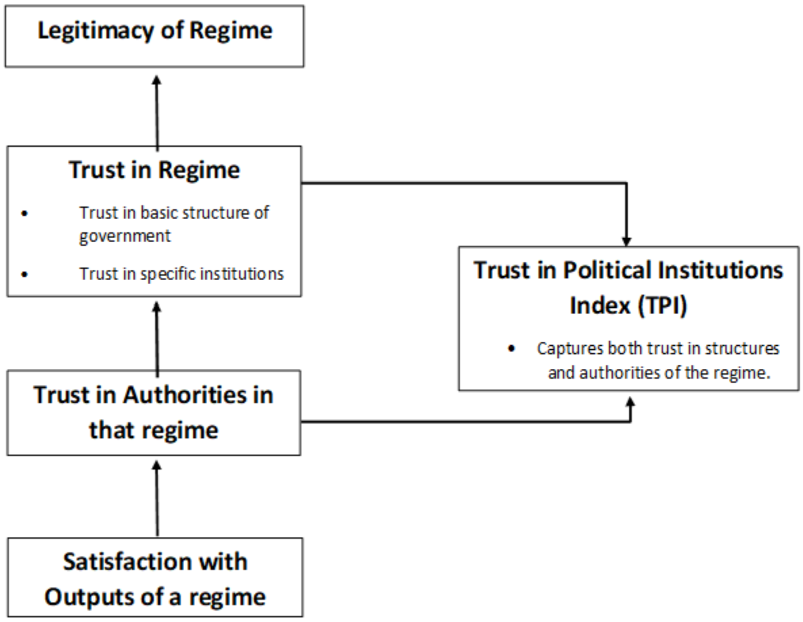
Hangartner et al., 2019; Edo et al., 2019; Dustmann et al., 2019). Moreover, migrants can increase the perceived subjective risk of the home population of increased unemployment (Finseraas, 2008; Brady & Finnigan, 2013). These observations are in line with the empirical results of Alesina et al. (1999) and Bluedorn (2011), who find that increasing ethical stratification diminishes the public support for redistribution and trust in the welfare state. Furthermore, critiques have insinuated that the economic benefits of migration can only be captured if the quality of political institutions does not deteriorate because of immigration, and it is unlikely that "billions of immigrants can move to the industrialized economies without importing the 'bad' institutions that led to poor economic conditions in the source country in the first place" (Borjas, 2015, p. 169). If this critical reading of refugees and migration more broadly is true, we could potentially observe a decrease in TPI for higher numbers of refugees in Germany.

On the other hand, long-term cross-country studies have found "no evidence of negative and some evidence of positive impacts in institutional quality as a result of immigration" (Clark et al., 2015, p. 321). Research from the United Kingdom has shown that migrants and refugees quickly express a higher level of trust in political institutions and higher satisfaction with democracy than native Britons. (Saggar et al., 2012, p. 1). Thus, social cohesion, satisfaction with democracy, and TPI of natives are not affected by increasing numbers of migrants (Saggar et al., 2012, p. 1). Furthermore, evidence from Austria has demonstrated that a higher number of refugees can even decrease the likelihood to vote for right-wing parties (Steinmayr, 2016). If these findings are also true for Germany, a decrease in TPI for higher numbers of refugees per state seems unlikely.

These conflicting results are my motivation to provide further evidence on the impact of refugees on TPI by looking at refugees coming to Germany between 2010 and 2018. This timeframe allows me to look in particular at the effect of the spike in refugees during the European migrant crisis in 2015.

A vast majority of the empirical literature measures the effect of refugees on political institutions using changes in voting behaviours, especially electoral outcomes for anti-immigration, right-wing parties. Using electoral outcome data as a dependent variable provides a comprehensive and comparable way of measuring changes in the political culture. However, it often suffers from reducing complex and comprehensive party programs to a single issue of migration policy because it implicitly assumes that far-right parties are primarily voted for because of their anti-immigration agenda (Dustmann et al., 2019). However, the decision of voting for a right-wing populist party can also be the result of a more general dissatisfaction with a political regime. As shown by Thomassen (2001), the legitimacy of political of a political regime is built upon 3 levels of general satisfaction with the regime (Figure 1).

Figure 1: The components of the legitimacy of a regime and the logic of the TPI



Source: Own creation, based on Thomassen, J. (2001), p. 182-183, Figure 2.

For example, a voter of the German right-wing populist party AfD might vote for the AfD because:

(1) She is dissatisfied with the outcome of the current government, i.e. in migration policy, but still thinks that the same cabinet within the same regime can produce a satisfactory outcome.

(2) She does not trust Angela Merkel and her cabinet to deliver a satisfactory outcome.

(3) She does not think that democracy or the parliament can produce a satisfactory outcome at all.

Research has shown that "AfD voters in 2017 were driven solely by two factors: Their attitudes towards immigrants/refugees and their anti-establishment sentiment/satisfaction with democracy in Germany" (Hansen & Olson, 2018, p. 1). By using the TPI index as my dependent variable, I try to pull dissatisfaction with immigration policy (level 1) and anti-establishment ressentiments (level 2/3) apart and specifically capture the effect of refugee inflows on levels 2 and 3 and therefore explore underlying changes in the legitimacy of a regime.

Empirical strategy and approach

In this paper, I employ the identification strategy of Aksoy, Poutvaara, and Schikora (2020) and use Germany's "exogenous placement of refugees upon arrival across counties [and states] and the fact that they cannot freely choose their place of residence for a period of at least three years" (Aksoy, Poutvaara & Schikora, 2020, p. 1) as exogenous treatment mechanism. This allows me to exploit plausibly exogenous allocation of refugees across states to estimate the causal effect of refugee-to-population ratio on natives' TPI while controlling for local circumstances. Furthermore, this approach circumvents the reverse causality that migrants prefer places with better overall institutional quality (Cebula & Clark, 2011).

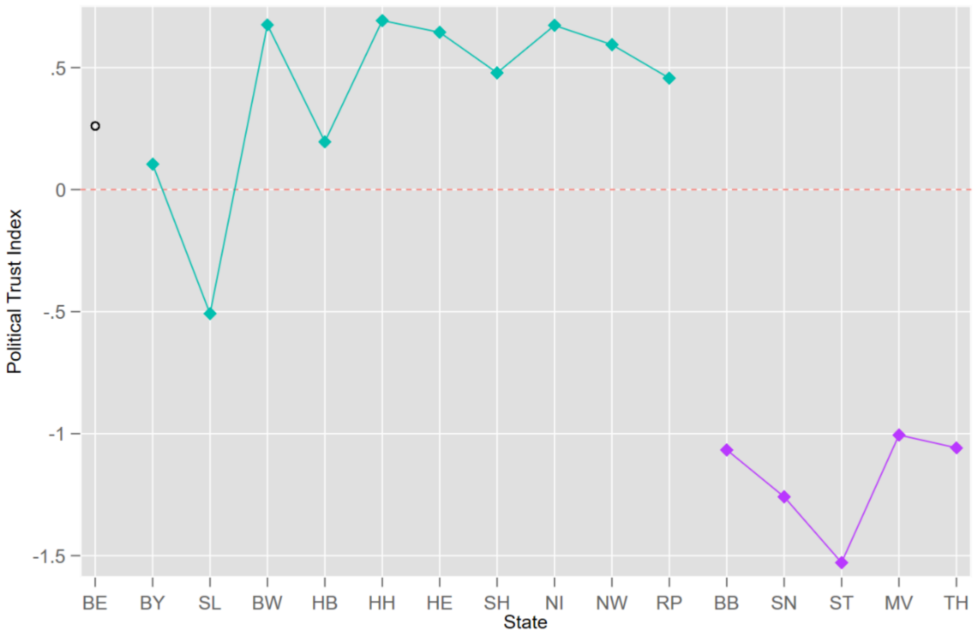
Measures and data sources

First, I construct an index of TPI based on ESS Data from round 5 to round 9 using Principal Component Analysis (PCA) that then serves as my dependent variable. The index is composed of the following variables of the "Political trust in institutions" ESS questionnaire (ESS, 2019).

- Trust in political parties
- Trust in the legal system
- Trust in the politicians
- Trust in the police
- Trust in the country's parliament

Questions on levels of trust in international institutions such as the EU or the UN are removed due to the national focus on Germany in this essay. All questions are answered on a scale from 1 to 10. Then, the index is constructed and standardized with a mean of 0 and a standard deviation of 1. A higher value of the index implies a higher level of trust in political institutions. Even though the ESS consists of cross-sectional individual survey data, one can still aggregate this individual data to state-level macro-variables and treat it as quasi panel data (Verbeek, 2008). A graphic analysis of the index shows that there is a significant difference in the average level of TPI between the old and the new states of Germany (Figure 2).

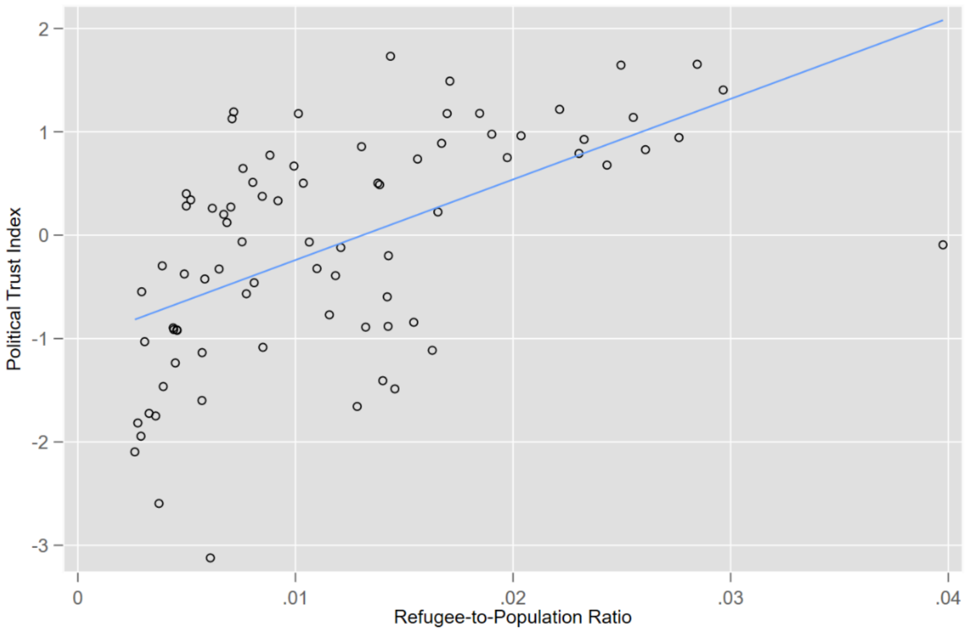
Figure 2: Average trust in political institutions for each state, separated between old and new states[3]



My main explanatory variable is the refugee-to-population ratio per state, which is calculated using data from the German Federal Office of Statistics. To account for the fact that ESS is only conducted every two years, I compute the 2-year average of the refugee-per-state ratio to match it with the ESS data. Since population changes can occur in response to refugee inflows, I fix the state population to the year 2010 to account for endogeneity. As shown in Figure 3, a simple scatterplot between TPI and refugee-to-population ratio without controlling for any state- or year-fixed effects yields a slightly positive relationship between both variables. The interesting question is whether this effect persists once control variables are introduced.

[3] The state Berlin was partly a member of the GDR and partly a member of the Federal Republic of Germany and is therefore not included in this distinction.

Figure 3: Linear relationship between TPI index and refugee-to-population ratio



In my analysis, I also employ economic control variables using the NUTS-1 control variables data set of the ESS. Using control variables under the conditional independence assumption with no selection bias based on observables accounts for the observable heterogeneity across states (Lechner, 2008). I include a) long-term (12 months) unemployment rate as a percentage of the active population and b) GDP per state at current market price measured in Euro per inhabitant. To account for possible endogeneity of unemployment and GDP per state, the economic control variables need to be lagged by a factor. Aslund and Rooth (2007) propose a lag of 2 years for unemployment to account for initial labour market conditions. However, a short analysis of alternative lags (Table 1) yields that a lag of 3 years for unemployment and a lag of 1 year for GDP seems to be most appropriate in my analysis.

Controlling for state-level political institutions in my model would only decrease variation between states and therefore is not helpful. However, including year-fixed effects in my model to account for different national political trends that affect all states equally, seems important. Therefore, I employ the national levels of satisfaction with the work of Angela Merkel, which is monthly monitored through representative survey data from *Forschungsgruppe Wahlen (*2021,*)* as a proxy for national shocks to the political culture that affects all states equally.

Then, the dataset is collapsed into a quasi panel data that now contains 80 overall observations (1 observation for every of the 5 ESS rounds for the 16 states). Therefore, the panel data is strongly balanced. In a panel data model, it is made sure that the unobserved heterogeneity across entities is controlled for without the use of first differencing (Wooldridge, 2019, p. 461). Last, the average macro-variables for each state are weighted according to the number of participants in the original ESS dataset.

Methodology

Using the aforementioned variables in a fixed-effect model yields the following equation:

$$TPI_{c,t} = \alpha + \beta_1 Ref - to - pop_{c,t} + \beta_2 SWM_t + \beta_3 GDP_{c,t-1} + \beta_4 Unemploy_{c,t-3} + u_{it}$$

$TPI_{c,t}$ refers to the trust in political institutions index in state c in year t. $Ref - to - pop_{c,t}$refers to the ratio of refugees per state population in state c at time t with the state population fixed to the year 2010 to account for endogeneity in population changes. SWM_t is a time-fixed effect that refers to the level of national satisfaction with German chancellor Angela Merkel in year t. $Unemploy_{c,t-3}$ refers to the long-term (12 or more months) unemployment level in state c in the year t-3 as a percentage of the active population. $GDP_{c,t-1}$refers to the gross domestic product of that state at current market prices per inhabitant in year t-1. $u_{i,t}$ describes the error term in my model. For the estimation to be unbiased, the "idiosyncratic error term $u_{i,t}$ must also be uncorrelated with each explanatory variable across all time periods." (Wooldridge, 2019, p. 463).

To meet the assumptions of a fixed effect regression, the data is checked and freed from multicollinearity using the Variance-Inflation Factor (VIF). Furthermore, a Breusch-Pagan test is employed to meet the assumption of homoskedasticity. As a result, robust standard errors are used, and standard errors are clustered on the state level. Since the outliers detected by a Cook's D test would remove nearly 10% of my sample, which can be a problem in small samples, I instead resort to a graphical detection of outliers and remove only 2 severe outlier observations (Bremen 2018 and Saarland 2010). Moreover, a Ramsey RESET test is employed to exclude model misspecification.

Results

The results of the fixed effects OLS regression are shown in Table 1. Model 5 is the model described in my methodology while models 1-4 show the effects of including alternative lag specifications. By using state- and time fixed-effects, it is assured that unobserved characteristics are accounted for. Since the refugee-to-population ratio is a percentage, it is multiplied by 100 to ease the interpretation in the regression.

Table 1: Regression output of the OLS-Model

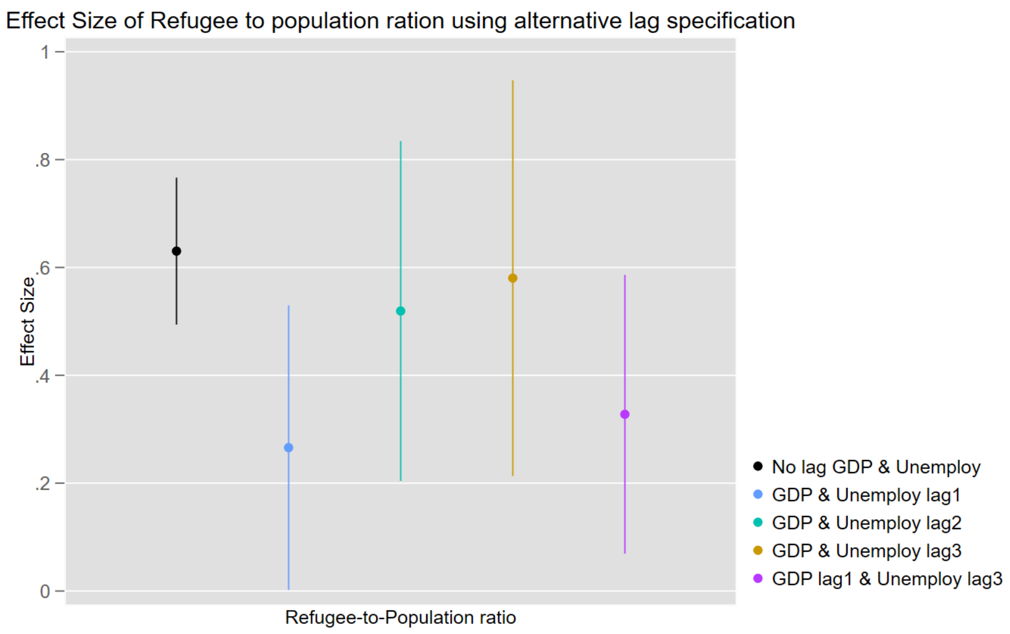
	TPI				
	(1)	(2)	(3)	(4)	**(5)**
VARIABLES	Model 1	Model 3	Model 2	Model 4	**Model 5**
Refugee to Population ratio	0.647***	0.277**	0.523***	0.582***	**0.353****
	(0.0652)	(0.126)	(0.140)	(0.169)	**(0.121)**
Satisfaction with Merkel		3.274***	4.166***	3.797***	**3.108*****
		(0.931)	(0.977)	(0.950)	**(0.872)**
unemployment_lagged1		0.0259			
		(0.0157)			
GDP_per_state_lagged1		8.35e-05**			**2.15e-05**
		(3.15e-05)			**(4.73e-05)**
unemployment_lagged2			-0.0211		
			(0.0267)		
GDP_per_state_lagged2			-8.32e-06		
			(3.18e-05)		
unemployment_lagged3				-0.0357***	**-0.0343****
				(0.00913)	**(0.0144)**
GDP_per_state_lagged3				-3.94e-05	
				(4.47e-05)	
Constant	-0.679***	-6.528***	-2.259	-0.369	**-1.677**
	(0.0712)	(0.685)	(2.219)	(1.103)	**(1.874)**
Observations	78	78	78	78	**78**
Number of state1	16	16	16	16	**16**
Adjusted R-squared	0.399	0.630	0.599	0.652	**0.649**

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Without controlling for any variables, a regression of the refugee-to-population on the TPI index yields a strong positive relationship and a highly significant coefficient of 0.647. That means that a one percentage point increase in the refugee-to-population ratio increases the TPI of the native population by 0.647 points. Therefore, my findings go beyond Saggar et al.'s (2019) results that refugees have no negative effect on natives' perception of political believes and even suggest that there is a positive relationship between higher levels of trust in political institutions and a higher refugee to population ratio per state.

This relationship remains significant when one includes different control variables. The economic control variables are significant depending on the specification of the lag. After $GDP_{c,t-1}$and $Unemployment_{c,t-3}$are the only significant lag specifications, I include them in my final model (Model 5). Whereas different lag specifications of the economic control variables do not affect the significance of the coefficient for the refugee-to-population ratio, the size of the coefficient is affected (Figure 5). Depending on the model, the effect size of the coefficient varies between 0.277 and 0.647. This further stresses the importance of a correct lag specification. A more detailed analysis could potentially use the tools of time series analysis to estimate an ARIMAX-model first to identify the right lags for the economic control variables.

Figure 4: Different effect sizes of refugee-to-population ratio using alternative lag specifications.

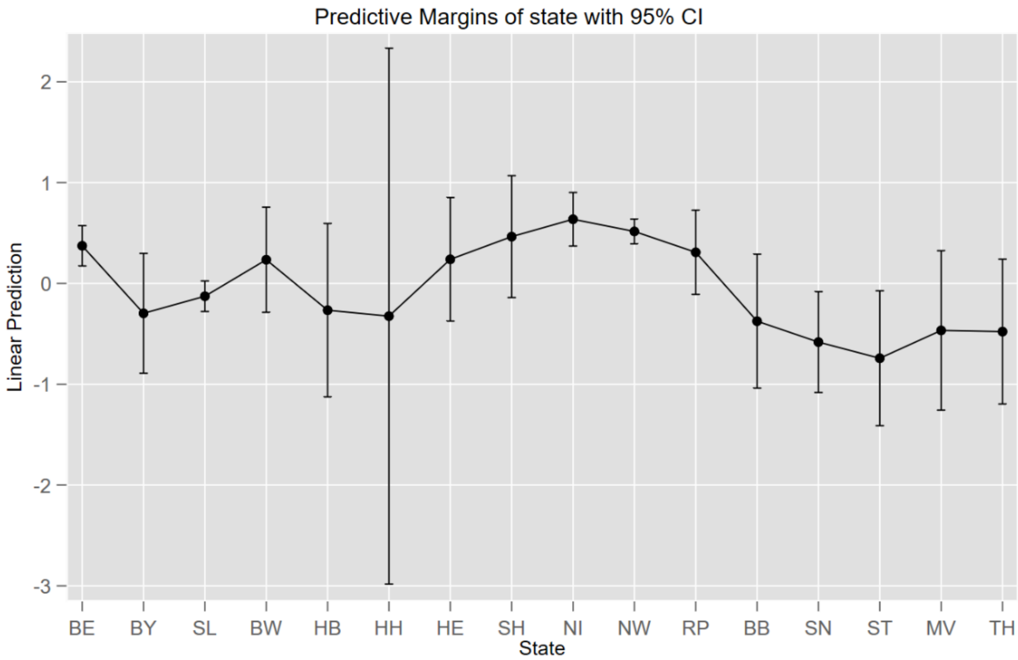


Another issue with the economic control variables is that they potentially suffer from endogeneity. Since the allocation mechanism ("Königssteiner Key") of refugees is based to 2/3rd of tax revenue and to 1/3rd on population size (BAMF, 2021), it is likely that a higher GDP and a lower unemployment lead to both a higher number of assigned refugees through the Königssteiner key and to an overall higher level of trust in political institutions. Due to the limited nature of this essay, I cannot include a more detailed examination of this possible endogeneity.

Furthermore, the variable Satisfaction with Merkel is highly significant in all models. This shows that including relevant time-fixed effects for national political trends affects the TPI index on a state level. Lastly, the adjusted R^2 has a size of 0.637, which is decent considering that the model includes only four explanatory variables.

One interesting finding is that the effect of a higher refugee-per-state ratio seems to have a larger impact on the TPI in states that already have a lower level of trust in political institutions (Figure 5). To estimate the margins, a different intercept for each cross-sectional observation in a dummy variable regression is used. Although this dummy variable regression is not advisable for panel data sets with many cross-sectional units, it is no problem in this case with only 16 units of observation (Wooldridge, 2019, p. 466).

Figure 5: Predictive margins for each state with a 95% CI.



An increase in the refugee-to-population ratio has a negative impact on the TPI in all new states of Germany (BB, SN, ST, MV, TH). Those states have, as it is shown in Figure 2, also an initially lower level of trust in political institutions. The positive effect of refugees on the TPI is therefore almost entirely driven by population large old states like North Rhine-Westphalia (NW), Lower Saxony (NI), Baden-Württemberg (BW), or Schleswig-Holstein (SH). The high confidence interval of Hamburg can be explained with the very low probably weights of participants from Hamburg in the ESS sample data.

Another regression that uses new and old states in Germany as cross-sectional units instead of states yields a negative coefficient of -1.297 for being a member of the former GDR (Table 2). This emphasizes that the main reason behind the cross-state variation in TPI seems to be driven by the divide between old and new states in Germany.

Table 2: OLS Regression output if one uses states group by former GDR members as entities.

VARIABLES	(1) TPI
Former_GDR	-1.297***
	(0.163)
Refugee-to-Population	0.598***
	(0.0704)
Satisfaction with Merkel	4.253***
	(0.822)
unemployment_lagged3	-0.0270***
	(0.00976)
GDP_per_state_lagged1	-2.19e-05*
	(1.12e-05)
Constant	-1.259
	(0.864)
Observations	73
Adjusted R-squared	0.834

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Discussion and limitations

Estimating the effect of refugees on natives' trust in political institutions is also a reflection of the different historical experiences of each state with migration. Especially western and southern German states have made very favourable experiences with migration through mostly Turkish guest workers in the late 20th century (Pischke, 1992). The immediate integration into the labour market, rising wages and more than enough job opportunities demonstrated that migration can has positive effects on both economic and political institutions (Licht & Steiner, 1992; Pischke, 1992). The fact that excessive labour demand was successfully filled, and integration of foreigners went smoothly established trust in the state's capabilities to integrate and absorb both refugees and migrants. Contrary, immigration into the GDR was significantly lower and less positively connotated (Weiss, 2002). The unlike historical experiences could be one potential explanation for the difference in TPI between old and new states

The main limitation of my approach is the huge variation within states that ignores crucial differences on a micro-level. It is likely that county-, city- and district-specific characteristics matter when estimating the effect refugees have on the native population (Geis & Orth, 2016; Aksoy, Poutvaraa & Schikora, 2020). Franz, Fratzscher and Kritikos (2018) suggest that it is not the former divide of Germany that is driving the effect, but rather that eastern German states have more rural areas with negative democratic trends, which tends to foster both votes for the AfD and lower levels of TPI.

However, ESS does not contain data on NUTS-2 or NUTS-3 levels in Germany, which makes a more local analysis difficult.

Moreover, the impact of refugees on natives' attitudes is also shaped by the individual profiles of the refugees. A recent study by Lergetporer, Piopiunik and Simon (2021) demonstrates that education levels of refugees shape the perception of the native German population significantly. A higher education level of refugees is correlated with an overall more positive attitude towards refugees and a higher TPI (Lergetporer, Piopiunik & Simon, 2021).

Even though the mobility of refugees is legally limited, there are bilateral collaborations between some states that recently allowed refugees to change their place of residency. Up to this day, Bremen and Lower Saxony, and Berlin and Brandenburg have an agreement that allows refugees to choose their residency between both states. This poses a further challenge to my identification strategy.

Conclusion

In this essay, the causal effect of refugees on natives' trust in political institutions was explored. My results suggest that there is indeed a positive causal effect of refugees on the levels of trust in political institutions in Germany that seems to be driven mostly by the old states. Therefore, my essay provides further evidence for Clark et al.'s (2015) hypothesis that migration can has positive effects on the quality of political institutions of the host country. Future research could examine how individual characteristics of refugees and micro-level circumstances influence the perception of TPI of the native population. Therefore, more research seems necessary to provide further evidence of the impact of refugees on natives' attitudes and political beliefs.

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Code

```
/*************************************************************************\
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* Title:                ESS setup for constructing an index of SWD
* Author:               Alexander Albrecht
* This version:         19.04.2021
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*                              Preliminaries                                  *
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set more off
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cd $path1
set scheme plottig
ssc install xttest2
ssc install coefplot
*-----------------------------------------------------------------------------*
*                              Setup of data set                              *
*-----------------------------------------------------------------------------*

//Using the ESS Cumulative Wizard on the Website, I can customize my dataset in the way that I want. For my analysis, I am only focussing on Germany. To better catch the effect of the inflow of refugees after the European Refugee crisis, I included rounds 5-9 (2010-2018) in my dataset. From this dataset, I then can construct an index of TPI on a NUTS-1 Level. Then, I can match the refugee inflow per year in that state with the index and see whether there is any relationship.

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*                                                                             *
*               Cleaning and Preparing the Refugee Dataset                    *
*                                                                             *
*-----------------------------------------------------------------------------*
//This Dataset can be obtained from the Federal German Office of Statistics. You can find it here: https://www-genesis.destatis.de/genesis//online?operation=table&code=12531-0020&bypass=true&levelindex=0&levelid=1618841480945#abreadcrumb

clear
import delimited "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course Essay\Datasets\Asylum Seekers per State 2008-2018.csv"
keep zeit _auspraegung_code _auspraegung_label v13 bev030__schutzsuchende__anzahl

//Renaming Variables
rename bev030__schutzsuchende__anzahl Asylumseekers
rename _auspraegung_label state
rename v13 gender
label var Asylumseekers "Number of Asylumseekers per State"

//Generation year2 variable
gen year=.
replace year = 2008 if zeit == "31.12.2008"
replace year = 2009 if zeit == "31.12.2009"
replace year = 2010 if zeit == "31.12.2010"
replace year = 2011 if zeit == "31.12.2011"
replace year = 2012 if zeit == "31.12.2012"
replace year = 2013 if zeit == "31.12.2013"
replace year = 2014 if zeit == "31.12.2014"
replace year = 2015 if zeit == "31.12.2015"
replace year = 2016 if zeit == "31.12.2016"
replace year = 2017 if zeit == "31.12.2017"
replace year = 2018 if zeit == "31.12.2018"
drop if zeit == "31.12.2019"

```

```
//Generate year2 because ESS is conducted only every 2 years
gen year2 =.
replace year2 = 2010 if year == 2009 | year == 2010
replace year2 = 2012 if year == 2011 | year == 2012
replace year2 = 2014 if year == 2013 | year == 2014
replace year2 = 2016 if year == 2015 | year == 2016
replace year2 = 2018 if year == 2017 | year == 2018

rename year year_old
rename year2 year
drop if year_old == 2008
keep if gender == "Insgesamt"


//Generate NUTS-1 Abbreviations
gen nuts1=""
replace nuts1 = "DE1" if state == "Baden-Württemberg"
replace nuts1 = "DE2" if state == "Bayern"
replace nuts1 = "DE3" if state == "Berlin"
replace nuts1 = "DE4" if state == "Brandenburg"
replace nuts1 = "DE5" if state == "Bremen"
replace nuts1 = "DE6" if state == "Hamburg"
replace nuts1 = "DE7" if state == "Hessen"
replace nuts1 = "DE8" if state == "Mecklenburg-Vorpommern"
replace nuts1 = "DE9" if state == "Niedersachsen"
replace nuts1 = "DEA" if state == "Nordrhein-Westfalen"
replace nuts1 = "DEB" if state == "Rheinland-Pfalz"
replace nuts1 = "DEC" if state == "Saarland"
replace nuts1 = "DED" if state == "Sachsen"
replace nuts1 = "DEE" if state == "Sachsen-Anhalt"
replace nuts1 = "DEF" if state == "Schleswig-Holstein"
replace nuts1 = "DEG" if state == "Thüringen"

//Generate Male to Female ratio by each year
// idea to get the female ratio: egen female_ratio = display(Asylumseekers if gender=="weiblich" / Asylumseekers if gender == "Insgesamt"), by(state, year)
//by state year, sort: gen female = Asylumseekers if gender == "weiblich"
//by state year, sort: gen Insgesamt = Asylumseekers if gender == "Insgesamt"
//by state year, sort: gen female_ratio = female / Insgesamt
//I cannot find a good solution to calculate female to male ration per state and year. Until then, I just keep the "Insgesamt" observations and drop the rest.

egen Refugees = mean(Asylumseekers), by(state year)
replace Refugees = round(Refugees)
drop if year_old == 2009 | year_old == 2011 | year_old == 2013 | year_old == 2015 |  year_old == 2017
drop year_old Asylumseekers zeit _auspraegung_code

label var nuts1 "NUTS-1 State Code"
label var year "Year to match with ESS Data"
label var Refugees "2-year mean number of refugees per state"

save "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course Essay\Datasets\Asylumseekers_cleaned.dta", replace

*-----------------------------------------------------------------------------*
*                                                                             *
*               Cleaning and Preparing Nuts-1 Controlls                       *
*                                                                             *
*-----------------------------------------------------------------------------*
//I obtain the Nuts-1 Controlls for my dataset directly from ESS: https://www.europeansocialsurvey.org/data/multilevel/guide/bulk.html.
//Merging ESS with NUTS-1 Controlls
use "Round 9 Nuts 1_DE.dta", clear
keep if cntry == "DE"
save "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course Essay\Datasets\Round 9 Nuts 1_DE.dta", replace

```

```
*--------------------------------------------------------------------------------*
*                                                                                *
*               Cleaning and Preparing Satisfaction with Merkel Dataset          *
*                                                                                *
*--------------------------------------------------------------------------------*
clear
import excel "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course
Essay\Datasets\11_Arbeit_Merkel.xlsx", sheet("Tabelle4") firstrow
drop year_old good bad
//Calculating 2 year averages by hand
//2010: .6161111
//2011-2012: (.6333333 + .7472222) / 2 = 0.6902776
//2013-2014: (.7938095 +  .8058824) / 2 = 0.79984595
//2015-2016: (.7694444 + .6766667) / 2 = 0.72805555
//2017-2018: (.7504762 + .6333333) / 2 = 0.6940475
gen swm=.
replace swm = 0.6161111 if year == 2010
replace swm = 0.6902776 if year == 2011 | year == 2012
replace swm = 0.79984595 if year == 2013 | year == 2014
replace swm = 0.72805555 if year == 2015 | year == 2016
replace swm = 0.6940475 if year == 2017 | year == 2018

drop if year == 2011 | year == 2013 | year == 2015 | year == 2017

save "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course
Essay\Datasets\Arbeit_Merkel.dta", replace


*--------------------------------------------------------------------------------*
*                                                                                *
*                           Merging the Datasets                                 *
*                                                                                *
*--------------------------------------------------------------------------------*

use "ESS4-9DE", clear
rename cregion nuts1
drop if essround == 4
merge m:m nuts1 using "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course
Essay\Datasets\Round 9 Nuts 1_DE.dta"
drop _merge


//Prepparation of ESS Data to merge with prepared RefugeeInflow Data
gen year=.

replace year = 2010 if essround == 5
replace year = 2012 if essround == 6
replace year = 2014 if essround == 7
replace year = 2016 if essround == 8
replace year = 2018 if essround == 9

merge m:m nuts1 year using "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course
Essay\Datasets\Asylumseekers_cleaned.dta"
drop if _merge == 2
drop _merge

//merge with Satisfaction with Merkel Dataset

merge m:m year using "C:\Users\User\OneDrive\Alex_s Zeug\King's\Causal Inference\Course
Essay\Datasets\Arbeit_Merkel.dta"
drop _merge

*--------------------------------------------------------------------------------*
*                                                                                *
*                   Cleaning and Preparing the Merged Dataset                    *
*                                                                                *
*--------------------------------------------------------------------------------*

```

```
***************************************
** Administrative variables and identifiers:
***************************************

lab var cntry "Country"
lab var cname "Title of cumulative dataset"
lab var cedition "Edition of cumulative dataset"
lab var cproddat "Production date of cumulative dataset"
lab var name "Title of dataset"
lab var essround "ESS round"
lab var edition "Edition"
lab var idno "Respondent's identification number"

***************************************
** Weights:
***************************************

lab var dweight "Design weight" /* In general design weights were computed for
each country as follows.
1.w = 1/(PROB1*...*PROBk)  is a  nx1 vector of weights ;
k depends on the number of stages of the sampling design.
2. All weights were rescaled in a way that the sum of the final weights equals n,
i.e. Rescaled weights = n*w/sum(w). */

lab var pspwght "Post Stratification weight" /*The ESS post-stratification
weights have been constructed using information about age, gender, education and
region. The ESS post-stratification weights also adjust for unequal selection
probabilities (design weights). A raking procedure has been used in the
production of the post-stratification weights. */

lab var pweight "Population size weight" /* The Population size weight (PWEIGHT)
corrects for population size when combining two or more country's data, and is
calculated as PWEIGHT=[Population aged 15 years and over]/[(Net sample in data file)*10 000] */

***************************************
*Creating the Refugee-to-Pop variable*
***************************************
//Creating a refugee-to-pop ration for each state with the population of the state fixed to 2012 to account for endogeneity.

by state, sort: gen ref_to_pop = Refugees / n1_tpopsz_2010
gen ref_to_pop2 = ref_to_pop * 100
label var ref_to_pop "Refugee to Population Ratio"

***************************************
*Creating Former GDR Dummy            *
***************************************

by state, sort: gen former_gdr = 1 if state == "Sachsen" | state == "Sachsen-Anhalt" | state == "Brandenburg" | state == "Thüringen" | state == "Mecklenburg-Vorpommern"
replace former_gdr = 0 if former_gdr==.
replace former_gdr = . if state == "Berlin"
label var former_gdr "Dummy if state was a member of the former GDR"
***************************************
*Creating the SWD Index               *
***************************************

//Creating an SWD Index
by state year, sort: egen swd = mean((stfeco + stfeco + stfgov) / 3)
sum swd
// Standardize the Index
by state year, sort: gen swd2 = (swd - 5.567381) / .577567
sum swd2
drop swd
rename swd2 swd
label var swd "Satisfaction with Democracy Index"

***************************************
```

```
*Creating the Political Trust Index      *
**************************************
by state year, sort: egen tpi = mean((trstprl + trstplc + trstplt + trstlgl + trstprt) / 5)
sum tpi
// Standardize the Index
by state year, sort: gen tpi2 = (tpi - 5.015717) / .4374078
sum tpi2
drop tpi
rename tpi2 tpi
label var tpi "Trust in Political Institutions Index"

**************************************
*Graphic Analysis of TPI x Ref-to-Pop*
**************************************

encode state, gen(state2)
gen state1=.


replace state1 = 1 if state == "Berlin"
replace state1 = 2 if state == "Bayern"
replace state1 = 3 if state == "Saarland"
replace state1 = 4 if state == "Baden-Württemberg"
replace state1 = 5 if state == "Bremen"
replace state1 = 6 if state == "Hamburg"
replace state1 = 7 if state == "Hessen"
replace state1 = 8 if state == "Schleswig-Holstein"
replace state1 = 9 if state == "Niedersachsen"
replace state1 = 10 if state == "Nordrhein-Westfalen"
replace state1 = 11 if state == "Rheinland-Pfalz"
replace state1 = 12 if state == "Brandenburg"
replace state1 = 13 if state == "Sachsen"
replace state1 = 14 if state == "Sachsen-Anhalt"
replace state1 = 15 if state == "Mecklenburg-Vorpommern"
replace state1 = 16 if state == "Thüringen"

label define valuelabes 1 "Berlin" 2 "Bayern" 3 "Saarland" 4 "Baden-Württemberg" 5 "Bremen" 6 "Hamburg" 7 "Hessen" 8 "Schleswig-Holstein" 9 "Niedersachsen" 10 "Nordrhein-Westfalen" 11 "Rheinland-Pfalz" 12 "Brandenburg" 13 "Sachsen" 14 "Sachsen-Anhalt" 15 "Mecklemburg-Vorpommern" 16 "Thüringen"
label variable state1 valuelabes

tab state1
by state1, sort: egen mean_tpi = mean(tpi)
egen mean_tpi2 = mean(tpi)
tab mean_tpi2

twoway scatter mean_tpi state1 if state1 == 1, msymbol(circle_hollow) || scatter mean_tpi state1 if state1 < 12 & state1 != 1, msymbol(circle_hollow) || connected mean_tpi state1  if state1 < 12 & state1 != 1, msymbol(diamond) || scatter mean_tpi state1 if state1 > 11, msymbol(circle_hollow) || connected mean_tpi state1  if state1 > 11, msymbol(diamond) ||, legend(off)  ytitle("Political Trust Index") xtitle("State") yline(0) xlabel(1 "BE" 2 "BY" 3 "SL" 4 "BW" 5 "HB" 6 "HH" 7 "HE" 8 "SH" 9 "NI" 10 "NW" 11 "RP" 12 "BB" 13 "SN" 14 "ST" 15 "MV" 16 "TH")

//Scattering it against SWD

gen outlier=1 if ref_to_pop > 0.035 | tpi < -3
gen outlier_label = "Bremen 2018" if outlier==1 & ref_to_pop > 0.035
replace outlier_label = "Saarland 2010" if outlier == 1 & tpi < -3
twoway scatter tpi ref_to_pop2 if outlier==., msymbol(circle_hollow) || lfit tpi ref_to_pop2 if outlier==., ytitle("Political Trust Index") xtitle("Refugee-to-Population Ratio") legend(off)
twoway scatter tpi ref_to_pop2, msymbol(circle_hollow) mlabel(outlier_label) || lfit tpi ref_to_pop2, ytitle("Political Trust Index") xtitle("Refugee-to-Population Ratio") legend(off)
twoway scatter tpi ref_to_pop2, msymbol(circle_hollow) mlabel (nuts1)|| lfit tpi ref_to_pop2, ytitle("Political Trust Index") xtitle("Refugee-to-Population Ratio") legend(off)

**************************************
*Creating the Unemployment + GDP      *
```

```
****************************************
by year state, sort: gen unemployment_lagged =.
replace unemployment_lagged = n1_loun_pc_une_2008 if year == 2010
replace unemployment_lagged = n1_loun_pc_une_2010 if year == 2012
replace unemployment_lagged = n1_loun_pc_une_2012 if year == 2014
replace unemployment_lagged = n1_loun_pc_une_2014 if year == 2016
replace unemployment_lagged = n1_loun_pc_une_2016 if year == 2018
label var unemployment_lagged "Unemployment per year lagged by 2 years"

by year state, sort: gen unemployment_lagged1 =.
replace unemployment_lagged1 = n1_loun_pc_une_2009 if year == 2010
replace unemployment_lagged1 = n1_loun_pc_une_2011 if year == 2012
replace unemployment_lagged1 = n1_loun_pc_une_2013 if year == 2014
replace unemployment_lagged1 = n1_loun_pc_une_2015 if year == 2016
replace unemployment_lagged1 = n1_loun_pc_une_2017 if year == 2018
label var unemployment_lagged1 "Unemployment per year lagged by 1 years"

by year state, sort: gen unemployment_lagged3 =.
replace unemployment_lagged3 = n1_loun_pc_une_2007 if year == 2010
replace unemployment_lagged3 = n1_loun_pc_une_2009 if year == 2012
replace unemployment_lagged3 = n1_loun_pc_une_2011 if year == 2014
replace unemployment_lagged3 = n1_loun_pc_une_2013 if year == 2016
replace unemployment_lagged3 = n1_loun_pc_une_2015 if year == 2018
label var unemployment_lagged3 "Unemployment per year lagged by 3 years"

by year state, sort: gen GDP_per_state =.
replace GDP_per_state = n1_gdp_eurhab_2010 if year == 2010
replace GDP_per_state = n1_gdp_eurhab_2012 if year == 2012
replace GDP_per_state = n1_gdp_eurhab_2014 if year == 2014
replace GDP_per_state = n1_gdp_eurhab_2016 if year == 2016
replace GDP_per_state = n1_gdp_eurhab_2017 if year == 2018
label var GDP_per_state "GDP per State"

by year state, sort: gen GDP_per_state_lagged =.
replace GDP_per_state_lagged = n1_gdp_eurhab_2008 if year == 2010
replace GDP_per_state_lagged = n1_gdp_eurhab_2010 if year == 2012
replace GDP_per_state_lagged = n1_gdp_eurhab_2012 if year == 2014
replace GDP_per_state_lagged = n1_gdp_eurhab_2014 if year == 2016
replace GDP_per_state_lagged = n1_gdp_eurhab_2016 if year == 2018
label var GDP_per_state_lagged "GDP per State lagged by 2 years"

by year state, sort: gen GDP_per_state_lagged1 =.
replace GDP_per_state_lagged1 = n1_gdp_eurhab_2009 if year == 2010
replace GDP_per_state_lagged1 = n1_gdp_eurhab_2011 if year == 2012
replace GDP_per_state_lagged1 = n1_gdp_eurhab_2013 if year == 2014
replace GDP_per_state_lagged1 = n1_gdp_eurhab_2015 if year == 2016
replace GDP_per_state_lagged1 = n1_gdp_eurhab_2017 if year == 2018
label var GDP_per_state_lagged1 "GDP per State lagged by 1 years"

by year state, sort: gen GDP_per_state_lagged3 =.
replace GDP_per_state_lagged3 = n1_gdp_eurhab_2007 if year == 2010
replace GDP_per_state_lagged3 = n1_gdp_eurhab_2009 if year == 2012
replace GDP_per_state_lagged3 = n1_gdp_eurhab_2011 if year == 2014
replace GDP_per_state_lagged3 = n1_gdp_eurhab_2013 if year == 2016
replace GDP_per_state_lagged3 = n1_gdp_eurhab_2015 if year == 2018
label var GDP_per_state_lagged3"GDP per State lagged by 3 years"

****************************************
*Preparing Data for Panel-Analysis    *
****************************************
by year state, sort: gen unique = _n==1
//count n and weight
by state1, sort: egen weight = count(_n)
by year state1, sort: egen weight2 = count(_n)

//Collapse the dataset
drop if unique == 0

```

```
//Declaring Data to be Time Series
tsset state1 year, yearly delta(2)




*-----------------------------------------------------------------------------*
*                              Running the regression                         *
*-----------------------------------------------------------------------------*

//Model 1, only ref_to_pop
xtreg tpi ref_to_pop2 [pweight = weight] if outlier==., fe robust cluster(state1)
outreg2 using myreg.doc, replace ctitle(Model 1) adjr2
estimates store model1

//Model2, including unemployment_lagged 1
xtreg tpi ref_to_pop2 swm unemployment_lagged1 GDP_per_state_lagged1     [pweight = weight] if outlier ==. , fe robust cluster(state1) //Robust standard Errors are included
outreg2 using myreg.doc, append ctitle(Model 3) adjr2
estimates store model2

//Model3, including controlls
xtreg tpi ref_to_pop2 swm unemployment_lagged GDP_per_state_lagged   [pweight = weight] if outlier ==. , fe robust cluster(state1) //Robust standard Errors are included
outreg2 using myreg.doc, append ctitle(Model 2) adjr2
estimates store model3

//Model4, including unemployment_lagged 1
xtreg tpi ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged3     [pweight = weight] if outlier ==. , fe robust cluster(state1) //Robust standard Errors are included
outreg2 using myreg.doc, append ctitle(Model 4) adjr2
estimates store model4

//Model5, Using the significant things
xtreg tpi ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1     [pweight = weight] if outlier ==. , fe robust cluster(state1) //Robust standard Errors are included
outreg2 using myreg.doc, append ctitle(Model 5) adjr2
estimates store model5

xtreg tpi ref_to_pop2 swm unemployment_lagged3   [pweight = weight] if outlier ==., fe robust cluster(state1)


//Creating the coefplot
coefplot model1 model2 model3 model4 model5, vertical drop(unemployment_lagged unemployment_lagged1 unemployment_lagged2 unemployment_lagged3 _cons GDP_per_state_lagged1 GDP_per_state_lagged GDP_per_state_lagged3 swm) xtitle("Refugee-to-Population ratio") xlabel("") ytitle("Effect Size") title("Effect Size of Refugee to population ration using alternative lag specification") legend(label(2 "No lag GDP & Unemploy") label(4 "GDP & Unemploy lag1") label(6 "GDP & Unemploy lag2") label(8 "GDP & Unemploy lag3") label(10 "GDP lag1 & Unemploy lag3"))

//Normal regression to show marginsplot
reg tpi i.state1 ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1  [pweight = weight] if outlier ==. , robust cluster(state1)
margins state1
marginsplot, xlabel(1 "BE" 2 "BY" 3 "SL" 4 "BW" 5 "HB" 6 "HH" 7 "HE" 8 "SH" 9 "NI" 10 "NW" 11 "RP" 12 "BB" 13 "SN" 14 "ST" 15 "MV" 16 "TH") xtitle("State") title("Predictive Margins of state with 95% CI")

//Running it with only i.former_gdr
reg tpi i.former_gdr ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1   [pweight = weight] if outlier ==. , robust
outreg2 using myreg2.doc, replace ctitle(Former_GDR) adjr2
margins i.former_gdr
marginsplot


*-----------------------------------------------------------------------------*
```

```
*                              Post Regression Diagnosis                               *
*------------------------------------------------------------------------------*

//Multicollinearity?
reg tpi i.state1 ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1  [pweight = weight] if outlier ==. , robust cluster(state1)
vif
//The only seemingly problematic variable is GDP, which should however stay in the euquation due to the theoretical importance, as elaborated in the essay.
//Heteroskedasticity?
xtreg tpi ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1 [pweight = weight], fe
xttest2
reg tpi i.state1 ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1,
hettest
//yes, we have Heteroskedasticity. Therefore, we include robust standard errors and cluster them on the state-level
//Outliers
reg tpi i.state1 ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1
predict d, cooksd
list state year d                                                        // An observation is an outlier if the D > (4 / N)
list state year d if d>4/(e(N)) & e(sample)
//Using Cooks'D for outliers would remove 8 observations from my sample, which would be equal to 10% ob my observations. Therefore, I rather use graphical approach and exclude only two observations: Saarland 2010 and Bremen 2018.

//Endogeneity
reg tpi i.state1 ref_to_pop2 swm unemployment_lagged3 GDP_per_state_lagged1  [pweight = weight] if outlier ==. , robust cluster(state1)
ovtest
estat endogenous
//Not Significant, we can exclude a model mispecification.
```