CENTER ON MIGRATION, CITIZENSHIP AND DEVELOPMENT

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Commuting patterns of Czech households exposed to flood risk

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Editorial

The conference "Tracing Social Inequalities in Environmentally-Induced Migration" was the second in a new series of conferences on "Environmental Degradation, Conflict and Forced Migration". It was organised by the European Science Foundation, in cooperation with Bielefeld University and its Center for Interdisciplinary Research. Already on the occasion of the first conference of the series the Center on Migration, Citizenship and Development (COMCAD), the university's unit responsible for scientific content and quality of the conference, had launched a COMCAD Working Paper Series on "Environmental Degradation and Migration". In the wake of the second conference, the editors are pleased to now start the second round of this working paper series. It intends to give conference participants the opportunity to share their research with an even broader audience.

The 2010 conference focused on how environmental change impacts the interplay between vulnerabilities on the one hand and capabilities on the other hand, and how this relationship affects mobility patterns. The 2012 conference concentrated on the societal backgrounds of this interplay and is meant to integrate a social inequalities perspective into current debates. Not all actors are equally vulnerable to climate and environmental change and environmentally-induced migration. Therefore, social inequalities between world regions, countries, geographical regions, organizations, groups and categories of people involved in environmental and climate-induced migration constitute the core thematic focus. Differential susceptibilities and capabilities to cope with environmental change on local, national and global scales rather depend on resource inequalities, power inequalities and status inequalities. Differences in vulnerability result from and are reproduced by the unequal impacts actors have upon politics and society as well as by the material and immaterial resources at their disposal. The 2012 conference was thus meant to shed light on the role of social inequalities in environmentally-induced migration and the mechanism of its reproduction.

The researchers invited represented a wide range of disciplines, including sociology, social anthropology, migration, conflict, gender and development studies, geography, political science, international law, as well as climate and environmental science. The conference was well balanced in terms of geographic origin, gender, and academic status of the participants. The conference programme and full report can be found at the conference website (http://www.uni-bielefeld.de/(en)/tdrc/ag_comcad/conferences/envimig2012.html).

Bielefeld, April 2013 Jeanette Schade and Thomas Faist

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Abstract

Using unique data collected from October to December 2012, we estimate the link between commuting to and from work and the level of household exposure to floods. The result suggests an empirical puzzle - individuals affected by only one flood are roughly 10% more likely to engage in the commuting activity, whereas households affected by two floods are 13% less likely to do so. We check the robustness of this result by operationalizing the past exposure to floods with variables that describe the geographical location of the house and its characteristics. We explain the puzzle by the fact that individuals commute to work in order to accumulate resources to decrease the household's vulnerability to flood risk, amongst other reasons. When the flood risk is high, some households out-migrate, and stayers commute less, probably, for similar reasons as why they stay. Further, we find evidence in support of the "network effect" hypothesis - an individual with an active commuter in the household is by 47% more likely to commence commuting. We also find that flood affected commuters travel shorter distance for work.

1 Introduction

In this paper we investigate the effects of floods on the economic activity of local residents. The underlying hypothesis is that households affected by floods act economically different than non-affected households. We postulate three interrelated research questions: “Are flood affected households more or less likely to engage in the commuting activities?”; “What is the character of the relationship between the number of floods experienced and the likelihood of commuting?”; and “Do flood-affected households commute shorter or longer distances?”. Our contribution to the growing literature is in extending the dimension of the current research to considering the relationship between exposure to floods and commuting.

Significant evidence suggests the devastating effects of floods on well-being of the local community (Kreibich and Thieken, 2009, Yeo, 2002). The research also indicates poor preparedness of households residing in risk areas, as well as the government in terms or providing recovery measures. Botzen *et al*. (2009) find that affected households in the Netherlands differently react to the purchase of the flood insurance and undertake measures to mitigate the risk of flooding. Masozera *et al.* (2007), Morrow and Enarson (1996) find that the socio - economic status plays an important role in individual’s ability to recover from the natural disaster. Those with more wealth have better access to transportation means (and can thus evacuate in a timely manner or out-migrate from the risk area), they can also afford faster reconstruction of affected property or get access to insurance. Masozera *et al.* (2007) finds that individual access to transportation greatly reduced the individuals’ vulnerability to the hurricane: “Lack of adequate transportation explains, in part, why more than 20,000 – 30,000 residents were stranded in the Superdome”.

Our main finding consists of two parts. Firstly, we find that individuals affected by only one flood are by 13.8% or 9.2%, depending on the regression specification, more likely to engage in the commuting activity. We also find that commuters earn higher income on average. More active involvement in commuting can be explained by individual’s willingness to accumulate resources to decrease their exposure to the flood risk and vulnerability during the response phase.

Secondly, we find that individuals affected by two floods are by 13% less likely to commute. With a positive effect of the first flood, the negative effect of the second flood is puzzling. However, the result is relatively straightforward to rationalize using findings of the existing research. When the second flood happens, commuters out-migrate from the risk area. Those individuals who stay are less likely to commute, in part, for similar reasons as why they stay (individual migration costs, access to transportation, attachment to property).

Besides the above result, we find support for the “network effect” hypothesis, according to which an average respondent with an active commuter is by 47% more likely to engage in commuting. Flood-affected individuals commute shorter distance.

The paper is organized as follows. We first describe the survey design and the survey instrument. Then we provide some descriptive statistics on respondents in the collected sample. Further, we formulate the econometric model, estimate it, interpret the results and conclude.

2 Survey design

The population of interest is households residing in risk areas of the Bečva river in the Eastern part of the Czech Republic. Occurrence and severity of floods from the river is depicted in Figure 2 of Appendix. We stratify the population of interest with respect administrative region and the level of past exposure to floods: badly affected areas (occurrence of at least two floods), moderately affected areas (occurrence of one flood) and unaffected areas (no floods occurred and location within 200 meters from the moderately affected area). The data on distribution of houses across the three risk areas is taken from ČHMÚ (2012). We distribute the total number of interviews proportionally to the population in each stratum. The distribution of interviews across regions is shown in Table 1.

Table 1: Distribution of observations across administrative regions.

	households	%	individuals	%
Choryně	30	9.87	84	9.6
Hrachovec	28	9.21	92	10.51
Hustopeče nad Bečvou	12	3.95	32	3.66
Juřinka	14	4.61	33	3.77
Krhová	31	10.2	84	9.6
Lhotka nad Bečvou	18	5.92	52	5.94
Milotice nad Bečvou	10	3.29	30	3.43
Poličná	32	10.53	91	10.4
Střítež nad Bečvou	29	9.54	85	9.71
Ústí	31	10.2	96	10.97
Zašová	31	10.2	76	8.69
Zubří	38	12.5	120	13.71
Total	**304**		**875**	

The survey instrument consists of two parts - household level questions and individual level questions. The household level questions consist of several blocks aimed at learning the past experience with floods, response during the recovery phase and preparedness for potential floods in the future. The individual level questions are aimed at learning characteristics, economic activity as well as intentions of each adult member of the household. These characteristics include age, marital status, education, employment details, income, experience, commuting and migration intentions. The questionnaire consists of many open-ended questions, in which respondents can evaluate their household's vulnerability to the flood risk and express their opinion on effectiveness of the government anti-flood measures. These questions help us understand the situation of each individual household.

3 Descriptive statistics

In the collected sample we have data on 304 households, 875 individuals and dates of five flood occurrences: 1997, 2002, 2006, 2009 and 2010. In line with the official data our research finds (see Table 2) that the most severe flood took place in 1997 - 184 households and 568 individuals in the collected sample were affected. All subsequent floods were much less severe. One third of all households had experience with only one flood, 28.3% experienced two floods and 8.2% of the surveyed households experienced at least three floods.

Table 2: Distribution of observations across administrative regions.

	households		individuals	
year	N	%	N	%
1997	184	60.5	568	64.9
2002	37	12.2	123	14.1
2006	23	7.6	66	7.5
2009	57	18.8	160	18.3
2010	66	21.7	193	22.1
	cumulative flood experience			
one flood	108	35.5	303	34.6
two floods	86	28.3	262	29.9
three floods	25	8.2	79	9.0

Table 3 provides data on the self-reported losses from floods. Most of households suffered up to CZK 50k (EUR 2k) in losses, which suggests persistent, but not devastating nature of the flood. From some of the conducted interviews we have two reasons to believe that the information on losses is slightly mismeasured. Firstly, in a few cases respondents had difficulty quantifying the loss to the exterior or interior of the house, because it was never fixed after the flood. Secondly, as the evidence in Table 4 suggests, insurance companies participated in refurbishing the affected houses or replacing damaged equipment. In this case a respondent could only give a subjective estimate of the value of that piece of equipment or services provided by the insurance company.

Table 3: Financial losses per household.

in *CZK* ->	0 – 50k	50k – 100k	100k – 200k	200k – 500k	500k – 1 mln
in *EUR* ->	0 – 2k	2k – 4k	4k – 8k	8k – 20k	20k – 40k
1997	121	26	13	13	5
2002	29	3	.	.	1
2006	5	4	1	3	1
2009	37	6	6	.	.
2010	55	7	4	.	.

Before all five flood occurrences at least three fourths of households had insurance contracts. Despite this fact, there remains a large fraction of with entire self - funding of the floods losses. After the 1997 flood slightly more than one third of households had to cover the losses by themselves, in the remaining three flood occurrence (except for year 2006) slightly less than half covered the losses with their own funds.

Table 4 shows the share of households who got a given fraction of losses covered by insurance. Interestingly, we find that after the flood in 1997 the insurance covered at least 40% of the losses to 69.2% of the affected households. However, at least 50% was covered only to 20.9% of the households. It means that for some reasons the insurance companies were unwilling or unable to cover more than half of the losses for the vast majority of households. This trend persists throughout the five flood events.

Table 4: Households that had a given share of the losses covered by insurance.

Year	10%	20%	30%	40%	50%	60%	70%	80%	90%
1997	89	82.4	75.8	69.2	20.9	19.8	16.5	9.9	8.8

2002	88.9	77.8	77.8	77.8	33.3	22.2	22.2	22.2	22.2
2006	100	83.3	50	50	33.3	33.3	16.7	16.7	16.7
2009	94.1	88.2	70.6	58.8	17.6	17.6	5.9	5.9	5.9
2010	100	90	90	86.7	50	50	46.7	33.3	30

Basic demographic characteristics are provided in Table 5. We have almost equal shares of males and females, most of whom (62%) are married, 23.2% are single, 9.5% are widowed and 4.2% are divorced. 40% of respondents have completed secondary education, slightly less, 34.6%, have incomplete secondary education and only 9,6% have Master's degree or above.

Table 5: Basic demographic characteristics.

	N	%		N	%
Male	439	50.17	Occupation type:		
Marital status:			low - skilled	136	15.5
single	203	23.2	medium - skilled	159	18.2
married	542	62.0	high - skilled	64	7.3
divorced	37	4.2	entrepreneur	45	5.1
widowed	83	9.5	retired	333	38.1
Education:			student	57	6.5
primary	101	11.6	maternity leave	25	2.9
incomplete secondary	302	34.6	unemployed	42	4.8
complete secondary	357	40.9			
professional	12	1.4	Commute for work:	146	37.15
Bachelor	15	1.7			
Master and above	84	9.6			

In the sample the retirees are 333 individuals, students and unemployed are 57 and 42 individuals respectively, and 25 women are on the maternity leave. In the questionnaire we developed a scale to rank the skill intensity of the employment occupation. We find that the distribution of respondents across low-, medium- and high-skilled occupations is 15.5%, 18.2% and 7.3% respectively. The share of commuters (out of the pool of working age sample excluding students and women on the maternity leave) is 279 individuals, or 68.1%.

Table 6: Descriptive statistics on continuous variables.

variable	mean	st. dev.	min	max
Age	51.5	18.8	16	92
Net income:				
non-commuters	16208.8	6008.4	7000	40000
commuters	18812.9	7902.9	7500	60000
Commuting distance	18.8	38.4	1	300

4 Wage regression

The data description section suggests that commuters earn more income than non-commuters. To infer more details about the distribution of income we have to estimate the Mincerian wage regression on the subsample of working individuals. We extend the standard set of covariates to include the occupation type and commuting behaviour. The occupation type is correlated with education - more educated will have better occupations. The inclusion of education and occupation related variables should capture the phenomenon of underemployment, if it exists in the data. From estimation we exclude pensioners, women on the maternity leave, students and the unemployed. We estimate the following regression:

$$ln(wage_i) = X_i^{'}\beta_1 + Z_i^{'}\beta_2 + \varepsilon_i \qquad (1)$$

where $X_i^{'}$ is a vector that includes gender, age, family status and number of children; $Z_i^{'}$ is a vector that includes education, experience, dummy variable for whether the person commutes and occupation type dummy variables. The error ε_i is assumed to satisfy the classical assumptions. Estimation results of regression (1) are presented in Table 7. Exact definitions of covariates are given in Table 12 of Appendix.

Table 7: OLS estimates of the Mincerian wage regression 1. Standard errors are clustered by family *id*. * - 1%, ** - 5%, * - 10% significance levels.**

variable	coeff.		robust SE.
age	0.036	**	0.016
age2	-0.001	***	0.000
educ2	0.168	***	0.050
educ3	0.254	***	0.074

exper	0.004	*	0.002
married	0.085		0.060
kids2	-0.090	*	0.048
kids3	-0.080		0.109
comm	0.194	***	0.049
male	0.239	***	0.041
occ_type2	0.186	***	0.048
occ_type3	0.313	***	0.069
occ_type4	0.340	***	0.083
_cons	8.438	***	0.340
N. obs. 225			
R2 = 0.4			

The signs of the estimates are in line with predictions of the economic theory. Age has a concave shape - earnings increase with age but at a declining pace. Those respondents with more education, experience as well as those in better occupations earn more. Males earn more than females, an established fact of gender inequality. The key finding of this regression is that those respondents who commute for work to nearby larger cities are paid more than those who work locally. In particular, commuters, on average, make 19.35% more than non-commuters.

1 Determinants of commuting

Given the fact that commuters are higher earners that non-commuters, we wish to investigate whether the choice to commute is somehow linked to the level of exposure of that household to floods. In attempts to cover the financial losses brought by floods, household members might wish to look for better paying jobs and thus commence the commuting activity or out-migrate from the risk area. Since out-migration is costly, individuals are more likely to decide to commute, because the marginal costs of doing so are low. A precise research question posed in this section is: “Do individuals in flood affected areas commute more?”

To answer the postulated research question it is necessary to properly define the the dependent variable. We wish to learn if those families exposed to floods commute more than those families without exposure. Therefore our treatment group are those individuals that started commuting after they had been exposed to floods. We identified five large and medium-size floods that occurred as depicted in Figure 1. For somebody who started commuting at some point between 1997 and 2002 it is important to know if that person was exposed to the flood that occurred in 1997. In the same fashion, for a respondent who started commuting between 2002 and 2006 it is crucial to know if that respondent was affected by floods that occurred in 2002 and 1997. It is of little informative value to know whether that respondent was affected by floods after he started commuting. Thus for somebody who started commuting after 2010 we wish to know if that respondent was affected by any of the five flood occurrences prior to the date when commuting commenced.

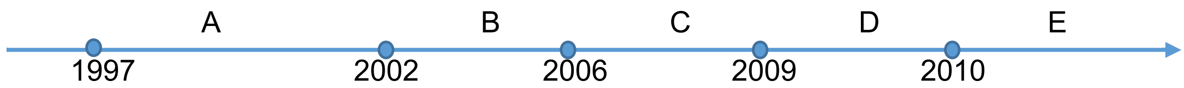

Figure 1: Occurrence of floods.

Based on the described intuition we create three key variables - $commute$, one_flood and two_floods. Variable $commute$ equals 1 if the respondent started commuting in any of the five areas - A, B, C, D or E; and 0 otherwise. Dummy variables one_flood and two_floods capture the first and second flood occurrences prior to starting commuting. Thus, for somebody who started commuting between 2002 and 2006 and was affected by all five floods, variable $commute = 1$, $one\_flood = 1$ and $two\_floods = 1$. It does not help us to know if that respondent was affected by floods in 2006, 2009 and 2010 after he started commuting between 2002 and 2006, because this fact does not entail causality - only floods that occurred prior to the start of commuting could be a contributing factor to the decision to commute. Table 8 depicts the relevance of the created variable. Out of those 267 individuals who commute on the survey date only 146, or 55%, can be classified as those, for whom whom the preceding flood occurrence could have been a contributing factor. The remaining 121 individuals commenced commuting prior to the flood date.

Table 8: Discrepancies between commuting on the survey date and the defined *commute* variable.

		commute on survey date		
		no	yes	Total
ed com- mute	no	126	121	247

yes	0	146	146
Total	126	267	393

To learn the determinants of commuting, we estimate the following regression:

$$commute_i = \beta_0 + \beta_1 one\_flood_i + \beta_2 two\_floods_i + \beta_3 fam\_com_i + \beta_4 fin\_loss_i$$
$$+ \beta_5 educ2_i + \beta_6 educ3_i + \beta_7 gender_i + \beta_8 age30_i + \beta_9 age40_i + \quad (2)$$
$$+ \beta_{10} age50_i + \beta_{11} married_i + \beta_{12} kids2_i + \beta_{13} kids3_i + v_i$$

Exact definitions of covariates are given in Table 12 of Appendix. Variables $commute$, one_flood and two_floods are defined as described above. Variable fam_com equals 1 if there is any other member in the family, who started commuting before the respondent; and 0 otherwise. With this variable we wish to test the "network effects" hypothesis, which means that it is easier for an individual to start commuting once there is already somebody in the family doing so. To a large extent it has to do with a decrease in information costs. Variable fin_loss measures the level of total self-reported household losses (expressed in monetary terms) from the experienced floods before the start of commuting. Under the assumption $v_i : N(0,\sigma^2)$ regression (2) is a standard probit model. The estimation results of regression (2) and the marginal effects are given in Table 9.

Table 9: Probit estimates of regression (2). Standard errors are clustered by family *id*. * - 1%, ** - 5%, * - 10% significance levels.**

variable	estimate		robust SE	dy/dx		SE	estimate		robust SE	dy/dx		SE
one_fl	0.590	***	0.183	0.138	***	0.041	0.397	*	0.207	0.092	*	0.047
two_fl							-0.575	**	0.290	-0.133	**	0.066
loss	-0.166	**	0.066	-0.039	**	0.015	-0.096		0.075	-0.022		0.017
married	-0.232		0.183	-0.054		0.043	-0.224		0.189	-0.052		0.044
male	0.249		0.172	0.058		0.039	0.256		0.172	0.059		0.039
age30	1.036	***	0.287	0.242	***	0.066	1.038	***	0.288	0.239	***	0.065
age40	0.649	***	0.248	0.151	***	0.057	0.681	***	0.255	0.157	***	0.058
age50	0.292		0.229	0.068		0.053	0.320		0.234	0.074		0.053
educ2	-0.345	*	0.183	-0.081	**	0.043	-0.327	*	0.184	-0.075	*	0.043
educ3	-0.086		0.242	-0.020		0.056	-0.094		0.242	-0.022		0.056
kids2	0.038		0.211	0.009		0.049	0.017		0.216	0.004		0.050
kids3	-0.053		0.392	-0.012		0.092	-0.073		0.384	-0.017		0.089
fam_com	1.997	***	0.212	0.466	***	0.037	2.067	***	0.216	0.477	***	0.037
_cons	-6.263	***	0.365				-6.194	***	0.366			
N. obs.			393						393			
log-likelihood			-164.934						-162.844			
Region fixed effects			yes						yes			

The estimation results suggest that the exposure to floods has a sizeable non-linear effect on the individual probability of commuting. Exposure to only one flood increases the commuting probability by 13.8% or 9.2%, depending on the inclusion of variable $second\_flood$ in the regression. This confirms our conjecture that flood affected households do in fact commute more. Though the exact link is unknown, we conjecture that individuals commute more, because, besides other things, they face the pressure to cover losses from floods and get ready for possible floods in the future. Alternatively, individuals save up to out-migrate. This brings us to the effect of the occurrence of the second flood - it is negative. Those individuals affected by two floods are by 13.3% less likely to commute.

The result produces a puzzle - a first flood pushes individuals to commute, whereas a second floods deters them from doing so. We suspect that those affected by one flood only commute more. However when the risk of a second flood is high or after a second flood has occurred, individuals out-migrate to safer areas. Those who stayed after a second flood are in fact those who were not able to out-migrate. Since they were unable to out-migrate for some reason, they commute much less, probably for the same reason as why they did not out-migrate.

We further confirm the “network effect” - a random individual with an active commuting family member is by 47% more likely to engage in commuting. Younger individuals aged below 40 are much more likely to commute than older cohorts. The variable fin_loss has somewhat a counter-intuitive sign. Since losses were partially covered by insurance and immediate government aid, we would be cautious about interpreting the estimate. Further, gender, family status, education or the number of children play no role in predicting the commuting behaviour.

The variables one_flood and two_floods are exogenous to the commuting decision, therefore the estimates are consistent. However, the occurrence of floods is endogenous with respect to the location - houses located on flat slopes closer to the river are more likely to be affected by the rising water. Thus if we find an instrument that predicts the location of the house and does not affect the $commute$ variable directly (but only through the variables one_flood and two_floods) we will be able to reduce the “location” bias. For this purpose we use variables that describe the location of the house (steep or flat slope) and house characteristics (presence of elevated floor) to instrument for the one_flood and two_floods variables. Using the result of Newey (1987), we estimate regression (2) using the probit model with endogenous covariates and present the results in Table 10.

If our story of the non-linear effects of the floods holds, and we wish to instrument for the second flood occurrence, i.e. variable $second\_flood$, we need to find an instrument, besides the above mentioned ones, that predicts the out-migration of residents from the flood affected areas. This issue remains to be addressed in further research.

Table 10: Alternative estimates of regression (2) using probit with endogenous covariates. Instrumented variable - one_flood **and** two_floods **. Instruments - house location and house characteristics. Standard errors are clustered by family *id*. *** - 1%, ** - 5%, * - 10% significance levels.**

variable	estimate		robust SE	estimate		robust SE
one_flood	2.596	***	0.399			
two_floods				-2.349	***	0.523
loss1	-1.648	***	0.413	0.141		0.190
loss2	-0.256		0.217	1.287	***	0.406
married	0.129		0.190	-0.196		0.186
male	0.151		0.126	0.246	*	0.142
age30	0.461	*	0.274	0.546	*	0.283
age40	0.109		0.246	0.484	*	0.263
age50	0.107		0.197	0.334		0.216
educ2	0.023		0.188	-0.126		0.188
educ3	0.325		0.229	0.051		0.247
kids2	-0.090		0.217	-0.162		0.273
kids3	-0.516		0.508	-0.252		0.337
fam_com	1.106	**	0.471	1.715	***	0.362
_cons	-1.257	***	0.256	-0.544		0.322
/athrho	-1.126	**	0.471	0.625	**	0.316
/lnsigma	-1.041	***	0.056	-1.025	***	0.059
N. obs.	393			393		
log-likelihood	-324.363			-325.238		
Wald test of exog.	Prob > chi2 = 0.017			Prob > chi2 = 0.048		

6 Commuting distance

At this point in the paper we have confirmed that exposure to floods affects the decision to commute in a hugely non-linear manner. The next question we address is whether those affected by the floods commute shorter or longer distances. For this we use the Heckman (1979) result and estimate the following model:

$$distance_i = \gamma_0 + \gamma_1 one\_flood_i + \gamma_2 two\_floods_i + \gamma_3 educ2_i + \gamma_4 educ3_i +$$
$$+ \gamma_5 male_i + \gamma_6 age30_i + \gamma_7 age40_i + \gamma_8 age50_i + \gamma_9 married_i + \quad (3)$$
$$+ \gamma_{10} kids2_i + \gamma_{11} kids3_i + \gamma_{12} \lambda_i + \mu_i$$

where $distance$ is commuting distance in km, $\lambda = \frac{\phi(\cdot)}{\Phi(\cdot)}$ is the inverse Mill's ratio estimated from the selection equation (2), and all other variables are defined in Table 12 of Appendix. As one can observe, for the exclusion restrictions we use region fixed effects, level of losses after floods and the variable that defines existence of an active commuting member (fam_com). The estimates of regression (3) are given in Table 11.

Table 11: OLS estimates of regression 3. Standard errors are clustered by family *id*. * - 1% significance level, ** - 5% significance level, * - 10% significance level.**

variable	estimate		robust SE
one_flood	-2.644	*	1.389
two_floods	-3.361	*	1.972
Married	0.151		1.192
male	-0.113		1.257
age30	0.504		1.720
age40	-0.425		1.774
age50	1.319		1.619
educ2	1.334		1.374
educ3	6.428	***	2.097
kids2	-1.103		1.330
kids3	-1.690		2.537
_cons	7.131	***	2.075
lambda	1.339		1.202
N. obs.		126	
R2		0.21	

The result suggests that those affected by floods commute shorter distances and those on the top of the education distribution commute longer distances. There is no evidence that the gender, family status, age or presence of kids in the family affects the commuting distance. The results also confirm the absence of the selection into commuting, as measured by the significance of the inverse Mill's ratio.

7 Conclusion

In this paper we found strong relationship between individuals' level and intensity of exposure to flood risk and the likelihood of commuting. Exposure to one flood pushes individuals to commute, in part, to accumulate resources to decrease the risk of exposure and vulnerability to floods. However, those exposed to the second flood occurrence are less likely to commute. We explain this by the fact that economically capable individuals out-migrate after the second flood occurrence, while stayers commute less for similar reasons as why they did not out-migrate and stayed in the risk areas.

This research contributes to the growing literature that researches how economic decision variables are affected by the climate change in a global sense. While the individual's economic decision is endogenous (it depends on intrinsic unobservables), the exposure to the flood risk is, to a large extend, exogenous - one does not choose if and when to have a flood. However, in this paper we claim that the exposure to flood risk is endogenous with respect to location - houses located closer to the river and on the same height level are more likely to be affected by floods. We take this information into account and instrument for the exposure to floods with variables that measure the slope of the house location and the floor height above the ground level. These variables satisfy the instrumental variable assumptions - they do not affect the probability of commuting directly, but only through the one_flood and two_floods variable. Estimating the probit model with endogenous regressors (Newey, 1987) we confirm the robustness of our result.

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Appendix

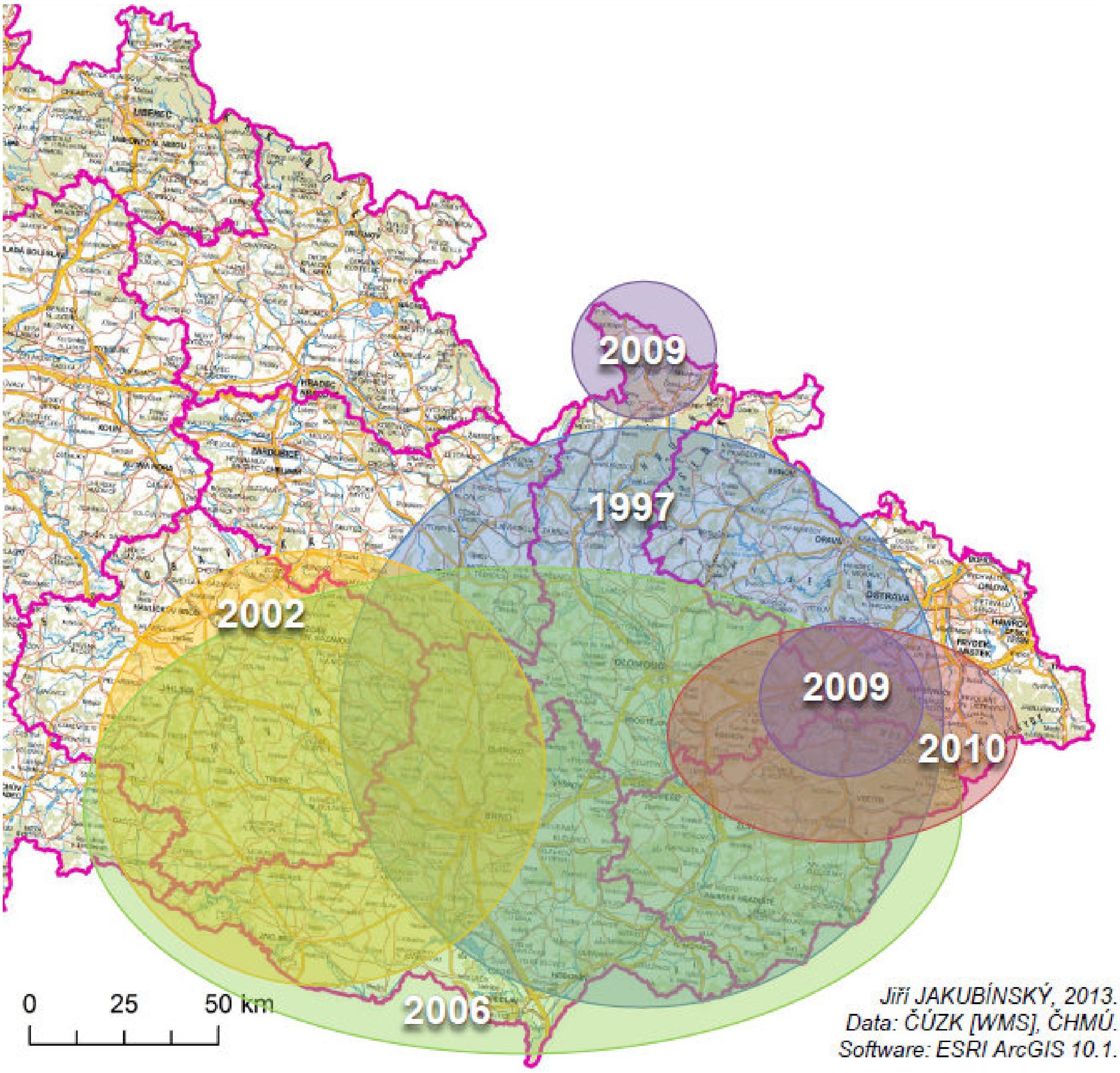

Figure 2: Flood map. Shaded areas show affected territory from respective floods. Authors' illustration.

Table 12: Definition of covariates in regressions (1), (2) and (3).

variable	definition
commute	= 1 if a respondent started commuting after a respective flood date; and 0 otherwise.
one_flood	= 1 if a respondent experienced only one flood; and 0 otherwise.
two_floods	= 1 if a respondent experienced two floods; and 0 otherwise.
age	continuous variable that measures reported individual's age.
age2	= age^2.
age30	= 1 if respondent's age is in range $(20\ 30]$; and 0 otherwise.
age40	= 1 if respondent's age is in range $(30\ 40]$; and 0 otherwise.
age60	= 1 if respondent's age is in range $(50\ 60]$; and 0 otherwise.
exper	continuous variable that measures reported individual's work experience.
educ2	= 1 if individual's education level is complete secondary or vocational training; and 0 otherwise.
educ3	= 1 if individuals' education level is Bachelor's or above; and 0 otherwise.
married	= 1 if the respondent is married; and 0 otherwise.
kids2	= 1 if there are two kids in the family; and 0 otherwise.
kids3	= 1 if there are three kids in the family; and 0 otherwise.
comm	= 1 if the respondent commutes on the date of interview; and 0 otherwise.
male	= 1 if the respondent is male; and 0 otherwise.
occ_type2	= 1 if the respondent's occupation is medium - skilled; and 0 otherwise.
occ_type3	= 1 if the respondent's occupation is high - skilled; and 0 otherwise.
occ_type4	= 1 if the respondent is entrepreneur; and 0 otherwise.
loss	categorical variable that measures the level of losses incurred after floods.
loss1	= 1 if respondent's loss after the respective flood is in range EUR (0, 2k]; and 0 otherwise.
loss2	= 1 if respondent's loss after the respective flood is in range EUR (2k, 4k]; and 0 otherwise.
fam_com	= 1 if a respondent has another member in the family who is already commuting; and 0 otherwise.