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Commuting patterns of Czech households exposed to flood risk from the Bečva river

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Using unique data collected in October–December 2012 we estimate the link between commuting for work and level of individual exposure to floods. We find that commuters on average have higher earnings than non-commuters. Individuals affected by one flood commute by 11.2% more than unaffected individuals. We conjecture that the increase is linked to intentions to cover flood-related losses, decrease households' vulnerability to flood risk or out-migrate from the risk areas. Individuals affected by at least two floods are by 20.2% less likely to commute relative to those unaffected. We explain this non-linear effect by the fact that many households out-migrate after the first flood. Stayers commute less, because they are different from non-stayers in some underlying characteristics related to education, employment and family circumstances, which strongly affect commuting behaviour. We further find that in a commuting family an individual is by 53.8% more likely to commence commuting relative to a non-commuting family. Choice of commuting destination is often similar to that of other family members.

Keywords: commuting; income gap; flood risk; selection; probit

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1. Introduction

Commuting for work is an economic decision. The benefits of commuting come from higher income that a commuter and his family can enjoy. The costs of commuting are related to less leisure and less time spent with the family. It is therefore interesting to know how various individuals weight these benefits and costs.

One has to separate two distinct but interrelated decisions: a decision to commute (extensive margin) and how far to commute (intensive margin). In this paper we research these two decisions in a unified framework. Our value added to the literature is in linking commuting for work to level and intensity of past exposure to floods. We postulate two research questions: 'Are flood-affected households more or less likely to commute for work and what is the character of this relationship?' and 'Do flood-affected individuals commute shorter or longer distances?'

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In our survey most individuals report a significant wage gap between what they get in destination cities and what they could get in areas of residence. Wages are endogenous, in that they are determined by many factors and often these factors are not entirely observed. One cannot expect much economic activity in regions that are frequently exposed to floods. Therefore, exposure to floods is an important determinant of economic activity, which affects the likelihood of commuting. This simple intuition explains why we think of commuting as an activity strongly related to individual flood experience.

Our study focuses on rural regions in the central part of the Bečva river basin in the Eastern part of the Czech Republic. Individuals there live in villages or small town and usually commute for work to nearby larger towns or cities. Christensen and Christensen (2003) and Kundzewicz, Pińskwar, and Brakenridge (2013) indicate that the Central Europe was severely affected by repeated floods within the last two decades. Borga, Anagnostou, Bloschl, and Creutin (2011) emphasize the necessity for more empirical research to fill in the data gap on flood evidence from small river basins and their effects on local residents. Our research contributes significantly to filling in this gap – we collect an individual-level data set which allows to research effects of floods on economic activity of households and their members. To our best knowledge this paper is one of the few attempts to systematically analyse floods from the Bečva river, its smaller water sources and their effects on economic behaviour of affected citizens.

The literature suggests that floods are devastating for the well-being of affected communities and companies (Kreibich, Müller, Thieken, & Merz, 2007; Kreibich, Müller, Thieken, & Thieken, 2009; Thieken, Kreibich, Müller, & Merz, 2007; Yeo, 2002). The research indicates poor preparedness of households, companies operating in risk areas and governments in providing recovery measures and timely compensation. Therefore, Kreibich et al. (2007) and Thieken et al. (2007) develop recommendations on how to improve the German flood warning system. Thieken et al. (2007) find that individual responses to the flood in 2002 in Germany differed greatly across individuals and affected areas. Botzen, Aerts, and van den Bergh (2009) find that affected households in the Netherlands differently react to the purchase of flood insurance than unaffected ones and undertake more measures to mitigate flood risk. Masozera, Bailey, and Kerchner (2007) and Morrow and Enarson (1996) find that the socioeconomic status plays an important role in individuals' ability to recover from a natural disaster. Those with more wealth can afford faster reconstruction of affected property or get access to insurance. Masozera et al. (2007) find that individual access to transportation greatly reduced 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 in the paper is the existence of a non-linear effect of floods on patterns of commuting of affected individuals. Individuals affected by only one flood are by 11.2% more likely to commute, whereas individuals affected by at least two floods are by 20.2% less likely to do so. We explain this finding by the fact that the affected individuals commute, in part, to accumulate financial resources to cover damages from floods and decrease households' vulnerability to flood risk. Some households manage to out-migrate permanently from risk areas. Those who remain and get exposed to the second flood are those who, for some reasons, were not active commuters after the first flood. These reasons are complex and are related to education, employment details, family circumstances and individual mobility costs. These findings are supported by qualitative information from households that we collected during face-to-face interviews.

Besides the above result, we find support for the 'network effect' hypothesis, according to which an average respondent with an active commuter is by 53% more likely to engage in commuting. New commuters who already have a long-distance commuter in the family are also likely to commute long distance.

In the paper we first describe the survey design and survey instrument. Then we provide descriptive statistics on respondents in the collected sample. Furthermore, we formulate an 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.[1] We stratify the population of interest with respect to the 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 m from the moderately affected area). Data on distribution of houses across the three risk areas is taken from Czech Hydrometeorological Institute (2012). We distribute the total number of interviews proportionally to the population in each stratum. Figure A1 in the appendix depicts the population of interest and location of houses across the risk zones on the example of Choryně and Poličná regions. The distribution of interviews across regions is shown in Table 1.

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, responses during recovery phase, insurance and preparedness for potential floods. 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, commuting for work and migration intentions. The questionnaire consists of many open-ended questions, in which respondents can evaluate their households' vulnerability to flood risk and express their opinions on effectiveness of government anti-flood measures. These questions help us to better understand circumstances of the surveyed households.

3. Descriptive statistics

The collected sample has data on 304 households and 875 individuals over five flood occurrences: 1997, 2002, 2006, 2009 and 2010. In line with the official aggregate data our research finds (Table 2) that the most severe flood took place in 1997; 184 households and 568 individuals in

Table 1. Distribution of observations across administrative regions.

	Households		Individuals	
Admin. region	*N*	%	*N*	%
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	

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Table 2. Flood occurrences and cumulative flood experience.

	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
At least three floods	25	8.2	79	9

the collected sample were affected. All subsequent floods were 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 3 provides data on self-reported losses from floods. Throughout all five floods, most households suffered up to CZK 50 k (EUR 2k) in losses, which suggests persistent but not devastating nature of the floods. We have two reasons to believe that the reported losses might be slightly mismeasured. Firstly, in a few cases respondents had difficulty quantifying losses, because their damaged houses were never fixed after the flood(s). Secondly, often insurance companies participated directly in fixing affected houses or replacing damaged equipment. In such cases respondents could not give reliable estimates of the value delivered by insurance companies.

Prior to the five flood occurrences three-fourths of households had insurance contracts. The remaining one-fourth did not have insurance because either it was too expensive to purchase or no insurance company agreed to insure their houses located in the high-risk area. Table 4 shows the distribution of insurance settlements across affected households. Settlements are shown as shares of reported losses. Interestingly, after the flood in 1997 insurance covered at least 40% of losses to 69.2% of the affected households. However, at least 50% was covered only to 20.9% of the households. This trend persists throughout the five flood events suggesting that the insurance companies were unwilling or unable to cover more than half of losses for the vast majority of households. We have two explanations for that. The first one comes from the way insurance companies operate. After the flood many customers claimed losses. Had insurance companies been generous in payments, many of them would have gone bankrupt. Indeed, several local insurance companies stopped operating after the flood in 1997. The second explanation concerns insurance customers and their contracts. Many respondents were under-insured, in that their contracts covered less assets than they thought. When the flood happened they claimed losses for assets that had not been insured.[2]

Table 3. Financial losses per household.

In CZK →	0–50 k	50 k–100 k	100 k–200 k	200 k–500 k	500 k–1 m
In EUR →	0–2 k	2 k–4 k	4 k–8 k	8 k–20 k	20 k–40 k
1997	121	26	13	13	5
2002	29	3	–	–	1
2006	5	4	1	3	1
2009	37	6	6	–	–
2010	55	7	4	–	–

Table 4. Number of 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

Table 5. Basic demographic characteristics.

	N	%		*N*	%
Male	439	50.2	*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	279	68.1
Bachelor's degree	15	1.7			
Master's degree and above	84	9.6			

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. Forty per cent of respondents have completed secondary education, slightly less, 34.6%, have incomplete secondary education and only 9,6% have a Master's degree or above.

In the sample 333 individuals are retirees, 57 and 42 individuals are students and unemployed, respectively, 25 respondents are women on maternity leave. In the questionnaire we developed a scale to rank the skill intensity of employment occupations. 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 unemployed, students and women on the maternity leave) is 279 individuals or 68.1%.

4. Wage regression

Basic descriptives in Table 6 suggest that the mean of commuters' reported earnings exceeds that of non-commuters. However, commuters' earnings are more dispersed around the mean.

To research trends in earnings we have to estimate the Mincerian wage regression on the sample of working individuals who reported their income. From the estimation we exclude pensioners, women on maternity leave, students and unemployed. We do not observe income for a significant share of working individuals due to non-reporting (response rate to the income question is 46%). It is therefore not convincing to rely on estimates of income gap that come from truncated distributions. There are reasons to suspect that non-reporting of income in our survey happens on a systematic (non-random) basis. To account for that we use the Heckman selection

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Table 6. Descriptive statistics on continuous variables.

Variable	Mean	SD	Min.	Max.
Age, years	51.5	18.8	16	92
Net income, CZK				
Non-commuters	16,208.8	6008.4	7000	40,000
Commuters	18,812.9	7902.9	7500	60,000
Commuting distance, km	18.8	38.4	1	300

procedure (Heckman, 1979) and write down a selection equation for whether a respondent reports income of each family member.[3] As an instrument for reporting income, we use the number of working adults in the family. The intuition is that for a respondent from a large family, it takes more time to report employment details about each member of the family. Thus, such respondents are more likely to say that they do not know or opt out of the interview completely.[4]

The wage equation can be written down as follows:

$$\mathbb{E}[\ln(\text{wage}_i)] = X_i'\delta_1 + Z_i'\delta_2 + D_i'\delta_3 + \mathbb{E}(\varepsilon_{1i}|\varepsilon_{0i} > -X_{i0}'\delta_0), \quad (1)$$

where wage_i is the reported wage of individual i, X_i' is a vector of individual characteristics that include gender, age, family status and number of children. Z_i' is a vector that includes education, experience, a dummy variable for whether a person i commutes and occupation type dummy variables. D_i' are region-fixed effects to account for regional heterogeneity in average incomes. The last term accounts for the fact that the income for some individuals is not reported and the observed income distribution is truncated. Vector X_{i0}' contains the same covariates as X_i' plus a variable for the number of working adults in the family. This variable is an instrument to predict respondent's decision to report income. Equation (1) is estimable with ordinary least squares (OLS), because the term $\mathbb{E}(\varepsilon_{1i}|\varepsilon_{0i} > -X_{i0}'\delta_0)$ can be expressed in a closed form assuming that the error terms are normally distributed. Exact definitions of the covariates are given in Table A1 in the appendix. Estimates of (1) are given in Table 7.

Signs of the estimates are in line with predictions of economic theory. Age has a concave shape – earnings increase with age but at a declining pace. Respondents with higher education, experience as well as those in more skill-demanding occupations earn more. Males earn more than females – an established fact of gender wage gap. The estimates suggest that respondents who commute for work to nearby larger cities are paid more than those who work locally. In particular, an average commuter earns 19.6% more than a non-commuter.

5. Determinants of commuting

Given the fact that commuters are higher earners than non-commuters, we wish to investigate whether selection into commuting is somehow linked to the level of exposure of that household to floods. In attempts to cover financial losses brought by floods, individuals might wish to look for better paying jobs and thus commence commuting or out-migrate permanently from risk areas. Since out-migration is costly, individuals are more likely to decide to commute, because the marginal costs of doing so are lower.

To answer the postulated research question, it is necessary to properly define the dependent variable. We wish to learn if flood-affected individuals commute differently relative to unaffected ones. We identified five large- and medium-size floods that occurred as depicted in Figure 1. For a respondent who started commuting at some point between 1997 and 2002, it is important to know if he/she was exposed to the flood in 1997. In the same manner, for a respondent who started

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Table 7. OLS estimates of the Mincerian wage regression (1).

	Estimate	Robust SE
commute	0.196	0.050***
male	0.248	0.043***
age	0.045	0.020**
age2	−0.001	0.000**
educ2	0.155	0.053***
educ3	0.197	0.089**
exper	0.002	0.003
married	0.091	0.064
kids1	0.231	0.117*
kids2	0.087	0.120
kids3	−0.086	0.093
occ_type2	0.085	0.063
occ_type3	0.225	0.080***
occ_type4	0.327	0.082***
_cons	8.140	0.441
λ_report	0.285	0.184
Region FE	Yes	
N. obs.	215	
R^2	0.45	

Note: Standard errors are clustered by family *id*.
*10% significance level.
**5% significance level.
***1% significance level.

Figure 1. Occurrence of floods.

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 had started commuting. Finally, for somebody who started commuting after 2010 we wish to know if that respondent was affected by any of the five researched floods.

Based on the described intuition we create three key variables – commute, first_flood and second_flood. Variable commute equals 1 if a respondent started commuting in any of the five areas – *A*, *B*, *C*, *D* or *E*; and 0 otherwise. Dummy variables first_flood and second_flood capture the first and second flood occurrences prior to the start of commuting. If a respondent was affected by all five floods and started commuting between 1997 and 2002, then first_flood = 1, first_flood = 1 and second_flood = 0. If the same individual started commuting between 2002 and 2006, then commute = 1, first_flood = 0 and second_flood = 1. It does not help us to know if that respondent was affected by floods in 2006, 2009 and 2010 after he started commuting, 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 267 individuals who commute on the survey date only 146, or 55%, can be classified as those for whom the preceding flood occurrence could have been a contributing factor. The remaining 121 individuals commenced commuting prior to the flood date and are not classified as commuters.

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

	Commute on survey date		
	No	Yes	Total
Commute variable			
No	126	121	247
Yes	0	146	146
Total	126	267	393

To learn determinants of commuting we estimate the following regression:

$$\begin{aligned} \text{commute}_i = {} & \beta_0 + \beta_1 \text{first\_flood}_i + \beta_2 \text{second\_flood}_i \\ & + \beta_3 \text{loss\_big\_ff}_i + \beta_4 \text{loss\_big\_sf}_i + \beta_5 \text{cov\_more\_ff}_i + \beta_6 \text{cov\_more\_sf}_i \\ & + \beta_7 \text{educ2}_i + \beta_8 \text{educ3}_i + \beta_9 \text{gender}_i + \beta_{10} \text{age30}_i + \beta_{11} \text{age40}_i \\ & + \beta_{12} \text{age50}_i + \beta_{13} \text{married}_i + \beta_{14} \text{kids1}_i + \beta_{15} \text{kids2}_i + \beta_{16} \text{kids3}_i \\ & + \beta_{17} \text{fam\_com}_i + D'_i \beta + \nu_i. \end{aligned} \tag{2}$$

Variables commute_i, first_flood_i and second_flood_i are defined as described above. The second line of the regression contains dummy variables that describe the level of reported losses and insurance settlements after each of the two floods. The third and fourth lines contain variables that describe individual demographic characteristics. Variable fam_com_i describes whether respondent's family already had a commuter before the start of commuting. With this variable we test the 'network effect' hypothesis, which conjectures 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. D'_i is a vector of region-fixed effects which account for the fact that each region is different in characteristics. Exact definitions of covariates are given in Table A1 of the appendix.

Under the assumption $\nu_i \sim N(0, \sigma^2)$ regression (2) is a standard probit model. Estimation results of regression (2) and the marginal effects are shown in panels one and two in Table 9. Clustering of observations by family *id* is done to account for the possibility of correlation of individual error terms within a household.

The estimation results suggest that the exposure to floods has a sizeable non-linear effect on the individual probability of commuting. Exposure to the first flood increases the probability of commuting by 11.2% as compared with unaffected individuals (panel two). When the second flood occurs, the probability of commuting decreases by 20.2% as compared with unaffected individuals. This non-linear effect is depicted in Figure 2.

Furthermore, we find that individuals with losses above EUR 2k from any flood are by a slight margin more likely to commute. Individuals for whom insurance settlements exceed 50% of reported losses are less likely to commute by 17.2% and 22% after the first and second floods, respectively.

These estimates suggest that commuting for work is indeed related to the intensity of household exposure to floods. Having high losses (above EUR 2k in this case) is a negative shock to households and pushes individuals to look for better employment in large cities to increase the sustainability of their households. Individuals who were sufficiently insured against flood losses, in that the settlements covered at least 50% of reported losses, recovered from the shock much easier than the under-insured individuals. The sustainability of these households was not badly affected by the flood.

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Table 9. Probit estimates of regression (2).

	Panel one				Panel two				Panel three	
	Probit, first flood				Probit, first and second floods				IV, both floods	
	Estimate	Robust SE	dy/dx	SE	Estimate	Robust SE	dy/dx	SE	Estimate	SE
first_flood	1.058	0.217***	0.189	0.036***	0.674	0.244***	0.112	0.039***	0.538	1.525
second_flood					−1.220	0.359***	−0.202	0.057***	−1.626	0.951*
loss_big_ff	0.128	0.362	0.023	0.065	0.083	0.370	0.014	0.061	0.084	3.336
loss_big_sf					0.523	0.485	0.087	0.079	4.054	3.951
cov_more_ff	−1.089	0.444**	−0.195	0.078**	−1.035	0.464**	−0.172	0.076**	−0.995	1.183
cov_more_sf					−1.326	0.677**	−0.220	0.112**	−1.281	1.168
married	0.111	0.231	0.020	0.041	0.221	0.252	0.037	0.042	0.190	0.384
male	0.515	0.200***	0.092	0.035***	0.541	0.215**	0.090	0.034***	0.497	0.267*
age30	1.521	0.372***	0.272	0.064***	1.787	0.417***	0.296	0.065***	1.827	0.459***
age40	1.058	0.304***	0.189	0.052***	1.347	0.332***	0.223	0.053***	1.341	0.401***
age50	0.761	0.287***	0.136	0.050***	0.919	0.295***	0.152	0.047***	1.018	0.370***
educ2	−0.276	0.208	−0.049	0.037	−0.381	0.221*	−0.063	0.036*	−0.456	0.411
educ3	−0.072	0.272	−0.013	0.049	0.016	0.291	0.003	0.048	−0.301	0.741
kids1	−0.291	0.294	−0.052	0.052	−0.613	0.339*	−0.102	0.055*	−0.660	0.340*
kids2	−0.098	0.283	−0.017	0.051	−0.370	0.303	−0.061	0.050	−0.287	0.490
kids3	−0.536	0.410	−0.096	0.073	−0.831	0.440*	−0.138	0.073*	−0.675	0.753
fam_com	2.686	0.256***	0.481	0.033***	3.246	0.319***	0.538	0.036***	3.346	0.503***
_cons	−7.119	0.493***			−7.427	0.616***			−7.622	464.801
Region FE	Yes				Yes				Yes	
N	378				378				378	
log-likelihood	−123.204				−113.631					
Wald test									Prob. > χ^2 = 0.74	

Note: Standard errors are clustered by family *id*.
*10% significance level.
**5% significance level.
***1% significance level.

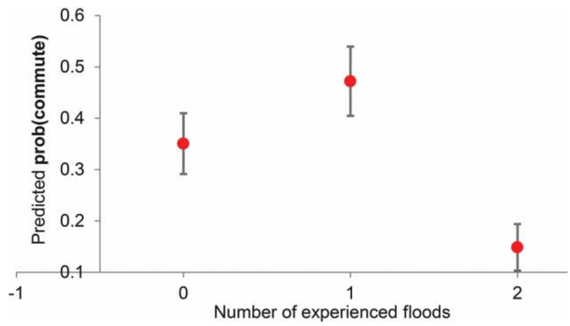

Figure 2. Probability of commuting. Point estimates with 95% confidence intervals. Illustration for mean values of the variables.

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The findings are in line with qualitative data from respondents. Many of them are unhappy to live in areas of high flood risk and would be glad to out-migrate permanently if only circumstances (in a wide sense) allowed for that. We saw several abandoned houses and learnt from neighbours that their owners had moved out. The houses could not be sold, because they had trivial value on the market. Unfortunately, we did not manage to learn any reliable details about the emigrated households.

Many respondents expressed concern about their insurance contracts, insurance settlements and rising insurance premia. Few respondents could not get an insurance contract, because an insurance company would not insure a house located in a high-risk area. For such a household any flood is a negative shock with which the household is left to cope on its own. In most cases insurance companies were parsimonious in settlements. For an under-insured household with low income, it means inability to completely recover from flood losses. Indeed, we saw individuals living in houses still unrepaired already several years after the flood(s). To all surveyed households the rising insurance premia is worrisome. They indicated that the price of an insurance contract doubled for the past decade.

Males, married, young and respondents with at least undergraduate degrees are more likely to commute. Having children is negatively associated with commuting, because individuals substitute their time at work and commuting for time with the family. We do not reject the 'network effect' hypothesis – an average individual who has somebody already commuting in the family is by 53.8% more likely to start commuting.

The variables first_flood, second_flood, loss_big_ff and loss_big_sf are exogenous to the commute decision, therefore the estimates are consistent. However, occurrence of floods and levels of losses are endogenous with respect to location. Houses located on flat slopes closer to the river are more likely to be affected by rising water and have higher losses than houses located on steep slopes. Thus, if we find an instrument that predicts house location and does not affect commute variable directly (but only through the endogenous variables first_flood, loss_big_ff, loss_big_ff and loss_big_sf) we will be able to reduce the 'location' bias. For this purpose we use variables that describe house location (steep or flat slope) and house characteristics (presence of elevated floor or cellar) to instrument for variables first_flood, second_flood, loss_big_ff and loss_big_sf. We estimate the probit model with endogenous covariates in regression (2) using the two-step estimator described in Newey (1987). The estimates are shown in panel three of Table 9. The signs of estimates do not change, however the Wald test statistics suggests that the instrumented variables are exogenous.

6. Commuting distance

In the previous section we estimated the extensive margin and found that exposure to floods affects the decision to commute in a non-linear manner. In this section we research the intensive margin to learn whether affected individuals commute shorter or longer distances. For this we use the Heckman (1979) result and estimate the following model:

$$\begin{aligned}\text{distance}_i = {} & \gamma_0 + \gamma_1\text{first\_flood}_i + \gamma_2\text{second\_flood}_i \\ & + \gamma_3\text{loss\_big\_ff}_i + \gamma_4\text{loss\_big\_sf}_i + \gamma_5\text{cov\_more\_ff}_i + \gamma_6\text{cov\_more\_sf}_i \\ & + \gamma_7\text{educ2}_i + \gamma_8\text{educ3}_i + \gamma_9\text{male}_i + \gamma_{10}\text{age30}_i + \gamma_{11}\text{age40}_i + \gamma_{12}\text{age50}_i \\ & + \gamma_{13}\text{married}_i + \gamma_{14}\text{kids1}_i + \gamma_{15}\text{kids2}_i + \gamma_{16}\text{kids3}_i \\ & + \gamma_{17}\text{fam\_dist} + \gamma_{18}\lambda_i + \mu_i,\end{aligned} \quad (3)$$

where distance is commuting distance in kilometres, $\lambda = \phi(\cdot)/\Phi(\cdot)$ is the inverse Mill's ratio estimated from the selection equation (2). fam_dist is a variable that describes distance travelled by a family member who started commuting before the respondent. This variable is analogous to fam_com from the probit regression (2). All other variables are defined in Table A1 of the appendix. As an exclusion restriction in the selection equation, we use variable fam_com. Estimates of regression (3) are given in Table 10.

The estimates suggest that individuals affected by one flood commute less than unaffected individuals, however this difference is not statistically significant. Individuals affected by two floods commuted on average almost 4 km less than unaffected commuters. Signs on variables

Table 10. OLS estimates of regression (3).

	Estimate	Robust SE
first_flood	−0.533	0.991
second_flood	−3.988	1.370***
loss_big_ff	0.509	1.291
loss_big_sf	1.431	1.563
cov_more_ff	−1.671	1.441
cov_more_sf	−0.137	2.181
married	0.667	1.050
male	1.926	0.781**
age30	0.546	1.180
age40	1.054	1.328
age50	3.298	1.162***
educ2	0.679	0.827
educ3	4.239	1.988**
kids1	−0.656	1.264
kids2	0.446	1.602
kids3	2.452	1.192**
fam_dist	0.829	0.071***
lambda_dist	4.235	0.910***
_cons	−0.888	1.279
Region FE	No	
N. obs.	114	
R^2	0.62	

Note: Standard errors are clustered by family *id*.
*10% significance level.
**5% significance level.
***1% significance level.

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that measure flood-related losses and insurance settlements have the same signs as in the probit regression. Individuals with higher losses commute slightly longer distances and individuals with high settlements commute shorter distances. Married, males, older and educated individuals commute to farther cities. New commuters commute slightly shorter distances compared with more experienced family members. This supports the fact that two commuters from the same family often work in the same city or share the same car. Furthermore, significance of the inverse Mill's ratio means that there is selection into commuting; the decision to start commuting and how far to commute are two interrelated decisions.

7. Conclusion

In this paper we find that the patterns of commuting for work among the Czech individuals living in flood risk areas are affected by exposure to floods. The effect is non-linear: an average individual affected by one flood is by 11.2% more likely to commute. Since commuting is on average associated with higher income, it allows the affected individuals to accumulate resources to cope with flood-related losses. Many respondents from the affected families expressed unhappiness about living in risk areas, because their assets are often damaged by rising water from the Bečva river or flash floods. These respondents would like to acquire anti-flood adaptation measures to reduce their households' vulnerability to floods or move to safer areas. Commuting gives them such an opportunity and 'successful' commuters do out-migrate eventually. Those who stay commute less, because they were not 'good' commuters in the first place. Compared with unaffected individuals, respondents who have experienced at least two floods are by 20.2% less likely to commute and they commute on average 4 km less. This implies that people who made it through two floods and stayed are indeed different from those who experienced only one or no floods in some fundamental characteristics, namely education, experience, family circumstances and individual migration costs.

Respondents with assets badly affected by floods are more likely to commute, though this difference is not significant. Residents who got generous insurance settlements are significantly less likely to commute. This suggests that commuting and insurance settlements are substitutes; they help affected households cope with flood losses and decrease vulnerability to flood risk.

We also find that the decision to commence commuting is to a large extent determined by presence of a commuter in the family. An individual with a commuting member in the family is by 53.8% more likely to start commuting than somebody with no commuter in the family. To decrease transportation costs commuters might choose to work in similar destinations and thus share transportation means. On average, 1 km increase in distance commuted by a family member is associated with 0.83 km increase in distance commuted by a new commuter within the same family.

We can think of two follow-up studies. It would be interesting to research characteristics of individuals who have permanently out-migrated from the surveyed risk areas. Comparing their characteristics with those of stayers will shed light on determinants of permanent out-migration. Further, researching the insurance contracts in more detail should unveil a pattern, if any, whether partially settled insurance claims after floods are due to households being under-insured or insurance companies being parsimonious in settling claims.

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Notes

1. In a related study, Brázdil et al. (2011) research the Morava river, however the Becva river remained rather unexplored in their analysis.
2. A typical insurance contract has separate provisions for insuring a house (walls, doors, cellar, etc.) and assets in the house (boiler, furniture, electronics, etc.).
3. An alternative procedure would be to construct a likelihood function in the spirit of the Tobit model.
4. This instrument indeed has a significant predictive power. If family size increases by one individual, the probability of reporting income drops by 5.2%. This estimate is significant at 5% significance level.

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Appendix

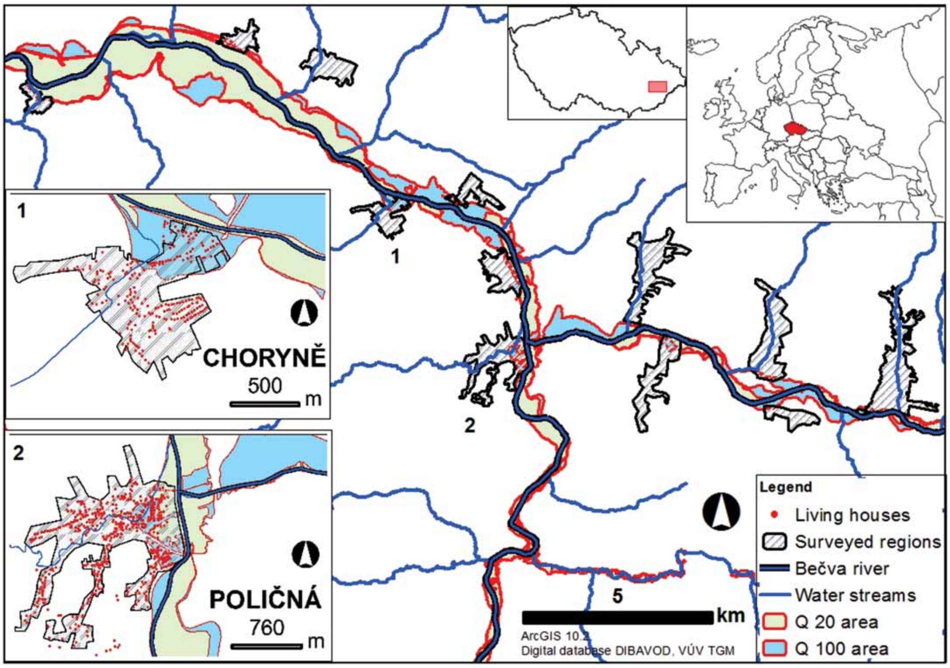

Figure A1. Population of interest. Authors' illustration.

Table A1. 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.
first_flood	= 1 if a respondent experienced only one flood; and 0 otherwise.
second_flood	= 1 if a respondent experienced at least two floods; and 0 otherwise.
loss_big_ff	= 1 if total reported losses after the first flood exceed EUR 2k; and 0 otherwise.
loss_big_sf	= 1 if total reported losses after the second flood exceed EUR 2k; and 0 otherwise.
cov_more_ff	= 1 if the insurance company covered more that 50% of claimed losses after the first flood; and 0 otherwise.
cov_more_sf	= 1 if the insurance company covered more that 50% of claimed losses after the second flood; and 0 otherwise.
age	continuous variable that measures reported individual's age.
age 2	= age^2.
age 30	= 1 if respondent's age is in range (20 30]; and 0 otherwise.
age 40	= 1 if respondent's age is in range (30 40]; and 0 otherwise.
age 60	= 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 an individual has complete secondary education or vocational training; and 0 otherwise.
educ3	= 1 if an individuals holds a Bachelor's degree or above; and 0 otherwise.
married	= 1 if the respondent is married; and 0 otherwise.

(*Continued*)

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Table A1. Continued.

Variable	Definition
kids1	= 1 if there is one child in the family; and 0 otherwise.
kids2	= 1 if there are two children in the family; and 0 otherwise.
kids3	= 1 if there are three children in the family; and 0 otherwise.
male	= 1 if a respondent is male; and 0 otherwise.
occ_type2	= 1 if respondent's occupation is in the medium-skilled category; and 0 otherwise.
occ_type3	= 1 if respondent's occupation is in the high-skilled category; and 0 otherwise.
occ_type4	= 1 if a respondent is an entrepreneur; and 0 otherwise.
fam_com	= 1 if respondent's family has another commuter who started commuting first; and 0 otherwise.
fam_dist	continuous variable that measures commuting distance (in km) for an individual who started commuting first.
λ_{report}, λ_{dist}	inverse Mill's ratios, $\lambda = \phi(\cdot)/\Phi(\cdot)$.

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