Supplemental material (SM) online for:

War and food insecurity in Ukraine

Contents

S1 Descriptive Statistics

Table S1: Sample descriptive statistics (Wave 1)

	N	Mean	Median	SD	Min	Max
Victim self	951	1.43	1.00	1.00	1.00	5.00
Victim family	961	1.92	1.00	1.40	1.00	5.00
Victim known	965	2.57	2.00	1.57	1.00	5.00
Victim municipal	1015	3.47	3.00	2.06	1.00	7.00
Age	1015	35.78	36.00	8.65	18.00	55.00
Gender	1015	0.57	1.00	0.49	0.00	1.00
Education	1007	4.79	5.00	1.50	1.00	7.00

Table S2: Sample descriptive statistics (Wave 2)

	N	Mean	Median	SD	Min	Max
Food shortage	791	1.14	0.00	1.87	0.00	7.00
Reduced meals	791	1.86	1.00	2.28	0.00	7.00
Liquid shortage	791	0.97	0.00	1.88	0.00	7.00
Victim self	753	1.30	1.00	0.83	1.00	5.00
Victim family	754	1.77	1.00	1.23	1.00	5.00
Victim known	749	2.48	2.00	1.49	1.00	5.00
Victim municipal	791	3.35	3.00	1.71	1.00	7.00
Age	791	36.32	37.00	8.48	18.00	54.00
Gender	791	0.59	1.00	0.49	0.00	1.00
SES	770	4.69	5.00	1.64	1.00	10.00

Table S3: Bivariate correlation matrix (Wave 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Victim known	1.000						
(2) Victim family	0.651	1.000					
(3) Victim self	0.319	0.453	1.000				
(4) Victim municipal	0.245	0.231	0.352	1.000			
(5) Age	0.046	-0.005	-0.003	0.046	1.000		
(6) Gender	0.016	0.029	-0.037	0.080	-0.038	1.000	
(7) Education	0.090	0.020	0.017	0.032	0.204	0.106	1.000

Table S4: Bivariate correlation matrix (Wave 2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Victim known	1.000										
(2) Victim family	0.628	1.000									
(3) Victim self	0.242	0.402	1.000								
(4) Victim municipal	0.201	0.187	0.230	1.000							
(5) Food shortage	0.067	0.144	0.249	0.216	1.000						
(6) Reduced meals	0.131	0.180	0.208	0.248	0.633	1.000					
(7) Liquid shortage	0.034	0.099	0.234	0.198	0.691	0.585	1.000				
(8) Age	0.013	-0.019	-0.044	0.052	-0.011	0.048	0.027	1.000			
(9) Gender	0.017	-0.016	-0.064	0.082	0.065	0.054	0.040	-0.083	1.000		
(10) Education	0.091	0.009	0.018	0.007	-0.116	-0.068	-0.076	0.154	0.083	1.000	
(11) SES	0.060	-0.003	0.029	-0.009	-0.149	-0.182	-0.139	-0.112	0.077	0.197	1.000

S2 Histograms

Figure S1: Food insecurity: Percentage frequency distribution

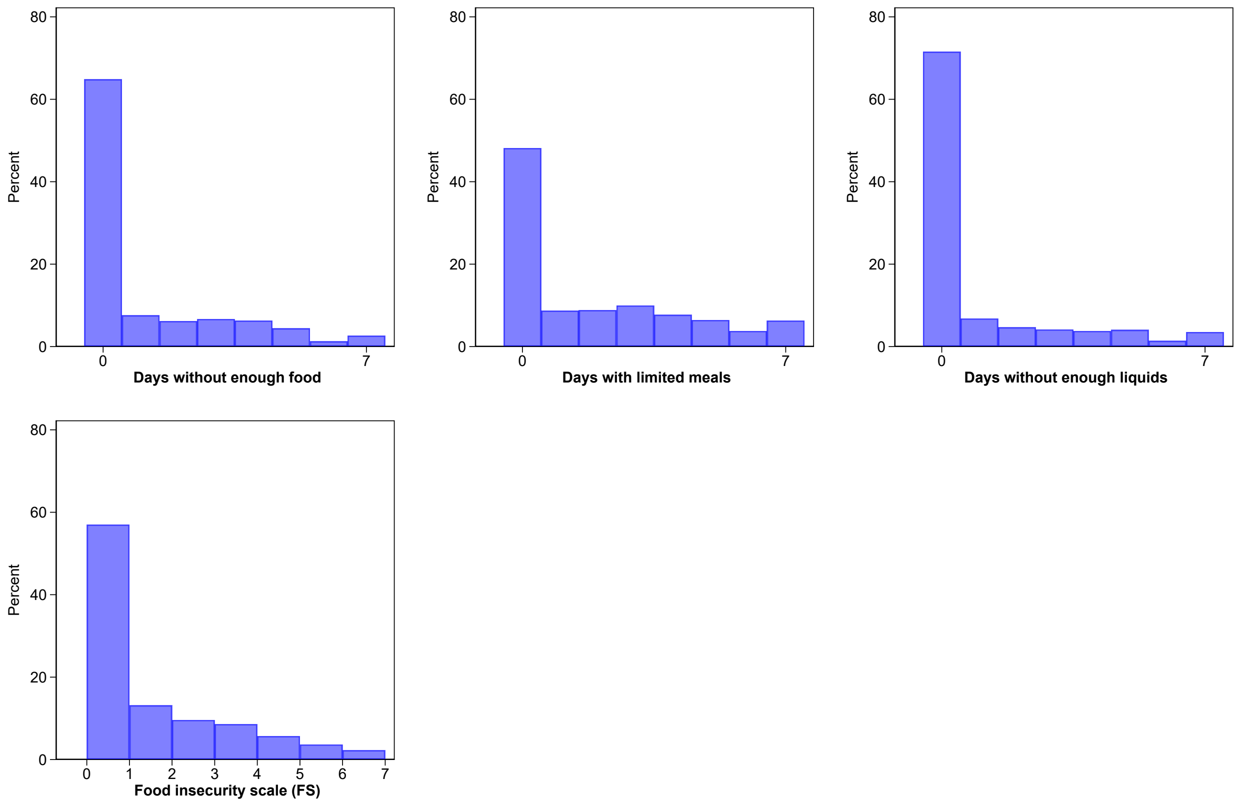


Figure S2: Victimization: Percentage frequency distribution

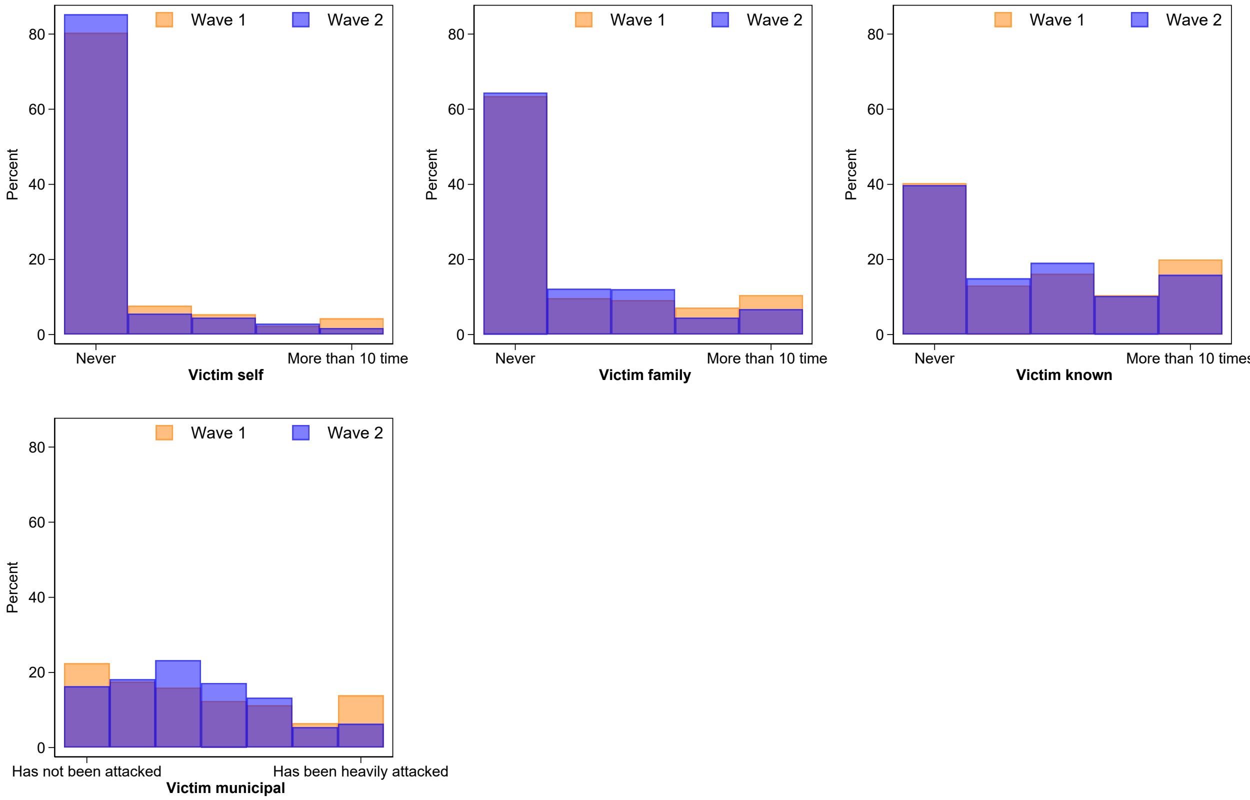
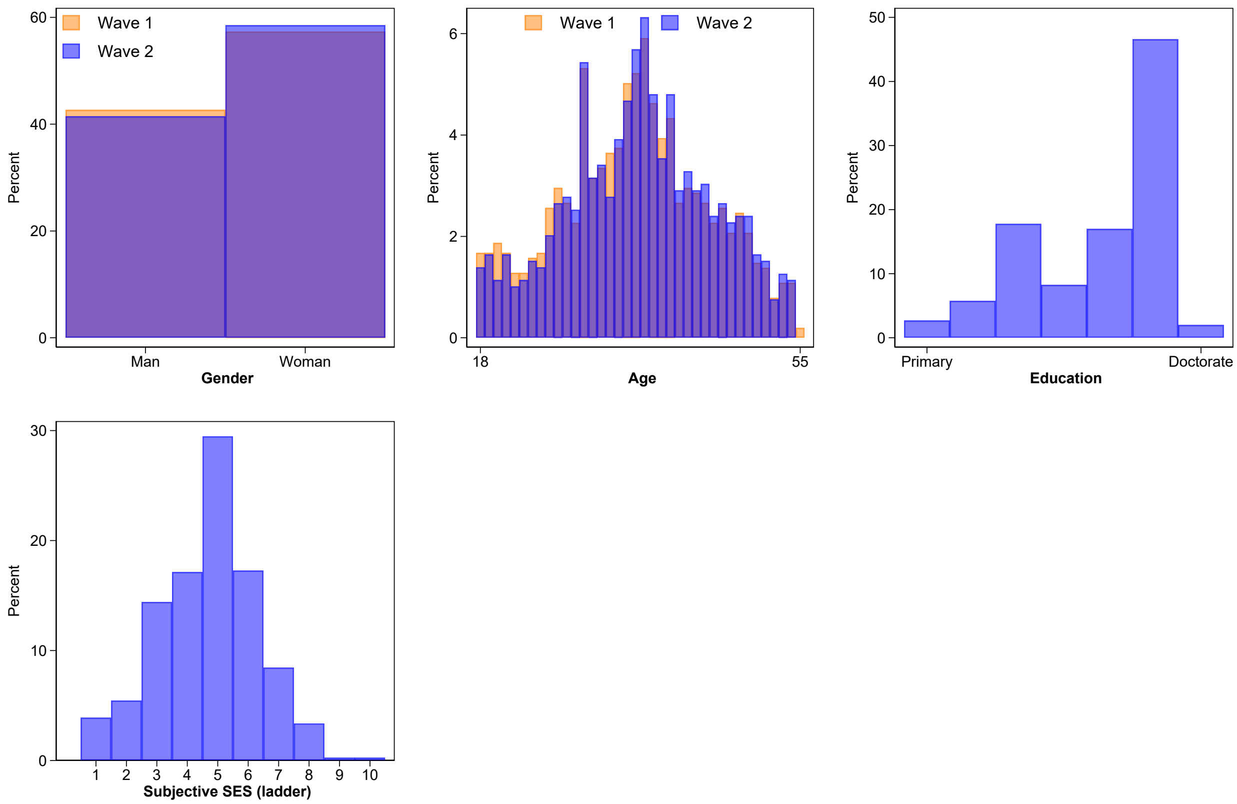
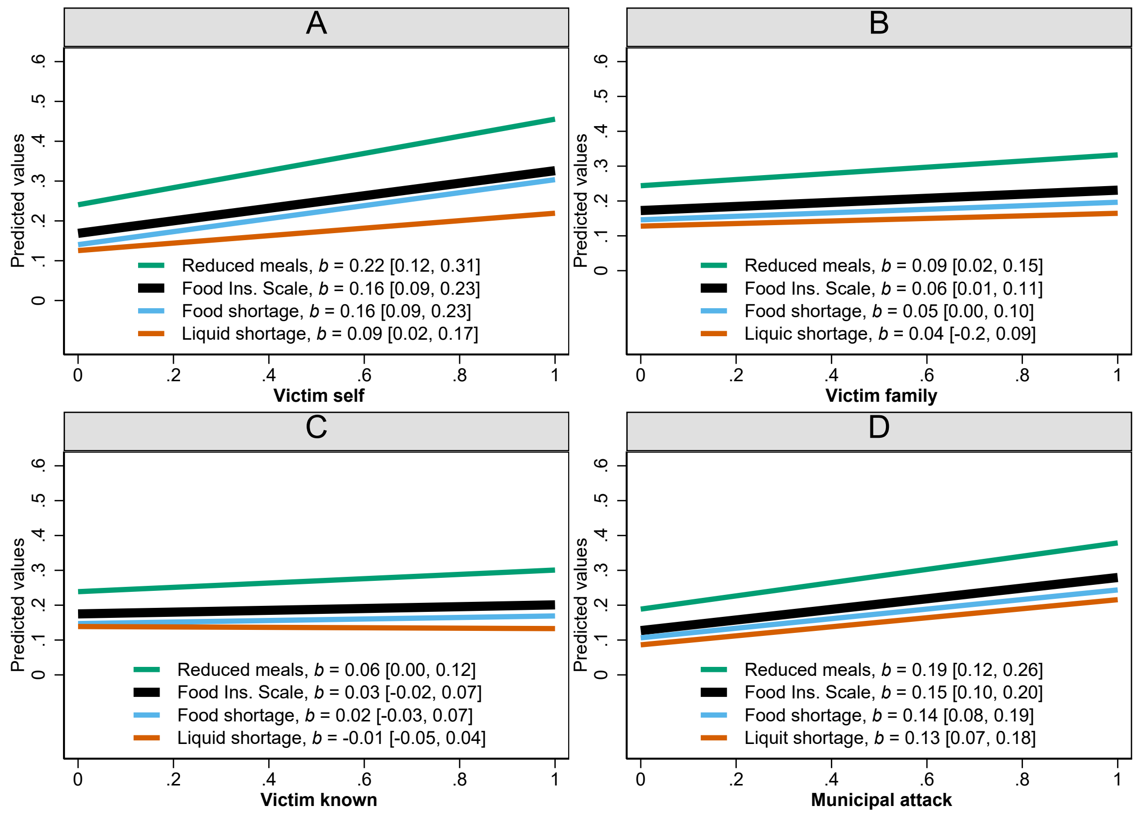


Figure S3: Gender, age, education, SES: Percentage frequency distributions



S3 Additional tests

Figure S4: Victimization and food insecurity: Regression results by type of victimization and by type of food insecurity. Predictors measured at Wave 1 and outcomes measured at Wave 2.



Controlling for potential confounders

Ukraine is administratively divided into 24 regions, called *oblasts*, plus two cities with special status (Kyiv and Sevastapol) and the Autonomous Republic of Crimea (our survey did not include Crimea). Arguably, some oblasts, for example, those bordering Russia, were a priori more likely to be attacked by the Russian forces and concurrently suffered greater a priori food insecurity levels. Fixed-effects analyses allow estimating "pure" within-region effects, so that the influences of such pre-war between-region differences are partitioned out of the coefficients representing the effects of wartime victimization on wartime food insecurity. As reported in the main text, the coefficients remained significant for VICTIM SELF and MUNICIPAL ATTACKS, but were reduced for VICTIM KNOWN, which only significantly predicted REDUCED MEALS, and VICTIM FAMILY, which no longer significantly predicted LIQUID SHORTAGE (see Figure S5 below).

Unlike higher-level units, individual citizens of Ukraine were less likely to be of strategic or tactical value to be systematically targeted by the Russian forces. However, some sub-groups of Ukrainians might still have been more predisposed to the attacks.

First, although Russian aerial attacks left no Ukrainian completely safe from victimization, wealthier Ukrainians were arguably more capable of avoiding contact with the Russian forces (e.g., by affording relocation to the less-targeted regions). Wealthier Ukrainians were also likely less susceptible to food insecurity (e.g., by simply having more money to buy food). Hence we controlled for socioeconomic status (SES), measured with the Subjective Social Status Scale (Operario et al., 2004). Second, pro-Russian citizens of Ukraine were perhaps less exposed to the attacks (e.g., they could align with the advancing Russian forces). Once the invasion started, pro-Russian individuals could have been blocked from food supplies, especially in the regions with stronger pro-Ukrainian sentiments. Therefore, we controlled for social IDENTIFICATION ("Below is a set of questions related to your personal identification. Please answer each of the questions on the scale from 1 = Not at all to 6 = Very strongly: How strongly do you identify with Russians?"). Third, the Russian forces first aimed to occupy large cities, most notably Kyiv, but soon faced strong resistance and were unable to advance. Arguably, large cities were less conquerable due to the nature of urban warfare, at the same time providing better safety for civilians. Large cities also likely had larger stockpiles of food. Citizens of large cities were thus potentially less vulnerable to both military attacks and food insecurity. Hence, we included a binary variable CITY RESIDENCE (0 = residence in cities with less than 500,000 inhabitants; 1 = residence in cities with more). Fourth, the capacity to change residence may relate to different levels of exposure to food insecurity and attacks; people who can change their residence can move to locations away from the frontlines and with better access to food. Thus, we included a binary indicator of having recently MOVED ("Is the region that you are in now, the same as the one you were in two weeks ago?" 0 = yes; 1 = no). Finally, those Ukrainians who joined the military resistance were likely more exposed to Russian attacks, while at the same time having better access to food (the Ukrainian army provided food to the fighters). Therefore, we included two indicators of engagement in resistance: "For each of the following statements, please indicate if in the last two weeks you have engaged in the described activity: A. I helped the resistance by joining direct military combat in fortified defense positions of the Ukrainian forces [RESISTANCE DEFENSE]; B. I helped the resistance by joining direct military combat in open battles against the Russian or pro-Russian forces [RESISTANCE ATTACK]" (0 = no; 1 = yes, once; 2 = yes, several times; 3 = yes, many times; 998 = Prefer not to say). As noted in the main text, analyses with these controls (see Tables S7 and S8 below) did not alter our substantive conclusions.

Figure S5: Victimization and food insecurity: Regression results by type of victimization and by type of food insecurity. Predictors measured at Wave 2 and outcomes measured at Wave 2 + region (oblast) fixed effects.

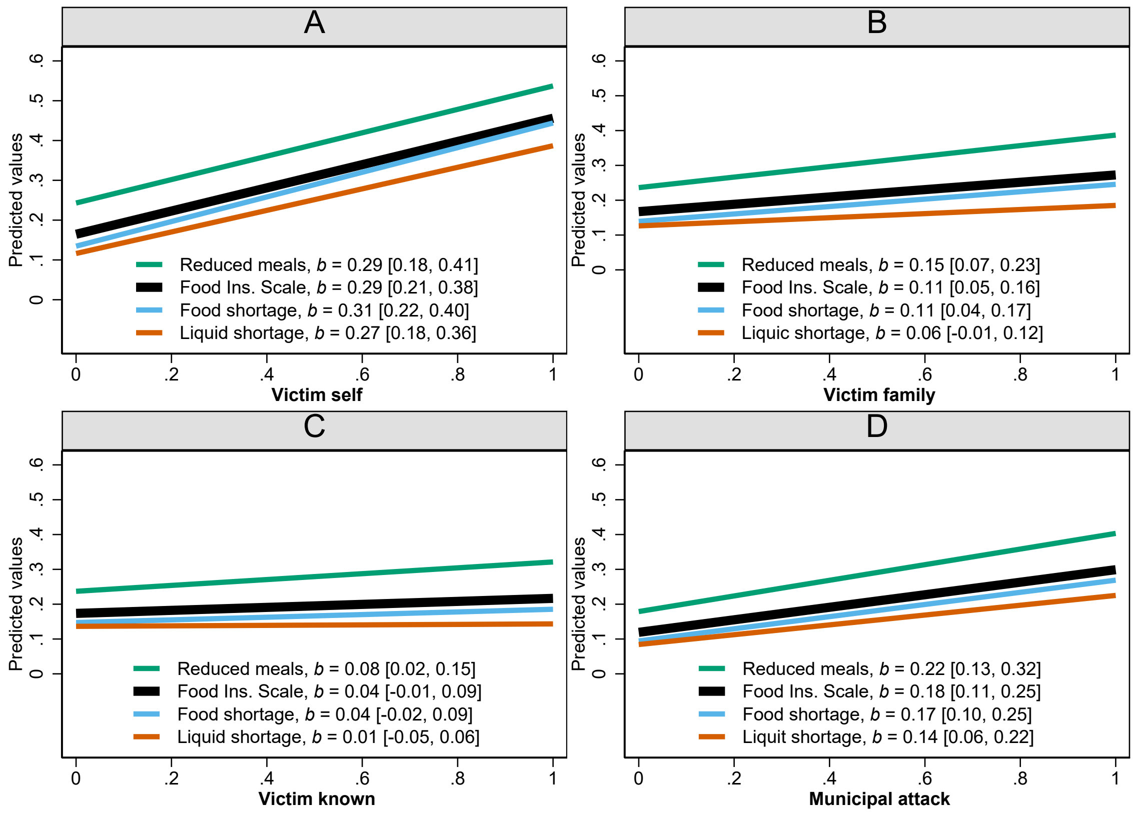


Table S5: Victim self as predictor of food insecurity: Exploring additional controls: Part 1. Wave 2 predictors. Wave 2 outcomes. Region fixed effects.

	(1)		(2)		(3)		(4)	
	b	ci95	b	ci95	b	ci95	b	ci95
Victim self	0.28	0.20,0.37	0.28	0.20,0.36	0.29	0.20,0.37	0.29	0.21,0.38
Age	0.05	-0.03,0.12	0.05	-0.02,0.13	0.06	-0.01,0.14	0.06	-0.01,0.13
Gender	0.05	0.01,0.08	0.05	0.01,0.08	0.04	0.01,0.08	0.04	0.00,0.07
Edu	-0.07	-0.15,-0.00	-0.10	-0.18,-0.03	-0.12	-0.19,-0.04	-0.11	-0.18,-0.04
Subj. SES	-0.22	-0.32,-0.12						
Identi. Russ.			0.22	0.12,0.33				
City residence					0.05	-0.00,0.11		
Recent move							0.03	-0.03,0.09
Constant	0.25	0.18,0.32	0.16	0.10,0.22	0.16	0.09,0.22	0.18	0.12,0.24
N	735		739		750		750	
R^2	0.094		0.094		0.076		0.073	

Table S6: Victim self as predictor of food insecurity: Exploring additional controls: Part 2. Wave 2 predictors. Wave 2 outcomes. Region fixed effects.

	(5)		(6)		(7)	
	b	ci95	b	ci95	b	ci95
Victim self	0.28	0.20,0.37	0.27	0.18,0.36	0.24	0.15,0.33
Age	0.07	-0.00,0.15	0.07	-0.01,0.14	0.06	-0.02,0.13
Gender	0.05	0.01,0.08	0.04	0.01,0.08	0.05	0.02,0.09
Edu	-0.11	-0.18,-0.03	-0.11	-0.18,-0.04	-0.09	-0.16,-0.01
Resistance (defence)	0.06	-0.01,0.14			0.03	-0.06,0.13
Resistance (attack)			0.16	0.04,0.28	0.15	-0.00,0.30
Subj. SES					-0.20	-0.30,-0.10
Identi. Russ.					0.21	0.11,0.32
City residence					0.04	-0.02,0.09
Recent move					0.03	-0.03,0.08
Constant	0.16	0.10,0.23	0.17	0.11,0.23	0.20	0.12,0.27
N	731		735		712	
R^2	0.077		0.081		0.127	

Table S7: Municipal attack as predictor of food insecurity: Exploring additional controls: Part 1. Wave 2 predictors. Wave 2 outcomes. Region fixed effects.

	(1)		(2)		(3)		(4)	
	b	ci95	b	ci95	b	ci95	b	ci95
Municipal attack	0.18	0.11,0.25	0.18	0.11,0.25	0.18	0.11,0.25	0.18	0.11,0.25
Age	0.03	-0.04,0.11	0.03	-0.04,0.11	0.04	-0.03,0.11	0.04	-0.03,0.11
Gender	0.03	-0.00,0.07	0.03	-0.00,0.07	0.03	-0.01,0.06	0.02	-0.01,0.06
Edu	-0.08	-0.15,-0.01	-0.11	-0.18,-0.04	-0.13	-0.20,-0.05	-0.12	-0.19,-0.05
Subj. SES	-0.22	-0.32,-0.12						
Identi. Russ.			0.25	0.15,0.35				
City residence					0.05	-0.00,0.11		
Recent move							0.04	-0.01,0.10
Constant	0.22	0.15,0.30	0.14	0.07,0.20	0.14	0.07,0.21	0.16	0.09,0.22
N	767		774		788		788	
R^2	0.076		0.075		0.053		0.052	

Table S8: Municipal attack as predictor of food insecurity: Exploring additional controls: Part 2. Wave 2 predictors. Wave 2 outcomes. Region fixed effects.

	(5)		(6)		(7)	
	b	ci95	b	ci95	b	ci95
Municipal attack	0.16	0.09,0.23	0.16	0.09,0.23	0.17	0.10,0.24
Age	0.05	-0.02,0.13	0.04	-0.03,0.12	0.04	-0.04,0.11
Gender	0.03	-0.00,0.07	0.03	-0.01,0.07	0.04	0.00,0.08
Edu	-0.11	-0.18,-0.03	-0.11	-0.18,-0.04	-0.08	-0.16,-0.01
Resistance (defence)	0.10	0.02,0.18			0.05	-0.05,0.14
Resistance (attack)			0.23	0.11,0.34	0.20	0.05,0.35
Subj. SES					-0.19	-0.29,-0.09
Identi. Russ.					0.25	0.14,0.35
City residence					0.04	-0.02,0.09
Recent move					0.04	-0.01,0.10
Constant	0.14	0.07,0.21	0.15	0.08,0.22	0.16	0.08,0.24
N	750		756		727	
R^2	0.050		0.062		0.117	

Table S9: All types of victimization combined as predictors of food insecurity: Wave 2 predictors. Wave 2 outcomes. Region fixed effects.

	(5)	
	b	ci95
Victim self	0.25	0.16,0.35
Victim family	0.05	-0.03,0.13
Victim known	-0.02	-0.08,0.04
Victim municipal	0.13	0.06,0.20
Age	0.07	-0.01,0.14
Gender	0.04	0.00,0.08
Edu	-0.10	-0.18,-0.03
Constant	0.13	0.06,0.19
N	730	
R^2	0.093	

S4 Sensitivity to unobserved confounding

While we cannot rule out that unobserved characteristics confound our results, we can evaluate the influence such features would need to have to change our conclusions. Here, we follow the analytical steps presented in our previous research (Bartusevičius and van Leeuwen 2022; Bartusevičius, van Leeuwen and Petersen 2023). This approach draws on research in applied economics suggesting that the amount of confounding by the observed controls serves as an indicator of the amount of confounding by the unobserved variables (e.g., Altonji, Elder and Taber, 2005; Oster, 2019; for applications, see, e.g., Bellows and Miguel, 2009; Gonzales and Miguel, 2015). Accordingly, coefficient stability across models with and without controls is taken as evidence against omitted variable bias (Gonzales and Miguel, 2015: 30). The robustness of VITIMIZATION SCALE to inclusion of 9 theoretically relevant controls (see Tables S5 and S6) is a preliminary evidence against omitted confounders driving our conclusions. Below, we present a formal evaluation of robustness to unobserved confounding, following the approach introduced by Altonji, Elder and Taber (2005) and further developed by Oster (2019).

We use the more conservative model with VICTIM SELF measured at Wave 1 and FOOD INSECURITY SCALE (FS) measured at Wave 2, as well as specified oblast fixed effects. The coefficient from a model that regresses FS on VICTIM SELF, with no controls, is $b_{nc} = 0.1266282$. The coefficient estimated in a model that regresses FS on VICTIM SELF, with 9 controls, is $b_{nc} = .1163907$. Hence, the observed controls reduce the effect of VICTIM SELF by $b_{nc} - b_c = 0.1266282 - 0.1163907 = 0.0102375$. To reduce it to zero, confounding by unobservables would thus have to be more than 10 times stronger than the confounding by the observed controls. To put this into perspective, Altonji, Elder and Taber derive a corresponding ratio of 3.55, suggesting that omitted variable bias is “highly unlikely” to explain away their identified effects (Altonji, Elder and Taber 2005: 155, 176). Correspondingly, and because we have considered theory-informed controls, we see it as unlikely that bias due to unknown variables would explain away the entire effect of VICTIM SELF.

This initial analysis assumed that the observed and unobserved confounders have equal variances. Oster (2019: 189-190) has noted that if these variances are unequal, coefficient stability across models with and without observed controls may fail to detect existing confounding. Oster (2019) argues, thus, we have to account for the variance in the outcome due to observed controls, and suggests scaling coefficient movements by the change in R^2 when controls are included. Accordingly, she derives the following formula:

$$b^* = b_c - (b_{nc} - b_c) \times (R_{max} - R_c)/(R_c - R_{nc}) \tag{1}$$

Where b_c and R_c are from the model including observed controls, and b_{nc} and R_{nc} are from the model with no controls. R_{max} represents R^2 from a model with all observable and unobservable controls (i.e., an unknown parameter).

If observables and unobservables have the same explanatory power in the outcome, (1) is a consistent estimator of bias-adjusted effects. All coefficients, aside from R_{max}, can be estimated from regressions with and without controls. For R_{max}, we can only derive some plausible bounds. R_c is a lower bound on R_{max} and 1 is a hypothetical upper bound. However, $R_{max} = 1$ is unrealistic because of likely measurement error (Gonzales and Miguel, 2015). Utilizing randomized experiments as empirical reference, Oster (2019) suggests the upper bound of $R_{max} = 1.3 \times R_c$, above which we can consider results robust. If we set R_{max} to $1.3R_c$, bias-adjusted effects of VICTIM SELF on FS is $b^* = 0.10085$. If we use a value of $R_{max} = 2.2R_c$—suggested by Oster (2019) in her earlier work—the effect drops to $b^* = 0.04052$. Hence, to reduce the coefficient to zero, confounding by unobservables would still have to be considerably stronger than the confounding by the observed controls.

Oster (2019) also advises to report the upper bound of R_{max} under which the effect would be 0 (assuming that confounding by unobservables is at least as strong as confounding by observables), which is 0.41 in our specific case. We also report values of another parameter, δ, the relative degree of selection on observed and unobserved variables, under which the effect would be 0. If $R_{max} = 1.3R_c$, then this value is 4.60437, and if $R_{max} = 2.2R_c$, then this value is 1.35021. To reduce the effect to zero, thus, confounding by unobservables would have to be between 4.6 and 1.4 times stronger than the confounding by the observed controls.

We can give empirical results a causal interpretation under the so-called conditional ignorability assumption (Rosenbaum and Rubin, 1983). To elaborate, the above identified association between VICTIM SELF and FS can be given causal interpretation under the assumption that VICTIM SELF is randomly assigned given the observed controls. However, we did not randomize VICTIM SELF, and—as we discussed—at least part of VICTIM SELF was not naturalisticaly randomly assigned. Therefore, the ignorability assumption may not be realistic in our case. The values of δ can be understood as the estimates of how sensitive the observed results are to the violation of the ignorability assumption. Conversely, the large δ values reported above indicate that our main results are robust to considerable departures from this assumption.

S5 Interactions

We conducted a series of multiplicative interaction tests using the core demographic variables as moderators: AGE, GENDER, EDUCATION, and SES. Here, we only analyzed the two remaining significant predictors, VICTIM SELF (see Table S10) and MUNICIPAL ATTACK (see Table S11). The models in Tables S10 and S11 assumed linear interaction effects. However, empirical studies show that this assumption commonly fails (Hainmueller et al., 2019). Given this, we also explored nonlinear interactions with the continuous variables—AGE, EDU, and SES, for both predictors, estimating fully flexible models (see the figure below). The estimates of the flexible models seem to correspond to those of the linear models, suggesting that the main results are unlikely to be artifacts of implausible modeling assumptions.

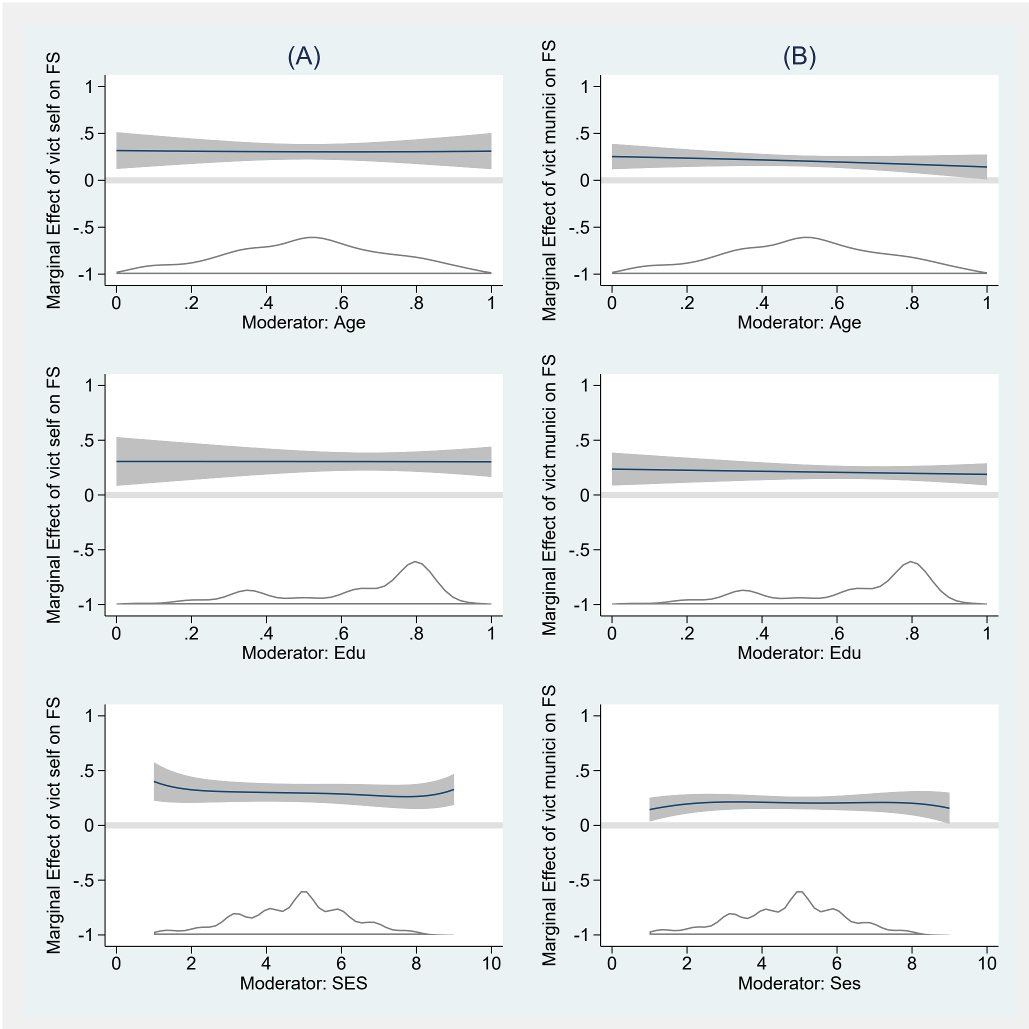
Table S10: Interactions of victim self with age, gender, education, and subjective SES. Wave 2 predictors. Wave 2 outcomes

	(1)		(2)		(3)		(4)	
	b	ci95	b	ci95	b	ci95	b	ci95
Victim self	0.35	0.16,0.54	0.29	0.17,0.41	0.33	0.09,0.57	0.29	0.10,0.47
Age	0.07	-0.00,0.15	0.07	-0.01,0.14	0.07	-0.00,0.14	0.05	-0.02,0.13
Gender	0.05	0.01,0.08	0.04	0.01,0.08	0.05	0.01,0.08	0.05	0.02,0.09
Edu	-0.11	-0.18,-0.04	-0.11	-0.18,-0.04	-0.11	-0.18,-0.03	-0.07	-0.14,0.00
Subj. SES							-0.24	-0.34,-0.13
Victim self*age	-0.07	-0.42,0.28						
Victim self*gender			0.05	-0.11,0.22				
Victim self*edu					-0.02	-0.37,0.32		
Victim self*SES							0.06	-0.36,0.47
Constant	0.17	0.10,0.23	0.17	0.11,0.23	0.17	0.10,0.23	0.25	0.18,0.32
N	750		750		750		735	
R^2	0.085		0.085		0.085		0.110	

Table S11: Interactions of victim municipal with age, gender, education, and subjective SES. Wave 2 predictors. Wave 2 outcomes

	(1)		(2)		(3)		(4)	
	b	ci95	b	ci95	b	ci95	b	ci95
Victim municipal	0.27	0.13,0.41	0.30	0.20,0.39	0.24	0.07,0.41	0.19	0.05,0.32
Age	0.09	-0.03,0.21	0.04	-0.04,0.11	0.04	-0.04,0.11	0.03	-0.04,0.10
Gender	0.03	-0.00,0.07	0.09	0.03,0.15	0.03	-0.00,0.07	0.04	0.00,0.07
Edu	-0.12	-0.19,-0.05	-0.12	-0.19,-0.05	-0.10	-0.21,0.02	-0.07	-0.15,-0.00
Subj. SES							-0.25	-0.41,-0.09
Victim municipal*age	-0.13	-0.39,0.12						
Victim municipal*gender			-0.15	-0.27,-0.03				
Victim municipal*edu					-0.05	-0.30,0.19		
Victim municipal*SES							0.05	-0.26,0.36
Constant	0.12	0.04,0.20	0.12	0.05,0.18	0.13	0.05,0.22	0.22	0.13,0.31
N	788		788		788		767	
R^2	0.075		0.080		0.074		0.104	

Figure S6: Interactions. Panel A: VICTIM SELF. Panel B: VICTIM MUNICIPAL.



S6 Data quality checks

Attention

To identify inattentive respondents, we used the following attention check, placed as the second-last question in the survey: *This is an attention check. Please pick 'Green' from the list of colors below:*

1. *Red*
2. *Blue*
3. *Green*
4. *Orange*
5. *Brown*

All respondents who selected other responses than 'Green' were excluded from the analyses (ns = 19 and 5 in Waves 1 and 2 respectively)

Speeding

"Speeders" are those participants who complete responses to questions implausibly fast. We followed Info Sapiens' suggestion to exclude all such speeders from the main analyses (ns = 42 and 15 in Waves 1 and 2 respectively).

Invalid comments

The questionnaire ended with the following open-ended question: *This is the last question. Do you have any comments that you would like to share with us?* As part of their standard routines, Info Sapiens checks such open comments for indicators of invalid data. Based on these comments, Info Sapiens recommended for to exclude 5 and 0 respondents in Waves 1 and 2 respectively.

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