Supplemental Materials for “The Political Consequences of External Economic Shocks” (intended for online publication only)

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# Survey question and experiment wording

The English translation of the questions and possible responses are:

**Government intervention question:** “How much should the government intervene to help Polish borrowers with Swiss franc loans?  Keep in mind that an intervention would require hurting banks or using tax dollars.”

* “Big intervention”, “some intervention”, “do not intervene”, and “not sure/don’t know”.

Note that analysis of the government intervention question is contained in the appendix only.

**Policy proposal question:** “The Polish parliament has recently debated two policy proposals on how to help households that took out home loans in Swiss francs. Both proposals would convert the Swiss franc mortgages into zlotys at an exchange rate that makes the loans more affordable. Both proposals limit the assistance to households living in apartments and houses no larger than 100-150 square meters. Both programs are expected to cost around 10 billion zlotys. One proposal (“Proposal A”) splits these costs equally between the banks issuing the loans and the households who borrowed the money. The other proposal (“Proposal B”) forces the banks to pay 90% of these costs and mortgage borrowers pay 10%. Which of the following do you support?”

* “Proposal A, where the cost is equally split between banks and borrowers”, “Proposal B, where banks pay 90% and borrowers 10% of the costs”, “The government should do nothing, meaning the mortgage borrowers bear all the costs.”, “The government should something but I do not support either Proposal A or Proposal B” and “Don’t know.”

### Survey Experiment treatments

Italicized text is the text added to the information treatment.

**Information condition:** “Several European currencies including the zloty have lost a lot of value against the Swiss franc since January 2015. Some Polish households took out loans in Swiss francs to buy cars and houses. The currency decline has increased debt payments for those borrowers.”

**History condition:**  “Several European currencies including the zloty have lost a lot of value against the Swiss franc since January 2015. Some Polish households took out loans in Swiss francs to buy cars and houses. The currency decline has increased debt payments for those borrowers. *When a similar situation occurred in 2008, the Polish government chose to do nothing in response*.”

**Hungary condition:** “Several European currencies including the zloty *and the Hungarian Forint* have lost a lot of value against the Swiss franc since January 2015. In Poland and Hungary some households took out loans in Swiss francs to buy cars and houses. The currency decline has increased debt payments for those borrowers*. In Hungary, the government has intervened by forcing banks to pay for these losses. In Poland, the government has not yet intervened*.”

# Selection into FX loans

Table A. 1 reports weighted logistic regression models for selection into FX borrowing. Age, income, marital status, urban location, education, employment status and household size are the strongest predictors of currently repaying an FX loan. Current income, household size, and marital and employment status are not significant predictors of having had an FX loan in the past. In neither case do the coefficients for provincial dummies cross traditional significance thresholds once we account for other covariates. The table reflects the fact that past FX borrowers are about 8 years older than current FX borrowers, on average.

Table A. 1: Selection into FX loans, current and past.

|  |  |  |
| --- | --- | --- |
|  | | |
|  | **Current FX borrower** | **Past FX borrower** |
| (Intercept) | -10.02\*\* | -7.45\*\* |
|  | (1.41) | (1.43) |
| 18-31 | -1.32\*\* | -1.71\*\* |
|  | (0.45) | (0.60) |
| 44-56 | -0.86\*\* | -0.16 |
|  | (0.36) | (0.38) |
| 57-66 | -0.33 | -0.35 |
|  | (0.41) | (0.47) |
| 66+ | -2.28\* | -0.95\* |
|  | (1.24) | (0.63) |
| female | 0.07 | -0.21 |
|  | (0.28) | (0.30) |
| married | 1.81\*\* | 0.35 |
|  | (0.50) | (0.38) |
| income | 0.43\*\* | 0.13 |
|  | (0.14) | (0.16) |
| education | 0.36\*\* | 0.62\*\* |
|  | (0.16) | (0.17) |
| urban | 0.45\*\* | 0.41\*\* |
|  | (0.19) | (0.21) |
| employed | 1.22\*\* | 0.03 |
|  | (0.48) | (0.40) |
| religiosity | -0.06 | 0.16 |
|  | (0.13) | (0.14) |
| Household size | 0.24\*\* | -0.04 |
|  | (0.12) | (0.15) |
| Left | -0.69\* | -0.06 |
|  | (0.41) | (0.38) |
| Right | 0.03 | -0.33 |
|  | (0.31) | (0.35) |
| *N*= | 2044 | 2044 |
| Logistic regression coefficients averaged over 20 imputed datasets and employing survey weights. Standard errors in parentheses. All models include province dummies (omitted from table). \*\**p* < 0.05, \**p* < 0.1 | | |

# 

# Vote & Seat Shares by party in 2011 and 2015

Table A. 2 Polish *Sejm* party vote and seat shares, 2011 to 2015.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Vote Share  2015** | **Change  from 2011** | **Sejm Seats (total 460)** | **Seat  Share** | **Seats / 1% vote share** |
| PiS | 37.6% | + 7.7% | 235 | 51.1% | 6.3 |
| PO | 24.1% | -15.1% | 138 | 30.0% | 5.7 |
| Kukiz’15 | 8.8% | new party | 42 | 9.1% | 4.8 |
| Nowoczesna (.N) | 7.6% | new party | 28 | 6.1% | 3.7 |
| PSL | 5.1% | -3.2% | 16 | 3.5% | 3.1 |

*Source*: <http://electionresources.org/pl/> Last visited 8/1/2019

# Full model results with covariates

## Government Intervention models

Figure A. 1: Preferences for government support by FX exposure



Here we report results for a binary logit as well as a model that interacts exposure with experimental treatments. We see no evidence of heterogeneous effects of treatments by FX exposure. We estimate positive effects for all our conditions but only the information treatment crosses traditional significance thresholds. Contrary to expectations, the Hungary treatment does not systematically enhance the information-only condition. Including covariates, as in Models A3, does not alter these conclusions. By way of interpretation,a respondent in the information treatment is eight percentage points more likely to favor some degree of government intervention to help FX borrowers compared to respondents in the control condition.

In Models A2 and A3 we identify exposed respondents as well as past FX borrowers. Respondents currently repaying FX loans are significantly more likely to support government intervention, whereas past FX borrowers are, if anything, *less* supportive (although standard errors are large for past borrowers). The predicted probability of demanding intervention among control group respondents currently paying back an FX loan is 0.71, compared to 0.44 among those with no FX debt exposure. Model 3 shows that this large difference in opinion between those with and without a direct material stake in the issue actually becomes *larger* after conditioning on covariates that predict FX borrowing and political preferences.

Table A. 3 Government intervention models with full covariate results and exposure x treatment interaction.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Model A1** | **Model A2** | **Model A3** | **Model A3-i** |
| (Intercept) | -0.22\*\* | -0.25\*\* | -0.58 | -0.58 |
|  | (0.09) | (0.09) | (0.40) | (0.40) |
| information | 0.30\*\* | 0.31\*\* | 0.36\*\* | 0.37\*\* |
|  | (0.13) | (0.13) | (0.13) | (0.13) |
| history | 0.12 | 0.14 | 0.18 | 0.15 |
|  | (0.13) | (0.13) | (0.14) | (0.14) |
| Hungary | 0.19 | 0.17 | 0.20 | 0.20 |
|  | (0.13) | (0.13) | (0.14) | (0.14) |
| FX-exposed |  | 1.12\*\* | 1.34\*\* | 1.24\*\* |
|  |  | (0.28) | (0.29) | (0.60) |
| past borrower |  | -0.35 | -0.16 |  |
|  |  | (0.28) | (0.30) |  |
| exposed x info |  |  |  | -0.40 |
|  |  |  |  | (0.78) |
| exposed x history |  |  |  | 2.37 |
|  |  |  |  | (1.64) |
| exposed x Hungary |  |  |  | 0.01 |
|  |  |  |  | (0.77) |
| 18-31 |  |  | 0.17 | 0.18 |
|  |  |  | (0.14) | (0.14) |
| 44-56 |  |  | -0.39\*\* | -0.39\*\* |
|  |  |  | (0.15) | (0.15) |
| 57-65 |  |  | 0.00 | 0.00 |
|  |  |  | (0.17) | (0.17) |
| 66+ |  |  | 0.01 | 0.02 |
|  |  |  | (0.18) | (0.18) |
| female |  |  | 0.13 | 0.13 |
|  |  |  | (0.10) | (0.10) |
| married |  |  | -0.21\*\* | -0.21\*\* |
|  |  |  | (0.11) | (0.11) |
| income |  |  | -0.05 | -0.05 |
|  |  |  | (0.05) | (0.05) |
| education |  |  | -0.13\*\* | -0.13\*\* |
|  |  |  | (0.05) | (0.05) |
| urban |  |  | 0.07 | 0.07 |
|  |  |  | (0.07) | (0.07) |
| employed |  |  | 0.00 | 0.01 |
|  |  |  | (0.12) | (0.12) |
| religiosity |  |  | 0.10\*\* | 0.10\*\* |
|  |  |  | (0.04) | (0.04) |
| household size |  |  | 0.11\*\* | 0.11\*\* |
|  |  |  | (0.04) | (0.04) |
| Left |  |  | -0.18 | -0.18 |
|  |  |  | (0.13) | (0.13) |
| Right |  |  | -0.04 | -0.04 |
|  |  |  | (0.11) | (0.11) |
| *N*= | 2044 | 2044 | 2044 | 2044 |
| Respondents answering “big” or “some” to the government intervention question coded as “1”. The table reports logistic regression coefficients averages over 20 imputed datasets and employing survey weights. Standard errors in parentheses. \*\**p* < 0.05, \**p* < 0.1 | | | | |

Table A. 4 reports results analogous to models A1 and A2 but estimated as weighted multinomial logistic regression with no imputation of missing values. These results again show that the information treatment shifts respondents into favoring intervention. We see some evidence that the Hungary treatment shifts respondents from DK to “some”. The FX exposed continue to be much more favorable to intervention, especially a large one.

Table A. 4: Preferences for government intervention, multinomial models.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **none** | **some** | **big** | **none** | **some** | **big** |
| (Intercept) | 1.09\*\* | 0.74\*\* | 0.09 | 1.05\*\* | 0.69\*\* | 0.01 |
|  | (0.14) | (0.15) | (0.17) | (0.14) | (0.15) | (0.17) |
| information | 0.37\* | 0.61\*\* | 0.56\*\* | 0.37\* | 0.61\*\* | 0.56\*\* |
|  | (0.21) | (0.22) | (0.24) | (0.21) | (0.22) | (0.25) |
| history | -0.01 | 0.20 | -0.06 | -0.01 | 0.21 | -0.04 |
|  | (0.20) | (0.21) | (0.24) | (0.20) | (0.21) | (0.24) |
| Hungary | 0.33 | 0.56\*\* | 0.20 | 0.33 | 0.54\*\* | 0.17 |
|  | (0.21) | (0.22) | (0.26) | (0.21) | (0.22) | (0.26) |
| FX-exposed |  |  |  | 2.00 | 2.65\*\* | 3.35\*\* |
|  |  |  |  | (1.24) | (1.23) | (1.24) |
| past borrower |  |  |  | 1.10\* | 0.60 | 0.52 |
|  |  |  |  | (0.62) | (0.64) | (0.72) |
| *N*= | 2036 | | | 2036 | | |
| AIC | 5154 | | | 5131 | | |
| The table reports multinomial logistic regression coefficients employing survey weights. “DK” is the reference category. Standard errors in parentheses. \*\**p* < 0.05, \**p* < 0.1 | | | | | | |

## Proposal Support models

Table A. 5 Full reporting of models: preferences over policy proposals.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Model A4** | | | | **Model A5** | | | |
|  | **DK** | **some** | **50/50** | **90/10** | **DK** | **some** | **50/50** | **90/10** |
| information | 0.17 | 0.33\* | 0.15 | 0.25 | 0.17 | 0.33\* | 0.15 | 0.26 |
|  | (0.23) | (0.19) | (0.18) | (0.20) | (0.23) | (0.19) | (0.18) | (0.20) |
| history | 0.30 | 0.40\*\* | 0.11 | 0.25 | 0.31 | 0.41\*\* | 0.13 | 0.29 |
|  | (0.23) | (0.19) | (0.18) | (0.21) | (0.24) | (0.19) | (0.19) | (0.21) |
| Hungary | 0.35 | 0.52\*\* | 0.23 | 0.43\*\* | 0.33 | 0.51\*\* | 0.21 | 0.41\*\* |
|  | (0.24) | (0.19) | (0.19) | (0.21) | (0.24) | (0.19) | (0.19) | (0.21) |
| FX-exposed |  |  |  |  | 0.37 | 0.68 | 1.13\*\* | 2.09\*\* |
|  |  |  |  |  | (0.76) | (0.44) | (0.40) | (0.40) |
| past borrower |  |  |  |  | -6.55 | -0.03 | -0.41 | 0.25 |
|  |  |  |  |  | (14.11) | (0.38) | (0.43) | (0.43) |
| 18-31 | -0.29 | -0.10 | -0.02 | 0.06 | -0.29 | -0.06 | 0.03 | 0.20 |
|  | (0.27) | (0.20) | (0.19) | (0.22) | (0.27) | (0.20) | (0.20) | (0.23) |
| 44-56 | -0.44 | -0.23 | -0.36\* | -0.32 | -0.43 | -0.21 | -0.32 | -0.23 |
|  | (0.27) | (0.20) | (0.20) | (0.23) | (0.27) | (0.20) | (0.20) | (0.23) |
| 57-66 | -0.07 | 0.17 | 0.26 | 0.38 | -0.06 | 0.19 | 0.29 | 0.46\* |
|  | (0.30) | (0.23) | (0.23) | (0.25) | (0.30) | (0.23) | (0.23) | (0.25) |
| 66+ | 0.21 | -0.03 | 0.06 | -0.04 | 0.22 | -0.005 | 0.10 | 0.08 |
|  | (0.32) | (0.26) | (0.26) | (0.28) | (0.32) | (0.26) | (0.26) | (0.29) |
| female | 0.78\*\* | 0.58\*\* | 0.28\*\* | 0.20 | 0.77\*\* | 0.58\*\* | 0.27\*\* | 0.19 |
|  | (0.17) | (0.14) | (0.13) | (0.15) | (0.17) | (0.14) | (0.13) | (0.15) |
| married | -0.45\*\* | -0.03 | -0.40\*\* | -0.29\* | -0.46\*\* | -0.04 | -0.42\*\* | -0.36\*\* |
|  | (0.18) | (0.15) | (0.15) | (0.16) | (0.18) | (0.15) | (0.15) | (0.16) |
| income | -0.27\*\* | -0.12\* | -0.06 | -0.15\*\* | -0.27\*\* | -0.12\* | -0.07 | -0.18\*\* |
|  | (0.09) | (0.07) | (0.07) | (0.07) | (0.09) | (0.07) | (0.07) | (0.07) |
| education | -0.40\*\* | -0.15\*\* | -0.10 | -0.29\*\* | -0.39\*\* | -0.15\*\* | -0.11 | -0.32\*\* |
|  | (0.10) | (0.07) | (0.07) | (0.08) | (0.10) | (0.07) | (0.07) | (0.08) |
| urban | -0.28\*\* | 0.03 | 0.02 | 0.11 | -0.29\*\* | 0.03 | 0.01 | 0.08 |
|  | (0.12) | (0.09) | (0.09) | (0.10) | (0.12) | (0.09) | (0.09) | (0.10) |
| employed | -0.06 | 0.03 | 0.15 | 0.06 | -0.06 | 0.03 | 0.13 | 0.02 |
|  | (0.22) | (0.17) | (0.17) | (0.18) | (0.22) | (0.17) | (0.17) | (0.18) |
| religiosity | -0.02 | 0.09 | 0.17\*\* | 0.16\*\* | -0.01 | 0.10 | 0.18\*\* | 0.16\*\* |
|  | (0.08) | (0.06) | (0.06) | (0.07) | (0.08) | (0.06) | (0.06) | (0.07) |
| Household size | -0.04 | 0.13\*\* | 0.12\*\* | 0.03 | -0.04 | 0.12\*\* | 0.11\*\* | 0.01 |
|  | (0.07) | (0.05) | (0.05) | (0.06) | (0.07) | (0.05) | (0.05) | (0.06) |
| Left | 0.25 | 0.04 | -0.23 | 0.01 | 0.26 | 0.05 | -0.22 | 0.04 |
|  | (0.25) | (0.19) | (0.19) | (0.20) | (0.25) | (0.19) | (0.19) | (0.21) |
| Right | 0.29 | 0.01 | -0.14 | 0.01 | 0.29 | 0.01 | -0.14 | 0.01 |
|  | (0.22) | (0.16) | (0.16) | (0.17) | (0.22) | (0.16) | (0.16) | (0.17) |
| (Intercept) | 1.22\* | -0.72 | -0.58 | -0.24 | 1.23\* | -0.68 | -0.52 | -0.05 |
|  | (0.71) | (0.57) | (0.56) | (0.61) | (0.71) | (0.57) | (0.56) | (0.62) |
| *N* = | 2044 | | | | 2044 | | | |
| Multinomial logistic regression coefficients averaged over 20 imputed datasets and employing survey weights. “None” is the reference category. Standard errors in parentheses. Covariates include indicators for province. \*\**p* < 0.05, \**p* < 0.1 | | | | | | | | |

Table A. 6: Preferences over policy proposals, observed data and no covariates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **DK** | **some** | **50/50** | **90/10** |
| (Intercept) | -1.00\*\* | -0.63\*\* | -0.39\*\* | -0.84\*\* |
|  | (0.16) | (0.14) | (0.13) | (0.15) |
| information | -0.00 | 0.27 | 0.12 | 0.19 |
|  | (0.22) | (0.18) | (0.17) | (0.20) |
| history | 0.20 | 0.39\*\* | 0.12 | 0.23 |
|  | (0.22) | (0.19) | (0.18) | (0.20) |
| Hungary | 0.15 | 0.46\*\* | 0.17 | 0.35\* |
|  | (0.23) | (0.19) | (0.18) | (0.20) |
| FX-exposed | -0.69 | 0.45 | 0.85\*\* | 1.39\*\* |
|  | (0.74) | (0.42) | (0.38) | (0.37) |
| past borrower | -12.60 | -0.26 | -0.71\* | -0.23 |
|  | (181.40) | (0.36) | (0.41) | (0.40) |
| AIC | 6339.74 | | | |
| *N=* | 2030 | | | |
| Multinomial logistic regression coefficients employing survey weights. “None” is the reference category. Standard errors in parentheses. \*\**p* < 0.05, \**p* < 0.1 | | | | |

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# Anti-immigrant sentiment and support for government intervention & specific policies

CBOS asked a battery of nine questions about views on migrants, with responses falling into a common 6-category Likert scale. We construct our measure of a respondent’s anti-immigrant sentiment by encoding responses using integers {1,...,6} and then averaging scores across all questions for which the respondent gave an answer.

Figure A. 2 Distribution of anti-immigrant sentiment by response categories

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Table A. 7: Policy opinions as a function of anti-immigrant sentiment

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Gov’t Intervention (logit)** | **Proposal Support**  **(multinomial logit)** | | | |
|  |  | **DK** | **some** | **50/50** | **90/10** |
| (Intercept) | -1.51\*\* | -2.28\*\* | -1.32\*\* | -1.00\*\* | -2.88\*\* |
|  | (0.28) | (0.49) | (0.38) | (0.37) | (0.46) |
| info | 0.29\* | -0.08 | 0.26 | 0.11 | 0.30 |
|  | (0.17) | (0.31) | (0.25) | (0.24) | (0.27) |
| history | 0.11 | 0.16 | 0.20 | -0.02 | 0.03 |
|  | (0.18) | (0.30) | (0.25) | (0.24) | (0.28) |
| Hungary | 0.17 | 0.05 | 0.41 | 0.17 | 0.33 |
|  | (0.18) | (0.32) | (0.25) | (0.25) | (0.29) |
| exposed | 1.70\*\* | 0.60 | 1.00 | 1.37\*\* | 2.31\*\* |
|  | (0.40) | (0.84) | (0.62) | (0.58) | (0.57) |
| Anti-immigrant sentiment | 0.31\*\* | 0.32\*\* | 0.21\*\* | 0.18\*\* | 0.50\*\* |
|  | (0.06) | (0.11) | (0.09) | (0.08) | (0.10) |
| *N* = | 1108 | 1104 | | | |
| Respondents answering “big” or “some” to the government intervention question coded as “1”. “None” is the reference category for the proposal support question. Estimates in the table reports employing survey weights. Standard errors in parentheses. \*\**p* < 0.05, \**p* < 0.1 | | | | | |

Table A. 8 Full reporting of models: voting behavior.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Model A6** | | | **Model A7** | | |
|  | **abstain** | **other** | **PiS** | **abstain** | **other** | **PiS** |
| FX-exposed | -0.48 | 0.59 | 0.63\* | -1.16\* | -0.91 | -0.73 |
|  | (0.44) | (0.37) | (0.39) | (0.65) | (0.74) | (0.70) |
| past FX borrower | -0.63 | -0.11 | -0.43 | -0.37 | 0.25 | -0.58 |
|  | (0.42) | (0.40) | (0.44) | (0.91) | (1.01) | (1.01) |
| PO/PSL 2011 |  |  |  | -2.57\*\* | -3.47\*\* | -5.52\*\* |
|  |  |  |  | (0.36) | (0.37) | (0.41) |
| exposed x 2011 PO/PSL |  |  |  | 0.50 | 2.04\*\* | 2.54\*\* |
|  |  |  |  | (0.99) | (0.89) | (0.93) |
| past x 2011 PO/PSL |  |  |  | -0.43 | -0.40 | 0.30 |
|  |  |  |  | (1.20) | (1.18) | (1.52) |
| past turnout | -2.06\*\* | -0.28 | -0.48\*\* | 0.02 | 2.33\*\* | 2.74\*\* |
|  | (0.19) | (0.23) | (0.23) | (0.36) | (0.38) | (0.39) |
| 18-31 | 0.23 | 1.00\*\* | 0.03 | 0.19 | 0.93\*\* | -0.10 |
|  | (0.22) | (0.24) | (0.26) | (0.23) | (0.26) | (0.29) |
| 44-56 | 0.20 | 0.47\* | 0.60\*\* | 0.17 | 0.37 | 0.50\* |
|  | (0.21) | (0.25) | (0.24) | (0.22) | (0.27) | (0.28) |
| 57-66 | -0.13 | 0.23 | 0.47\* | -0.13 | 0.16 | 0.42 |
|  | (0.24) | (0.28) | (0.26) | (0.25) | (0.29) | (0.31) |
| 66+ | 0.09 | -0.41 | 0.37 | 0.05 | -0.51 | 0.32 |
|  | (0.26) | (0.33) | (0.29) | (0.28) | (0.35) | (0.35) |
| female | 0.02 | -0.47\*\* | -0.23 | 0.04 | -0.38\*\* | -0.11 |
|  | (0.14) | (0.16) | (0.16) | (0.15) | (0.17) | (0.19) |
| married | 0.005 | -0.27 | -0.30\* | -0.01 | -0.31 | -0.39\* |
|  | (0.16) | (0.18) | (0.17) | (0.16) | (0.19) | (0.21) |
| income | -0.22\*\* | -0.12 | -0.004 | -0.18\*\* | -0.06 | 0.07 |
|  | (0.07) | (0.08) | (0.08) | (0.07) | (0.08) | (0.09) |
| education | -0.15 | 0.19\*\* | -0.10 | -0.10 | 0.24\*\* | -0.03 |
|  | (0.08) | (0.09) | (0.09) | (0.08) | (0.10) | (0.11) |
| urban | -0.11 | 0.32\*\* | -0.25\*\* | -0.09 | 0.36\*\* | -0.22\*\* |
|  | (0.10) | (0.11) | (0.11) | (0.10) | (0.12) | (0.13) |
| employed | 0.24 | -0.03 | 0.26 | 0.26 | 0.004 | 0.33 |
|  | (0.18) | (0.20) | (0.20) | (0.19) | (0.22) | (0.24) |
| religiosity | 0.09 | 0.07 | 0.53\*\* | 0.08 | 0.06 | 0.52\*\* |
|  | (0.06) | (0.07) | (0.08) | (0.07) | (0.08) | (0.09) |
| household size | -0.05 | -0.02 | 0.04 | -0.03 | 0.01 | 0.07 |
|  | (0.05) | (0.06) | (0.06) | (0.06) | (0.07) | (0.07) |
| Left | 0.54\*\* | 0.67\*\* | -0.44\* | 0.31 | 0.37\* | -1.00\*\* |
|  | (0.18) | (0.20) | (0.27) | (0.19) | (0.22) | (0.30) |
| Right | 0.31\* | 0.001 | 1.16\*\* | 0.10 | -0.26 | 0.58\*\* |
|  | (0.16) | (0.19) | (0.17) | (0.17) | (0.21) | (0.21) |
| (Intercept) | 1.97\*\* | -0.90 | -1.86\*\* | 1.83\*\* | -1.13 | -1.82\*\* |
|  | (0.56) | (0.65) | (0.65) | (0.59) | (0.70) | (0.77) |
| *N*= | 2044 | | | | | |
| Multinomial logistic regression coefficients averaged over 20 imputed datasets and employing survey weights. “PO/PSL” is the reference category. Standard errors in parentheses. Covariates include indicators for province. \*\**p* < 0.05, \**p* < 0.1 | | | | | | |

# 

# Details of the election counterfactual

In interpreting counterfactual election outcomes, we focus on the PiS seat share. Our approach is admittedly and necessarily rough. Our survey is not representative at the province level and we do not know the electoral constituency of our respondents. We are therefore unable to account for the distribution of votes across electoral constituencies, nor do we get in to the details of Poland’s electoral formula. Instead we use our estimated models to generate a predicted PiS vote share in the absence of the CHF shock. We subtract these predicted vote shares from the observed PiS vote share in our survey, 0.389 and then map this difference in to an approximate change in the number of seats. We generate our counterfactual vote shares as follows:

1. For each imputed dataset, construct a parallel dataset in which the FX-exposed dummy is set to 0 for all respondents. This represents our counterfactual scenario of an election in which there was no CHF revaluation shock.
2. For the multinomial logit model described as Model A7 above, sample 500 vectors of regression coefficients from *N*() for each *m*,where are the estimated regression coefficients from the multinomial logistic regression model fit to imputed dataset *m*=1, …, 20.
3. From the counterfactual data matrix in (1) and the coefficient vectors in (2), generate a 2044x 4 x 10,000 array in which each 2044 x 4 slice is a matrix of the predicted probabilities of choosing each of the four options (abstain, PiS, PO/PSL, other) for each respondent under the counterfactual scenario and one draw of coefficient values.
4. For each row in (3), we generate a predicted probability of voting for PiS by multiplying the predicted probability of choosing PiS times the survey weight. Summing this value across all 2044 rows produces the PiS votes for that simulated election.
5. To calculate turnout for each simulated election we multiply the predicted probability of abstain times the survey weight, sum across all 2044 rows and subtract from 2044.
6. We divide the quantities in (4) by those in (5) to produce 10,000 counterfactual PiS vote shares.

We assume that, in the neighborhood of the winning vote proportions in the 2015 election, every 1% of the party vote share yields 6 seats. In other words, we use the average of the first two rows in Table A. 2 to produce our seats-to-votes ratio and we assume this ratio is constant across space. We calibrate this against the actual PiS seat share in the election. Applying Model 7 to all 20 imputed datasets and assuming 6 seats/1% of the vote produces a mean prediction of 233 seats for PiS; the actual seats won was 235. If we assume 5.73 (the average from the past 5 elections) then we get a mean prediction of 223 seats. In short, our assumption of 6 produces predictions close to actual election outcomes with our data and model.

If the (observed survey PiS vote share) - (counterfactual predicted PiS vote share) > 5/6% then we code that simulation as one in which the CHF shock induced a shift in PiS vote share sufficient to push PiS over the threshold for a majority in the *Sejm*. Figure A. 3 displays the distribution of these differences across all our counterfactual vote shares.

Figure A. 3: Distribution of simulated vote shares



# Voter behavior models and policy preferences

In

Table A. 9 we re-estimate the turnout and vote choice model (Model 6) but substituting the dichotomous government intervention variable and the proposal support variable for FX exposure. These policy preference variables are clearly “post-treatment” from the perspective of the CHF shock and we know that the FX-exposed are much more likely to be in the extreme policy preference categories than other voters. But we can use the estimates here to evaluate whether voters were voting prospectively about policy or simply punishing the incumbent.

The results in

Table A. 9 suggest that at least some voters were, in fact, prospective. We see that voters supporting government intervention were much more likely to vote for the PiS over the incumbent. Similarly, those supporting the most generous bailout package (associated with the PiS) were more likely to support the PiS or abstain relative to supporting the incumbent. Voters supporting the 50/50 proposal (associated with the PO) were more likely to vote and less likely to support third parties relative to the incumbent. In short, we see convincing evidence that those who had strong policy preferences around the bailout policies intended to vote for parties that promised those policies, consistent with prospective voting among this group. Voters without an opinion were less likely to vote, displaying some evidence of retrospective voting among this group.

Table A. 9: Turnout and vote choice as a function of policy preferences

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Model A8-GI** | | | **Model A8-PS** | | |
|  | **abstain** | **other** | **PiS** | **abstain** | **other** | **PiS** |
| Pro-intervention | -0.13 | -0.11 | 0.36\*\* |  |  |  |
|  | (0.14) | (0.16) | (0.15) |  |  |  |
| 90/10 |  |  |  | 0.58\*\* | 0.21 | 0.96\*\* |
|  |  |  |  | (0.23) | (0.26) | (0.25) |
| 50/50 |  |  |  | -0.51\*\* | -0.40\*\* | 0.04 |
|  |  |  |  | (0.19) | (0.20) | (0.20) |
| DK |  |  |  | 0.66\*\* | -0.76\*\* | 0.34 |
|  |  |  |  | (0.25) | (0.37) | (0.29) |
| Some |  |  |  | 0.11 | -0.24 | 0.34 |
|  |  |  |  | (0.19) | (0.22) | (0.22) |
| past turnout | -2.06\*\* | -0.29 | -0.46\*\* | -2.08\*\* | -0.31 | -0.46\*\* |
|  | (0.19) | (0.23) | (0.23) | (0.19) | (0.23) | (0.23) |
| 18-31 | 0.26 | 0.97\*\* | -0.02 | 0.26 | 0.95\*\* | -0.04 |
|  | (0.22) | (0.24) | (0.26) | (0.22) | (0.24) | (0.26) |
| 44-56 | 0.19 | 0.42 | 0.59\*\* | 0.21 | 0.41 | 0.58\*\* |
|  | (0.21) | (0.25) | (0.24) | (0.22) | (0.25) | (0.24) |
| 57-66 | -0.13 | 0.20 | 0.44\* | -0.12 | 0.22 | 0.41 |
|  | (0.24) | (0.27) | (0.26) | (0.24) | (0.27) | (0.26) |
| 66+ | 0.11 | -0.43 | 0.35 | 0.09 | -0.41 | 0.35 |
|  | (0.26) | (0.32) | (0.29) | (0.27) | (0.32) | (0.29) |
| female | 0.02 | -0.47\*\* | -0.24 | -0.01 | -0.43\*\* | -0.24 |
|  | (0.14) | (0.16) | (0.16) | (0.14) | (0.16) | (0.16) |
| married | -0.01 | -0.25 | -0.26 | -0.01 | -0.26 | -0.27 |
|  | (0.16) | (0.18) | (0.17) | (0.16) | (0.18) | (0.18) |
| income | -0.23\*\* | -0.12 | 0.01 | -0.21\*\* | -0.12 | 0.01 |
|  | (0.07) | (0.08) | (0.08) | (0.07) | (0.08) | (0.08) |
| education | -0.16\*\* | 0.19\*\* | -0.09 | -0.13 | 0.19\*\* | -0.08 |
|  | (0.08) | (0.09) | (0.09) | (0.08) | (0.09) | (0.09) |
| urban | -0.12 | 0.33\*\* | -0.26\*\* | -0.11 | 0.32\*\* | -0.26\*\* |
|  | (0.10) | (0.11) | (0.11) | (0.10) | (0.11) | (0.11) |
| employed | 0.23 | -0.01 | 0.26 | 0.24 | 0.005 | 0.27 |
|  | (0.18) | (0.20) | (0.20) | (0.18) | (0.20) | (0.20) |
| religiosity | 0.09 | 0.07 | 0.52\*\* | 0.09 | 0.07 | 0.52\*\* |
|  | (0.06) | (0.07) | (0.08) | (0.06) | (0.07) | (0.08) |
| household size | -0.05 | -0.01 | 0.04 | -0.04 | -0.01 | 0.05 |
|  | (0.05) | (0.06) | (0.06) | (0.05) | (0.06) | (0.06) |
| Left | 0.53\*\* | 0.65\*\* | -0.44 | 0.50\*\* | 0.66\*\* | -0.46\* |
|  | (0.18) | (0.20) | (0.27) | (0.19) | (0.20) | (0.27) |
| Right | 0.30\* | -0.01 | 1.17\*\* | 0.27 | -0.003 | 1.15\*\* |
|  | (0.16) | (0.19) | (0.17) | (0.16) | (0.19) | (0.17) |
| (Intercept) | 2.07\*\* | -0.91 | -2.06\*\* | 1.75\*\* | -0.76 | -2.19\*\* |
|  | (0.57) | (0.65) | (0.65) | (0.58) | (0.67) | (0.67) |
| *N*= | 2044 | |  | 2044 | | |
| Multinomial logistic regression coefficients averaged over 20 imputed datasets and employing survey weights. “PO/PSL” is the reference category. Standard errors in parentheses. Covariates include indicators for province. \*\**p* < 0.05, \**p* < 0.1 | | | | | | |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |

# Matching

To further investigate selection into FX loans and show that functional form assumptions do not drive our key findings regarding the FX-exposed, we undertake a matching analysis. Specifically, we conduct coarsened exact matching (Iacus, et al. 2012) to select balanced sets of FX-exposed and unexposed from each of the 20 imputed datasets. We include age, marital status, income, education level, employment status, urban/rural location, and household size in the matching model (see Table A. 1 for variables predicting selection into FX loans).

We use two different matching approaches to deal with imputation. In the “common match” approach, each observation is assigned to the stratum in which it has been matched most frequently across imputed datasets, producing the same matching solution for each multiply imputed data set. In our data this produces a matched dataset with 32 FX-exposed and 76 unexposed respondents, with the remainder discarded. In the “imputation specific” approach, we match independently across imputed datasets, allowing for matched data sets with different numbers of exposed and unexposed respondents across imputations. In the imputation specific approach, we have a maximum of 43 exposed respondents and a minimum of 38 matched to a maximum of 109 and a minimum of 81 unexposed respondents.

Under both approaches we estimate the “effect” of FX exposure using logistic regression for ease of comparison with coefficient estimates reported in the tables above. We do not adjust for any covariates in the estimation. We consider the following outcomes, all of which are coded as binary: government intervention; preference for the 90/10 policy; preference for no intervention policy; choice to vote for the PiS in the election; and choice to abstain in the election. In Table A. 10 we display matching-weighted logistic regression coefficients and standard errors (both combined across imputations in the usual fashion). For ease of comparison, we also highlight the table and model where the coefficient from the full dataset can be found. In all cases coefficients are quite close to those estimated on the full dataset and inference remains the same.

Table A. 10 Effect of FX exposure on various outcomes using matched datasets.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Logit coefficient (SE) | |  |
| Outcome | Common match | Imputation-specific | Compare to FX-exposed  coefficient in… |
| Gov't intervention | 1.38\*\*  (0.45) | 1.50\*\*  (0.44) | Table A. 3  Model 3 |
| 90/10 | 2.13\*\*  (0.56) | 2.07\*\*  (0.58) | Table A. 5  Model 5 |
| None | -1.75\*\*  (0.58) | -1.67\*\*  (0.54) | Table A. 5  Model 5 |
| PiS | 0.81\*  (0.48) | 0.87\*  (0.49) | Table A. 8  Model 6 |
| Abstain | -0.91\*  (0.50) | -0.90\*  (0.55) | Table A. 8  Model 6 |
|  | | |  |
| Logistic regression coefficients on a dummy variable indicating “FX-exposed”, averaged over 20 imputed datasets and employing matching weights. Standard errors in parentheses. \*\**p* < 0.05, \**p* < 0.1 | | | |