A Online Appendix A

A.1 Heuristic Model

The model assumes that individuals are guided by self-interest. Financial literacy is expected to have an impact on an individual's accuracy at calculating the effects of a specific policy on their expected utility. For simplicity, I consider two types of individuals: financially literate and financially illiterate. Each individual has his or her own prior probability distribution over U, a random variable describing the unknown levels of utility that a policy will bring. The individuals' prior beliefs about U can be represented by a uniform distribution on bounded intervals (Calvert, 1985), so no utility level is any more likely than another. This will be the unit interval, so that all utility values lie between zero and one. Both types of individuals' prior subjective probability density functions for the policy's utility are:

$$
\begin{aligned}
f(u) &= 1, \text{if } 0 \leq u \leq 1 \\
&= 0, \text{otherwise}
\end{aligned}
$$

Each individual then observes X, a signal with information about U. The utility inferred from the signal may vary across different individuals: its content depends on the true, but hidden, utility of the policy, and on the individual's accuracy in interpreting it. The latter is represented by α, an inaccuracy parameter which will be described below.

The signal X will be more informative for financially literate people, as they can conduct more accurate cost-benefit analyses. Conversely, it will be less clear and less informative for financially illiterate people, who are less likely to be accurate at estimating the effects of a policy on their individual economic well-being and who may be more likely to rely on other decision-making factors such as core personal values (for example culture, political ideology, identity, etc.), or cues from reference groups, and on less correct cost-benefit analyses to make their decisions. The signal X is a continuous variable. Its mean value, μ, represents the utility inferred from the signal, and the distance between the policy's actual utility and the utility inferred from the signal is the bias. Its variance, σ^2, represents the precision over the signaled utility, and it increases as inaccuracy increases.

$$X \sim TN(\mu, \sigma^2, 0, 1)$$
$$\mu = u^{\alpha}$$
$$\sigma^2 = (log\alpha + \hat{\sigma^2})^2$$

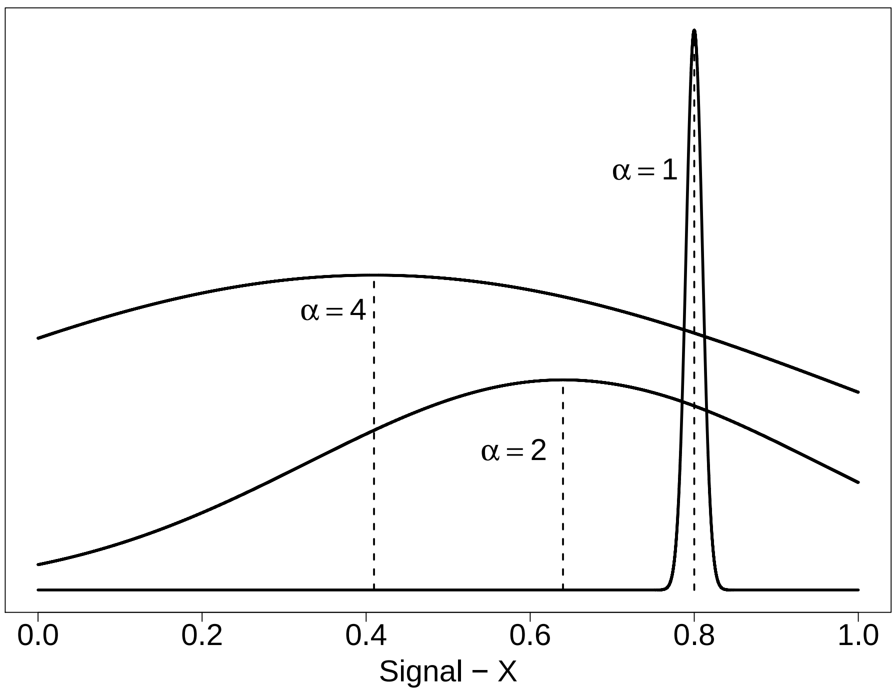


Figure A1: Truncated normal distributions of signal X when inaccuracy α=1, 2, 4 and true utility u=0.8. In this example, the true utility of the policy is set to u=0.8. For a financially literate individual ($\alpha = 1$), the utility inferred from the signal μ equals 0.8, and $\hat{\sigma^2}$ is set to 0.0001. For a financially illiterate person, when $\alpha = 2$, their inferred utility from the signal is about 0.6 and the variance increases with α. Finally, when $\alpha = 4$ the signal wrongly indicates that u is equal to 0.4, with larger uncertainty.

The signal X has a truncated normal distribution and lies within the interval $X \in [0, 1]$. The closer the signal is to 1 the higher the expected utility of the policy is argued to be, the closer the signal is to 0 the lower the expected utility of the policy is argued to be. The constant $\alpha \in [1, 10]$, which I will call the inaccuracy parameter[1], has two effects on the signal X itself, one on bias and

[1]If I allowed $0 < \alpha < 1$, it would be possible to also overestimate the benefits of a policy, whereas in the current

the other on precision. I argue that α is low for financially literate individuals as their ability to do more sophisticated cost-benefit analyses will give them a more precise and unbiased estimate of the expected utility of the policy, hence the verdict from the signal will most likely be very close to the true utility of the policy (see Figure A1). Moreover, the variance around the signal will be smaller (it will be assumed fixed at $\hat{\sigma^2}$ for financially literate individuals and in these examples it is set at 0.0001 for simplicity) as they can be more confident of their estimate. Conversely, for financially illiterate individuals α will be any number greater than 1, suggesting that as there are varying degrees of inaccuracy, there is more uncertainty over the expected utility of the policy. As a result of this, when the signal is more inaccurate (so α is greater than one) the verdict is unlikely to be close to the true utility of the policy (see Figure A1 for examples). Furthermore, X will also have larger variance, as the signal might not be as clear and informative.

After observing the signal, the individual updates their prior, using Bayes rule, which gives $f(u|x)$, the posterior distribution of U.

$$f(u|x) = \frac{f(u) \cdot P(X = x|U = u)}{\int_0^1 f(u) \cdot P(X = x|U = u)du}$$

.

As inaccuracy α approaches 1, the updated belief about the expected utility of the policy is more likely to be closer to the true utility of the policy. Conversely, as inaccuracy α increases, the distance between the expected utility and the true utility of the policy increases.

In order to show what type of individual is more likely to more accurately assess the effect on her economic well-being of a specific economic policy, we have to first calculate the expected utility of the policy given the signal:

$$E(U|X) = \int_0^1 u \cdot f(u|x)du$$

setting a financially illiterate person would always be more likely to underestimate the benefits of a policy; for this model this complication is unnecessary. Since each policy under discussion can go in both directions (e.g. Brexit or Remain, free trade or protectionism, immigration or protectionism. If you are a financially illiterate loser from globalization, overestimating the benefits of free trade is equivalent to saying you are underestimating the benefits of protectionism), the accuracy can be in either direction even with $\alpha > 1$

and then calculate the difference between $E(U|X)$ and the true utility of the policy u:

$$| \, (E(U|X) - u) \, |$$

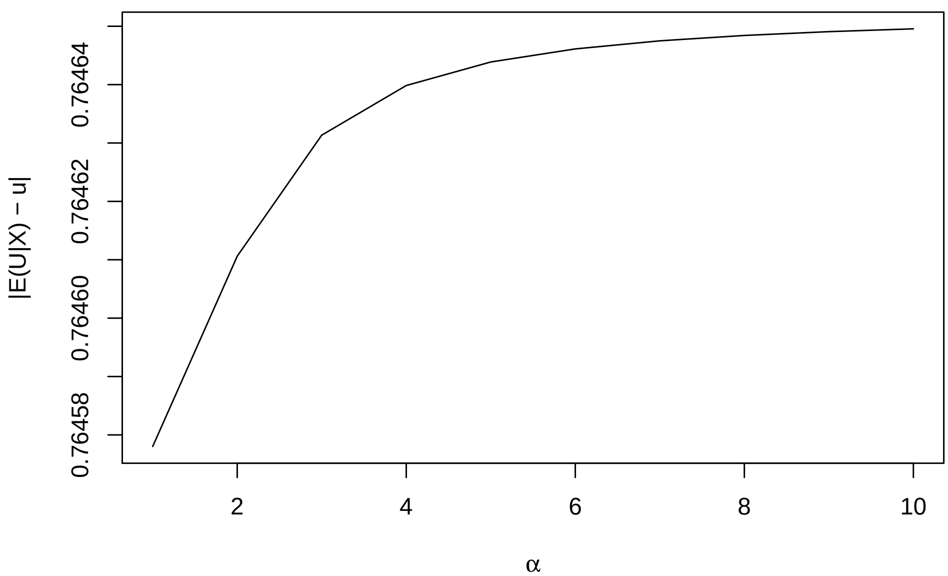
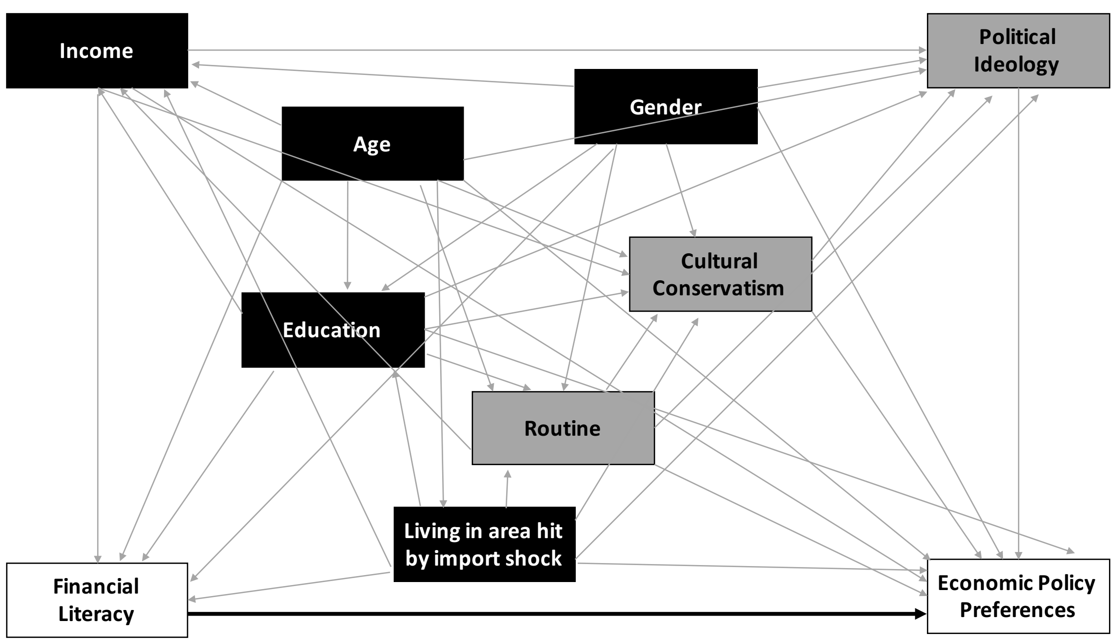


Figure A2: Difference between $E(U|X)$ and true utility with u=0.8 for all values of α

For all levels of utility (Figure A2 shows that this is the case for u=0.8), indeed the difference between the expected utility of a policy after receiving the signal x and the true utility of the policy u is smallest when α is equal to 1, hence implying that financially literate individuals are more likely to more accurately assess the effect of a specific economic policy on their expected utility than financially illiterate individuals.

A.2 DAG

The theory can also be represented by a causal diagram (or directed acyclic graph - DAG), which is a visual representation of qualitative causal assumptions. This helps us disentangle the causal mechanisms and understand which variables we need to adjust for. The arrows represent potential direct causal effects between variables, while missing arrows suggest that there is no causal effect between two variables. It is often argued that we should control for any variable that is correlated with both our dependent and our independent variable, but this is not necessarily true. In fact, we do not want to control for a collider, which is a variable with two arrows pointing into it, otherwise we would find a relationship between two variables when there is not one. We do instead want to control for confounders, which represent common causes to our treatment and outcome variables. Finally, we do not want to control for a mediator, a variable on the causal path between our treatment and outcome, as this would bias the total causal effect of the treatment on the outcome (Elwert, 2013; Pearl and Mackenzie, 2018).



Note: The white squares represent the treatment, financial literacy, and the outcome variable, economic policy preferences. The gray arrows represent biasing paths, while the black one represents the causal path. The gray squares are variables that should not be adjusted for, while the black squares represent the variables that we should adjust for.

Figure A3: Causal diagram of the relationship between financial literacy and economic policy preferences

Prior studies reveal that age, income, gender, and education may all affect financial literacy (Lusardi and Mitchell, 2014; Monticone, 2010). Men, the middle-aged, highly educated individuals, and people on higher incomes all tend to have higher levels of financial literacy. One possibility further considered here is that living in a more globalized region may also have an effect on people's decisions to become financially literate, as people receiving more globalization spoils may have more resources to invest in the first place, and this would require them to become more financially literate. Furthermore, income may be affected by age, gender, education, the type of job that one does, and globalization, as individuals living in areas highly exposed to the Chinese import shock experienced larger declines in income as documented by Colantone and Stanig (2018). In an analogous way, education may also be determined by demographic variables like age and gender, but it could also be affected in different ways by globalization's pressures: living in a highly globalized region encourages individuals to pursue more education, while living in areas more exposed to the Chinese import shock, which led to persistent economic decline, is more likely to be associated with lower levels of education, due to the lack of opportunities. The routineness of jobs tend to be associated with skills, which will be proxied with education, and by age and gender. The routineness of jobs may also be affected by globalization's pressures: living in a highly globalized areas increases the probability that you perform non-routine tasks. Conversely, living in areas more exposed to the Chinese import shock is more likely to be associated with the prevalence of routine tasks, which are more likely to be automated or outsourced. Age is also likely to be associated with living in an area highly exposed to the Chinese import shock, as we can expect younger people to be less likely to live in such areas due to the prevalence of long-term economic decline and lack of opportunities. As suggested by the literature review, economic policy preferences may be affected by income, education, the routine content of jobs, demographic factors, globalization's pressures, political ideology, and cultural conservatism. In a similar way, political ideology and cultural conservatism may be affected by education, income, globalization's pressures, and demographic variables. Political ideology may also be affected by the type of job that one does. In DAGs we cannot have bidirectional arrows, however, it is possible to have situations in which two variables cause one another. These situations can be dealt with by adding a time dimension, so that the variables can have different relationships with each other at different points in time. For instance, globalization pressures, education, income, and routine jobs may all affect each other at different points in time. At time 1 the Chinese import shock is more likely to be higher in areas where there are already more low-skilled people (we proxy this with education), however, this will reinforce this relationship further and change the direction of causality at time 2, as people with higher levels of education (and hence highly-skilled) will move to areas where there is a higher demand for them, leaving these areas characterized by persistent economic decline with a prevalence of low-skilled individuals. Here we are looking at the effects of the Chinese import shock between 1990 and 2007, hence we expect that most of its effects (in terms of different levels of income and education) have materialized already by 2015 when the survey is conducted. Another example is that here we assume that political ideology affects economic policy preferences, but it is also possible that economic policy preferences may affect political ideology. In either case, political ideology should not be controlled for, as all backdoor paths have already been closed. Finally another possibility is that, as suggested by Montagnoli et al. (2016), financial literacy affects political ideology, which in turn affects economic policy preferences (Montagnoli et al., 2016). Even if that were the case, political ideology would become a mediator, and as such, it should not be conditioned on, or it would bias the total effect of financial literacy on economic policy preferences. In order to make sure that the causal assumptions that were made are consistent with the data, we test the restrictions identified in the form of conditional independencies. If at least one implied independence does not hold in the dataset, this means that the causal processes encoded by the DAG cannot have generated these data. If the independencies are not refused by the data, this will give credibility to the data, but it still does not mean that the DAG is necessarily correct (Textor et al., 2016).

The conditional independencies tested, as suggested by the DAG on *dagitty.net*, are:

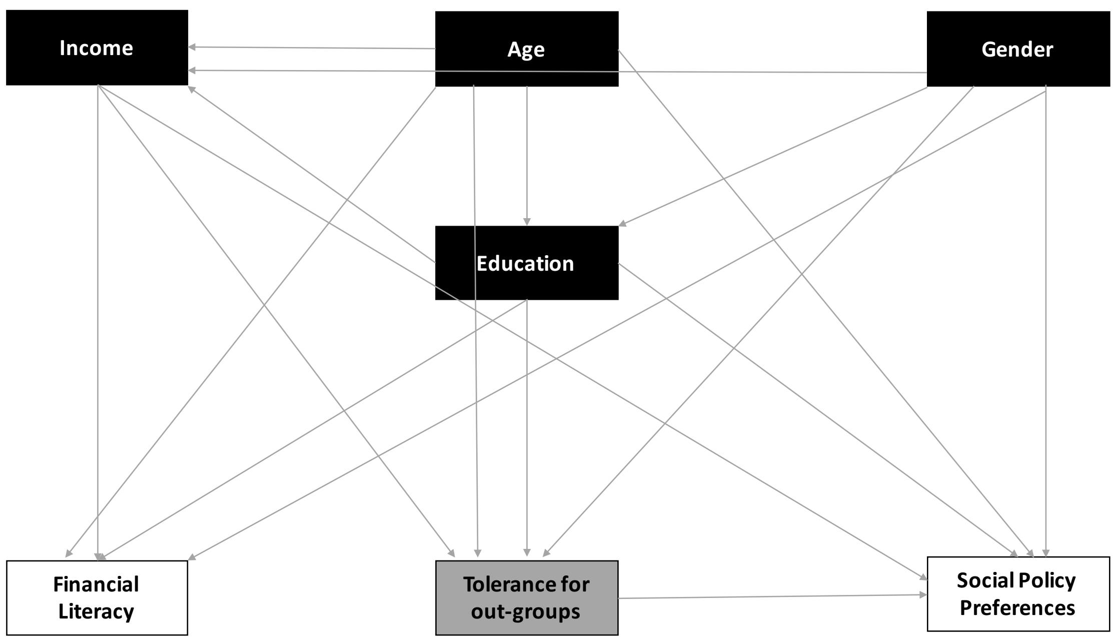
- Cultural conservatism $\perp$ Financial literacy | Age, gender, education, income, living in high import shock area
- Cultural conservatism $\perp$ Routine Job | Age, gender, education, income, living in high import shock area
- Financial literacy $\perp$ Political Ideology | Age, gender, education, income, living in high import shock area
- Financial literacy $\perp$ Routine Job | Age, gender, education, income, living in high import shock area

- Age $\perp$ gender[2]

All of the testable implications have been found to be consistent with the dataset and have been tested with the R package dagitty following Textor et al. (2016). Following these rules and what prior studies reveal about the relationship between our variables of interest, it emerges that in order to estimate the total causal effect of financial literacy on economic policy preferences we should condition on age, gender, income, education, and living in high import shock area (as measured by the Chinese import shock). Furthermore, we do not need to control for routine jobs, political orientation, and cultural conservatism since controlling for income, education, and demographic variables already blocks all backdoor paths from the treatment to the outcome.

Furthermore, the following causal diagram lays out the hypothesized causal relationships between financial literacy and social policy preferences. The lack of an arrow connecting financial literacy and social policy preferences suggests the lack of a direct relationship between financial literacy and social policy preferences, as people are not expected to make decisions on social policies based on costs and benefits calculations. There is also no arrow connecting directly tolerance for out-groups and financial literacy, instead they are expected to both be affected by the same set of variables: age, gender, education, and income. In this specification, financial literacy and social policy preferences are conditionally independent given a set of variables Z (here income, education, age, and gender). This means that any relationship that may exist between financial literacy and social policy preferences can be explained by income, education, gender, and age. Hence, financial literacy and social policy preferences may appear related if Z were not considered, but if we control for Z by holding it constant, then any apparent relationship between financial literacy and social policy preferences should disappear. This is also tested with the R package daggity, which after specifying a dataset and a DAG tests conditional independence parametrically, using a test of residual independence after linear regression is performed. The findings from this test already suggest that social policy preferences and financial literacy are independent once we condition on age, gender, income, and education.

[2]When testing independencies it emerges that age and gender are not independent. This might have to do with the fact that the online BES survey is not entirely representative of the British population, and there are actually more males than females in older age groups.



Note: The white squares represent the treatment, financial literacy, and the outcome variable, social policy preferences. The gray arrows represent biasing paths between variables. The black squares represent potential confounders, while the gray square represents an unmeasured variable.

Figure A4: Causal diagram for the relationship between financial literacy and social policy preferences

B Online Appendix B

Table B1: Multinomial logit models for Brexit: Log-odds and standards errors in parentheses

	DV: Brexit (ref. category: Remain)		
	Leave	Not vote	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.212^{***}	-0.609^{***}	-0.319^{***}
	(0.037)	(0.074)	(0.046)
High education	-0.929^{***}	-0.680^{***}	-0.498^{***}
	(0.068)	(0.163)	(0.091)
Income	-0.166^{***}	-0.404^{***}	-0.267^{***}
	(0.046)	(0.110)	(0.062)
Age	0.024^{***}	-0.008	-0.002
	(0.002)	(0.005)	(0.003)
Male	0.164^{**}	-0.158	-0.361^{***}
	(0.066)	(0.154)	(0.090)
Import shock	0.854^{***}	0.731	1.093^{***}
	(0.254)	(0.578)	(0.335)
Constant	-0.306	0.689^{*}	0.568^{**}
	(0.193)	(0.383)	(0.239)
Akaike Inf. Crit.	11,263.800	11,263.800	11,263.800
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B2: Clustered bootstrap p-values for Brexit

	Leave	Not vote	Don't know
Constant	0.209	0.143	0.124
Financial Literacy (# correct)	0.165	0	0.001
High Education	0	0.004	0.005
Income	0	0.052	0.017
Age	0.054	0.783	0.014
Male	0	0.033	0.642
Import shock	0.133	0.483	0.078

Table B3: Multinomial logit models for immigration: Log-odds and standards errors in parentheses

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	0.174***	0.268***	−0.425***
	(0.044)	(0.039)	(0.065)
High education	0.612***	1.177***	0.602***
	(0.084)	(0.071)	(0.143)
Income	0.020	0.113**	−0.377***
	(0.057)	(0.048)	(0.099)
Age	−0.012***	−0.020***	−0.031***
	(0.003)	(0.002)	(0.004)
Male	−0.232***	0.093	−0.166
	(0.081)	(0.069)	(0.137)
Import shock	−0.382	−1.438***	−1.256**
	(0.307)	(0.267)	(0.527)
Constant	−0.839***	−0.412**	1.539***
	(0.233)	(0.199)	(0.339)
Akaike Inf. Crit.	11,755.290	11,755.290	11,755.290
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B4: Clustered bootstrap p-values for immigration

	Neither good nor bad	Good	Don't know
Constant	0.010	0.219	0.024
Financial Literacy (# correct)	0.097	0.002	0.001
High Education	0	0	0.001
Income	0.074	0.046	0.054
Age	0.004	0.067	0.234
Male	0.122	0.001	0
Import shock	0.103	0.091	0.032

Table B5: Multinomial logit models for free trade: Log-odds and standards errors in parentheses

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.276^{***}	-0.525^{***}	-0.722^{***}
	(0.040)	(0.054)	(0.048)
High education	-0.558^{***}	-0.477^{***}	-0.421^{***}
	(0.077)	(0.114)	(0.102)
Income	-0.194^{***}	-0.286^{***}	-0.175^{**}
	(0.051)	(0.075)	(0.068)
Age	0.011^{***}	-0.003	-0.017^{***}
	(0.003)	(0.004)	(0.003)
Male	-0.352^{***}	-0.207^{*}	-0.691^{***}
	(0.073)	(0.106)	(0.099)
Import shock	0.661^{**}	0.570	0.424
	(0.278)	(0.403)	(0.368)
Constant	-0.096	0.511^{*}	2.037^{***}
	(0.215)	(0.289)	(0.254)
Akaike Inf. Crit.	10,937.890	10,937.890	10,937.890
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B6: Clustered bootstrap p-values for free trade

	Neither good nor bad	Bad	Don't know
Constant	0.936	0.423	0.004
Financial Literacy (# correct)	0.003	0.001	0
High Education	0	0.025	0.001
Income	0.004	0.005	0.165
Age	0.004	0.403	0.001
Male	0.040	0.877	0.010
Import shock	0.047	0.461	0.834

Table B7: Multinomial logit models for Brexit with education and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Brexit (ref. category: Remain)		
	Leave	Not vote	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.169^{***}	-0.607^{***}	-0.293^{***}
	(0.045)	(0.091)	(0.059)
High education	-0.786^{***}	-0.428	-0.436
	(0.244)	(0.427)	(0.287)
Income	-0.155^{***}	-0.455^{***}	-0.223^{***}
	(0.046)	(0.114)	(0.062)
Male	0.144^{**}	-0.126	-0.337^{***}
	(0.066)	(0.158)	(0.089)
Age	0.024^{***}	-0.014^{***}	0.001
	(0.002)	(0.005)	(0.003)
Import shock	0.768^{***}	1.338^{**}	0.925^{***}
	(0.254)	(0.580)	(0.335)
Financial literacy: high education	-0.047	-0.141	-0.002
	(0.072)	(0.151)	(0.088)
Constant	-0.445^{**}	0.832^{**}	0.262
	(0.208)	(0.407)	(0.262)
Akaike Inf. Crit.	11,198.360	11,198.360	11,198.360
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B8: Clustered bootstrap p-values for Brexit (interaction education and financial literacy)

	DV: Brexit (ref. category: Remain)		
	Leave	Not Vote	Don’t know
Constant	0.092	0.084	0.110
Financial Literacy (# correct)	0.019	0.003	0.003
High education	0.055	0.270	0.088
Income	0.010	0.002	0
Male	0.119	0.044	0.028
Age	0	0.061	0.901
Import shock	0.051	0.243	0.004
Financial literacy: high education	0.925	0.058	0.878

Table B9: Multinomial logit models for Brexit with routineness and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Brexit (ref. category: Remain)		
	Leave	Not vote	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.187^{***}	-0.538^{***}	-0.290^{***}
	(0.042)	(0.092)	(0.053)
Routine occupation	-0.066	0.811^{*}	0.100
	(0.245)	(0.414)	(0.293)
High education	-0.870^{***}	-0.965^{***}	-0.584^{***}
	(0.069)	(0.182)	(0.093)
Income	-0.185^{***}	-0.375^{***}	-0.174^{***}
	(0.046)	(0.115)	(0.062)
Male	0.120^{*}	-0.032	-0.314^{***}
	(0.066)	(0.160)	(0.089)
Age	0.024^{***}	-0.011^{**}	0.003
	(0.002)	(0.005)	(0.003)
Import shock	0.961^{***}	0.895	1.217^{***}
	(0.253)	(0.597)	(0.332)
Financial literacy: routine occupation	0.022	-0.312^{*}	-0.045
	(0.076)	(0.160)	(0.095)
Constant	-0.416^{**}	0.459	0.048
	(0.207)	(0.423)	(0.258)
Akaike Inf. Crit.	11,245.400	11,245.400	11,245.400
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B10: Clustered bootstrap p-values for Brexit (interaction routineness and financial literacy)

	DV: Brexit (ref. category: Remain)		
	Leave	Not Vote	Don't know
Constant	0.164	0.054	0.238
Financial Literacy (# correct)	0.150	0.006	0.001
Routine occupation	0.836	0.190	0.079
High education	0.003	0.001	0.022
Income	0.001	0.003	0.009
Male	0.030	0.994	0.027
Age	0	0.020	0.990
Import shock	0.103	0.642	0
Financial literacy: routine occupation	0.666	0.415	0.048

Table B11: Multinomial logit models for Brexit with income and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Brexit (ref. category: Remain)		
	Leave	Not vote	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	−0.068	−0.470**	−0.291**
	(0.093)	(0.190)	(0.116)
Income	−0.012	−0.060	−0.197
	(0.156)	(0.273)	(0.186)
High education	−0.860***	−0.898***	−0.527***
	(0.068)	(0.171)	(0.091)
Male	0.131**	−0.175	−0.405***
	(0.066)	(0.157)	(0.089)
Age	0.023***	−0.014***	0.001
	(0.002)	(0.005)	(0.003)
Import shock	0.798***	0.311	0.854**
	(0.253)	(0.597)	(0.335)
Financial literacy: Income	−0.061	−0.087	−0.016
	(0.046)	(0.096)	(0.058)
Constant	−0.658**	0.624	0.411
	(0.334)	(0.596)	(0.399)
Akaike Inf. Crit.	11,274.520	11,274.520	11,274.520
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B12: Clustered bootstrap p-values for Brexit (interaction income and financial literacy)

	DV: Brexit (ref. category: Remain)		
	Leave	Not Vote	Don't know
Constant	0.022	0.520	0.372
Financial Literacy (# correct)	0.408	0.047	0.034
Income	0.810	0.513	0.402
High education	0	0	0.090
Male	0.112	0.043	0.042
Age	0	0.067	0.890
Import shock	0.045	0.262	0.002
Financial literacy: Income	0.231	0.459	0.756

Table B13: Multinomial logit models for immigration with education and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	0.185***	0.273***	−0.450***
	(0.054)	(0.050)	(0.081)
High education	0.872***	1.224***	0.577
	(0.293)	(0.253)	(0.364)
Income	−0.013	0.100**	−0.351***
	(0.057)	(0.048)	(0.099)
Male	−0.222***	0.105	−0.162
	(0.081)	(0.069)	(0.137)
Age	−0.009***	−0.019***	−0.026***
	(0.003)	(0.002)	(0.004)
Import shock	−0.343	−1.364***	−1.240**
	(0.308)	(0.267)	(0.529)
Financial literacy: high education	−0.053	−0.012	0.014
	(0.087)	(0.074)	(0.127)
Constant	−1.011***	−0.467**	1.296***
	(0.252)	(0.221)	(0.359)
Akaike Inf. Crit.	11,768.940	11,768.940	11,768.940
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B14: Clustered bootstrap p-values for immigration (interaction education and financial literacy)

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
Constant	0.009	0.396	0.033
Financial Literacy (# correct)	0.007	0	0.022
High education	0.156	0.025	0.154
Income	0.116	0.138	0.015
Male	0.010	0.071	0.276
Age	0.092	0	0
Import shock	0.113	0.060	0.032
Financial literacy: high education	0.647	0.723	0.444

Table B15: Multinomial logit models for immigration with routineness and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	0.148***	0.268***	−0.420***
	(0.051)	(0.045)	(0.076)
Routine occupation	−0.319	−0.200	−0.007
	(0.296)	(0.267)	(0.361)
Income	−0.021	0.087*	−0.366***
	(0.057)	(0.049)	(0.099)
High education	0.674***	1.148***	0.562***
	(0.087)	(0.073)	(0.147)
Male	−0.231***	0.091	−0.177
	(0.082)	(0.069)	(0.137)
Age	−0.009***	−0.020***	−0.026***
	(0.003)	(0.002)	(0.004)
Import shock	−0.341	−1.363***	−1.237**
	(0.308)	(0.267)	(0.530)
Financial literacy: routine occupation	0.056	−0.003	−0.085
	(0.092)	(0.082)	(0.138)
Constant	−0.811***	−0.328	1.356***
	(0.248)	(0.213)	(0.355)
Akaike Inf. Crit.	11,766.300	11,766.300	11,766.300
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B16: Clustered bootstrap p-values for immigration (interaction routine and financial literacy)

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
Constant	0	0.415	0.010
Financial Literacy (# correct)	0.105	0.001	0
Routine occupation	0.953	0.967	0.529
Income	0.147	0.149	0.013
High education	0	0	0.001
Male	0.006	0.062	0.269
Age	0.096	0	0
Import shock	0.115	0.069	0.031
Financial literacy: routine occupation	0.663	0.738	0.358

Table B17: Multinomial logit models for immigration with income and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	0.217*	0.157	−0.418***
	(0.112)	(0.098)	(0.161)
Income	0.198	−0.071	−0.151
	(0.189)	(0.166)	(0.242)
High education	0.620***	1.128***	0.508***
	(0.085)	(0.071)	(0.145)
Male	−0.233***	0.106	−0.167
	(0.081)	(0.069)	(0.137)
Age	−0.006**	−0.018***	−0.020***
	(0.003)	(0.002)	(0.004)
Import shock	−0.389	−1.438***	−1.281**
	(0.307)	(0.266)	(0.528)
Financial literacy: Income	−0.035	0.059	−0.030
	(0.057)	(0.049)	(0.085)
Constant	−1.393***	−0.150	0.792
	(0.400)	(0.349)	(0.509)
Akaike Inf. Crit.	11,811.830	11,811.830	11,811.830
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B18: Clustered bootstrap p-values for immigration (interaction income and financial literacy)

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
Constant	0.024	0.638	0.046
Financial Literacy (# correct)	0.014	0.127	0.012
Income	0.225	0.534	0.518
High education	0	0.001	0.009
Male	0.002	0.060	0.169
Age	0.274	0.005	0.001
Import shock	0.065	0.062	0.023
Financial literacy: Income	0.374	0.138	0.668

Table B19: Multinomial logit models for free trade with education and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.233^{***}	-0.464^{***}	-0.616^{***}
	(0.048)	(0.064)	(0.059)
High education	-0.527^{**}	-0.363	-0.779^{***}
	(0.267)	(0.335)	(0.287)
Income	-0.115^{**}	-0.173^{**}	-0.194^{***}
	(0.051)	(0.075)	(0.068)
Male	-0.389^{***}	-0.133	-0.725^{***}
	(0.072)	(0.106)	(0.098)
Age	0.010^{***}	-0.004	-0.016^{***}
	(0.003)	(0.004)	(0.003)
Import shock	0.549^{**}	0.942^{**}	0.324
	(0.277)	(0.397)	(0.365)
Financial literacy: high education	-0.024	-0.093	0.102
	(0.079)	(0.106)	(0.093)
Constant	-0.237	0.094	1.801^{***}
	(0.227)	(0.304)	(0.267)
Akaike Inf. Crit.	11,094.600	11,094.600	11,094.600
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B20: Clustered bootstrap p-values for free trade with EU (interaction education and financial literacy)

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
Constant	0.268	0.798	0
Financial Literacy (# correct)	0.004	0.002	0
High education	0.062	0.414	0.032
Income	0.076	0.127	0.126
Male	0.006	0.201	0.005
Age	0.001	0.064	0.007
Import shock	0.034	0.082	0.331
Financial literacy: high education	0.776	0.537	0.194

Table B21: Multinomial logit models for free trade with routineness and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.239^{***}	-0.484^{***}	-0.640^{***}
	(0.047)	(0.063)	(0.056)
Routine occupation	0.095	0.123	-0.572^{**}
	(0.256)	(0.319)	(0.285)
High education	-0.583^{***}	-0.615^{***}	-0.504^{***}
	(0.078)	(0.118)	(0.104)
Income	-0.108^{**}	-0.168^{**}	-0.197^{***}
	(0.051)	(0.076)	(0.068)
Male	-0.379^{***}	−0.124	-0.731^{***}
	(0.073)	(0.106)	(0.099)
Age	0.010^{***}	−0.004	-0.015^{***}
	(0.003)	(0.004)	(0.003)
Import shock	0.548^{**}	0.930^{**}	0.359
	(0.277)	(0.398)	(0.365)
Financial literacy: routine occupation	0.005	−0.017	0.199^{**}
	(0.080)	(0.107)	(0.097)
Constant	−0.294	0.099	1.882^{***}
	(0.231)	(0.310)	(0.268)
Akaike Inf. Crit.	11,095.090	11,095.090	11,095.090
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B22: Clustered bootstrap p-values for free trade with EU (interaction routine and financial literacy)

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
Constant	0.081	0.731	0.002
Financial Literacy (# correct)	0	0	0.001
Routine occupation	0.545	0.637	0.015
High education	0.007	0	0.007
Income	0.059	0.159	0.106
Male	0.003	0.272	0.006
Age	0.003	0.089	0.008
Import shock	0.041	0.101	0.305
Financial literacy: routine occupation	0.915	0.857	0.013

Table B23: Multinomial logit models for free trade with income and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	−0.266***	−0.385***	−0.781***
	(0.101)	(0.136)	(0.122)
Income	−0.160	−0.010	−0.501***
	(0.171)	(0.214)	(0.189)
High education	−0.604***	−0.628***	−0.502***
	(0.077)	(0.116)	(0.102)
Male	−0.390***	−0.131	−0.731***
	(0.072)	(0.106)	(0.098)
Age	0.010***	−0.004	−0.016***
	(0.003)	(0.004)	(0.003)
Import shock	0.547**	0.941**	0.324
	(0.277)	(0.397)	(0.365)
Financial literacy: Income	0.014	−0.061	0.111*
	(0.051)	(0.069)	(0.062)
Constant	−0.130	−0.109	2.249***
	(0.360)	(0.462)	(0.401)
Akaike Inf. Crit.	11,092.230	11,092.230	11,092.230
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B24: Clustered bootstrap p-values for free trade with EU (interaction income and financial literacy)

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
Constant	0.682	0.763	0.006
Financial Literacy (# correct)	0.016	0.031	0
Income	0.371	0.931	0.016
High education	0.008	0	0.019
Male	0.005	0.195	0
Age	0.001	0.064	0.009
Import shock	0.043	0.088	0.321
Financial literacy: Income	0.782	0.328	0.045

Table B25: Multinomial logit models for Brexit with import shock and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Brexit (ref. category: Remain)		
	Leave	Not vote	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.351^{***}	-1.137^{***}	-0.611^{***}
	(0.093)	(0.193)	(0.116)
Import shock	-0.923	-2.610^{*}	-2.113^{**}
	(0.877)	(1.482)	(1.068)
Income	-0.156^{***}	-0.462^{***}	-0.226^{***}
	(0.046)	(0.115)	(0.062)
Male	0.144^{**}	-0.122	-0.337^{***}
	(0.066)	(0.158)	(0.089)
Age	0.024^{***}	-0.014^{***}	0.001
	(0.002)	(0.005)	(0.003)
High education	-0.942^{***}	-0.809^{***}	-0.453^{***}
	(0.068)	(0.173)	(0.092)
Financial literacy: import shock	0.523^{**}	1.468^{***}	0.989^{***}
	(0.266)	(0.532)	(0.334)
Constant	0.148	2.260^{***}	1.250^{***}
	(0.333)	(0.590)	(0.403)
Akaike Inf. Crit.	11,185.960	11,185.960	11,185.960

Note: *p<0.1; **p<0.05; ***p<0.01

Table B26: Clustered bootstrap p-values for Brexit (interaction import shock and financial literacy)

	DV: Brexit (ref. category: Remain)		
	Leave	Not Vote	Don’t know
Constant	0.472	0.001	0.008
Financial Literacy (# correct)	0.132	0.001	0.013
Import shock	0.336	0.004	0.064
Income	0.002	0.020	0
Male	0.026	0.357	0.004
Age	0	0.001	0.712
High education	0.001	0.027	0.014
Financial literacy: import shock	0.263	0.018	0.054

Table B27: Multinomial logit models for immigration with import shock and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	0.216*	0.493***	−0.179
	(0.113)	(0.097)	(0.164)
Import shock	0.093	0.882	0.935
	(1.056)	(0.934)	(1.297)
Income	−0.012	0.102**	−0.349***
	(0.057)	(0.048)	(0.099)
Male	−0.221***	0.105	−0.165
	(0.081)	(0.069)	(0.137)
Age	−0.009***	−0.019***	−0.026***
	(0.003)	(0.002)	(0.004)
High education	0.701***	1.189***	0.606***
	(0.085)	(0.072)	(0.145)
Financial literacy: import shock	−0.152	−0.705**	−0.840*
	(0.322)	(0.282)	(0.486)
Constant	−1.097***	−1.175***	0.579
	(0.399)	(0.348)	(0.508)
Akaike Inf. Crit.	11,761.340	11,761.340	11,761.340
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B28: Clustered bootstrap p-values for immigration (interaction import shock and financial literacy)

	DV: Immigration (ref. category: Bad)		
	Neither good nor bad	Good	Don't know
Constant	0.002	0.001	0.121
Financial Literacy (# correct)	0.051	0	0.339
Import shock	0.961	0.057	0.464
Income	0.087	0.114	0.012
Male	0.007	0.054	0.256
Age	0.081	0	0
High education	0	0	0
Financial literacy: import shock	0.416	0.005	0.238

Table B29: Multinomial logit models for free trade with import shock and financial literacy interaction: Log-odds and standards errors in parentheses

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
	(1)	(2)	(3)
Financial Literacy (# correct)	-0.363^{***}	-0.614^{***}	-0.645^{***}
	(0.101)	(0.136)	(0.121)
Import shock	−0.668	−0.197	−0.326
	(0.952)	(1.166)	(1.028)
Income	-0.115^{**}	-0.174^{**}	-0.195^{***}
	(0.051)	(0.076)	(0.068)
Male	-0.389^{***}	−0.132	-0.727^{***}
	(0.072)	(0.106)	(0.098)
Age	0.010^{***}	−0.004	-0.015^{***}
	(0.003)	(0.004)	(0.003)
High education	-0.605^{***}	-0.631^{***}	-0.502^{***}
	(0.077)	(0.116)	(0.102)
Financial literacy: import shock	0.385	0.378	0.207
	(0.291)	(0.383)	(0.349)
Constant	0.178	0.545	1.916^{***}
	(0.362)	(0.460)	(0.398)
Akaike Inf. Crit.	11,095.070	11,095.070	11,095.070
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B30: Clustered bootstrap p-values for free trade with EU (interaction import shock and financial literacy)

	DV: Free Trade with EU (ref. category: Good)		
	Neither good nor bad	Bad	Don't know
Constant	0.520	0.143	0.001
Financial Literacy (# correct)	0.004	0	0
Import shock	0.443	0.714	0.635
Income	0.079	0.134	0.110
Male	0.002	0.173	0.006
Age	0.002	0.061	0.011
High education	0.005	0	0.015
Financial literacy: import shock	0.172	0.177	0.299

Table B31: Multinomial logit models for attitude towards gay rights: Log-odds and standards errors in parentheses

	DV: Attempts to give gays equal rights gone (ref. category: Not nearly far enough)				
	Not far	About right	Too far	Way too far	Don't know
	(1)	(2)	(3)	(4)	(5)
Financial Literacy (# correct)	0.002	−0.057	−0.023	−0.091	-0.530^{***}
	(0.069)	(0.064)	(0.071)	(0.074)	(0.079)
High education	−0.105	-0.537^{***}	-0.732^{***}	-0.962^{***}	-0.826^{***}
	(0.135)	(0.123)	(0.136)	(0.143)	(0.165)
Income	−0.019	0.140^{*}	−0.007	−0.022	−0.107
	(0.089)	(0.082)	(0.091)	(0.094)	(0.109)
Age	0.015^{***}	0.040^{***}	0.058^{***}	0.073^{***}	0.016^{***}
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Male	-0.290^{**}	−0.078	0.324^{**}	0.728^{***}	-0.280^{*}
	(0.130)	(0.118)	(0.132)	(0.138)	(0.158)
Constant	0.402	0.264	-1.714^{***}	-2.706^{***}	1.366^{***}
	(0.271)	(0.250)	(0.293)	(0.316)	(0.303)
Akaike Inf. Crit.	16,655.290	16,655.290	16,655.290	16,655.290	16,655.290
Note:					*p<0.1; **p<0.05; ***p<0.01

Table B32: Clustered bootstrap p-values for attitude towards gay rights

	DV: Attempts to give equal opp. to gays gone (ref. category: Not nearly far)				
	Not far	About right	Too far	Way too far	Don't know
Constant	0.380	0.500	0.003	0	0.113
Financial Literacy (# correct)	0.984	0.554	0.835	0.324	0.020
High education	0.203	0	0.002	0	0.002
Income	0.850	0.379	0.954	0.859	0.451
Age	0.092	0	0	0	0.080
Male	0.033	0.472	0.051	0.022	0.040

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