Replication:
Personal Economic Shocks and Public Opposition to Unauthorized Immigration

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Abstract (original research)

Do negative economic shocks heighten public opposition to immigration, and through what mechanisms? Extant research suggests that economic circumstances and levels of labour market competition have little bearing on citizens' immigration attitudes. Yet personal economic shocks have the potential to trigger the threatened, anti-immigration responses – possibly through channels other than labour market competition – that prior cross-sectional research has been unable to detect. To examine these propositions, we used a unique panel study which tracked a large, population-based sample of Americans between 2007 and 2020. We found that adverse economic shocks, especially job losses, spurred opposition to unauthorized immigration. However, such effects are not concentrated among those most likely to face labour market competition from unauthorized immigrants. Instead, they are concentrated among white male Americans. This evidence suggests that the respondents' anti-immigration turn does not stem from economic concerns alone. Instead, personal experiences with the economy are refracted through salient socio-political lenses.

Keywords: immigration; unemployment; public opinion; panel data

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Replication objectives

The key objectives of the replication is as follows:

- Establish credibility to the researchers original work
- Learn how to perform various statistical analysis on primary data
- Add value to the research by making contributions

The researchers created a binary dependent variable to map whether respondent support deportation of unauthorised immigrants or not. The original variable captures responses on a 7-point scale ranging from 1 (‘Return illegal immigrants to their native countries’) to 7 (‘Create a pathway to U.S. citizenship for illegal immigrants’). As we can see, the original 7-point scale variable provides more food for thought and so, for the replication exercise, I will be using a multinomial ordered logit model and use this original variable to measure the effect.
When using a 7-point scale variable, the ordered multinomial model will help us understand how a unit change in independent variable is associated with the change in log odds on average for each one step jump in support of unauthorised immigrants.

As first step, the dependent variable is ordered and level ”1” is set as the reference category using the following `R` code:

```
# Using the 7-level dependent variable as ordered outcome and setting ”1” as
   the reference
data$path <- relevel(factor(data$path), ref=”1”)
levels(data$path) #Ensuring the levels are in order: 1, 2, 3, 4, 5, 6, 7
```

Dataset

A population-based panel of American respondents who were eighteen or older in 2008 was employed. Knowledge Networks (later GfK and then Ipsos) recruited panelists offline via address-based sampling or random-digit dialing. The first wave was administered in October 2007, and the fifteenth wave in October 2020. However, it is important to note that the dependent variable was measured from 2012 onward.

The table below shows the key demographics of the respondents. We can see that the respondents in the latest October 2020 survey are quite similar to the respondents in the October 2012 survey in terms of demographics. The survey has 12 per cent Black, 11 per cent Hispanic, and about 71 per cent White people, with 38 per cent reporting a college degree.

The `R` code for producing the descriptive summary for both rounds of survey is:

```r
## Descriptive statistics ##
# Oct '12 - Jan '13
subset_data_w6 <- subset(data, wave == 6 & dep_d < Inf & !is.na(pre_party1))

options(scipen=999)
desc_w6 <- subset_data_w6 %>%
  transmute(`Education (BA or more)` = ppeducat_4,
            `Female` = female6,
            `Black'12` = black6,
            `Hispanic'12` = hisp6,
            `White'12` = white6,
            `Union'07` = union0,
            `Republican'07` = pre_party1,
            `Age` = AGE,
            `Income` = INCOME)

datasummary(`Education (BA or more)`
            + `Female`
            + `Black'12`
            + `Hispanic'12`
            + `White'12`
            + `Union'07`
            + `Republican'07`
            + `Age`
            + `Income`
            ~ (`Unique (#)` = NUnique)
            + Min * Arguments(fmt = "%.0f")
            + Max * Arguments(fmt = "%.0f")
            + (Median = median)
            + (Mean = mean)
            + (SD = sd),
            fmt = 4,
            data = desc_w6,
            title = "Descriptive statistics (Oct '12 - Jan '13)",
            output = "descriptives_w6.docx")

# Oct '20
subset_data_w15 <- subset(data, wave == 15 & dep_d < Inf & !is.na(pre_party1))

options(scipen=999)
desc_w15 <- subset_data_w15 %>%
  transmute(`Education (BA or more)` = ppeducat_4,
            `Female` = female6,
            `Black'12` = black6,
            `Hispanic'12` = hisp6,
            `White'12` = white6,
            `Union'07` = union0,
            `Republican'07` = pre_party1,
            `Age` = AGE,
            `Income` = INCOME)

```

```
datasummary(`Education (BA or more)`
            + `Female`
            + `Black'12`
            + `Hispanic'12`
            + `White'12`
            + `Union'07`
            + `Republican'07`
            + `Age`
            + `Income`
            ~ (`Unique (#)` = NUnique)
            + Min * Arguments(fmt = "%.0f")
            + Max * Arguments(fmt = "%.0f")
            + (Median = median)
            + (Mean = mean)
            + (SD = sd),
            fmt = 4,
            data = desc_w15,
            title = "Descriptive statistics (Oct '20)",
            output = "descriptives_w15.docx")
```

Descriptive statistics

	Oct '12 - Jan '13		Oct '20	
	Mean	***SD***	***Mean***	***SD***
Education (BA or more)	0.3563	0.4790	0.3838	0.4865
Female	0.5203	0.4997	0.5161	0.5000
Black'12	0.1244	0.3301	0.1212	0.3265
Hispanic'12	0.0993	0.2992	0.1056	0.3075
White'12	0.7116	0.4531	0.7062	0.4557
Union'07	0.1244	0.3301	0.1368	0.3438
Republican'07	0.4374	0.4962	0.4252	0.4946
Age (in years)	52.2998	14.9846	59.2094	13.8748
Income (in $K)	63.7511	43.3514	80.1768	62.4847

N.B.: *The table output is formatted and inserted as image to reduce clutter and give a neat look to the document.*

Results

In this section, I will be first replicating the findings of the author and then running the multinomial ordered logit model with the 7-point scale dependent variable.

Model: Unemployment and support for deportation of unauthorised migrants

```r
# Table 1 (author)
models <- list(
  "(1)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
             data = data,
             subset = (wave == 7)),
  "(2)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
             data = data,
             subset = (wave == 8)),
  "(3)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
              data = data,
              subset = (wave == 10)),
  "(4)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
              data = data,
              subset = (wave == 11)),
  "(5)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
              data = data,
              subset = (wave == 13)),
  "(6)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
              data = data,
              subset = (wave == 14)),
  "(7)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
              data = data,
              subset = (wave == 15)),
  "(8)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    state),
              data = data),
  "(9)" = lm(dep_d ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + union0 + white6 + male + AGE + pre_party1 + INCOME + factor(
    Year) + mno + factor(state),
```

```
                  data = data,
                  subset = (samp1011 == 1)))
```

N.B.: *The script is truncated and contains more information on table formatting which can be found in the* `R` *script file.*

Table 1:
Contemporaneous unemployment and support for deportation of unauthorized migrants

	(1) Nov'12	(2) Oct'14	(3) Jan'16	(4) Sep'16	(5) Oct'18	(6) Jan'20	(7) Oct'20	(8) Pooled	(9) Pooled
Unemployed	-0.0011	-0.0753	0.0347	-0.0897	-0.0568	-0.0052	-0.1870**	-0.0233	-0.0312
	(0.0435)	(0.0704)	(0.0652)	(0.0742)	(0.0862)	(0.1139)	(0.0682)	(0.0259)	(0.0258)
Year FE									Yes
Individual FE									Yes
Obs. (N)	2149	1589	1454	1148	951	1035	1055	9381	9381
Adjusted R-squared	0.145	0.145	0.116	0.128	0.165	0.152	0.159	0.143	0.160
RMSE	0.46	0.46	0.46	0.45	0.44	0.44	0.43	0.46	0.45
Std.Errors	HC2	HC2	HC2	HC2	HC2	HC2	HC2	HC2	HC2

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: *Outcome variable is a binary indicator that equals 1 if the respondent supports deporting unauthorized migrants, and 0 otherwise. All regressions control for respondents' age, race, gender, level of education, income employment status (retired, disabled or other), and partisanship (an indicator variable for Republicans). Robust standard errors in parentheses.*

From the above table we see that there is no evidence to suggest that if respondent is unemployed, it is associated with them supporting deportation of unauthorised migrants (for the full model).

Next, I run the multinomial ordered logit model with the 7-point scale dependent variable.

```
# Running the ordered multinomial model
multinom_or <- polr(path ~ UNEMPLOYED + RETIRED + DISABLED + OTHER_EMP +
    ppeducat + union0 + white6 + male + AGE + pre_party1 + INCOME + Year +
    state,
                        data = data, Hess = T)

summary(multinom_or) #Producing the output

# Calculating the -pvalue
ctable <- coef(summary(multinom_or))
p <- round(pnorm(abs(ctable[, "t value"]), lower.tail = FALSE) * 2, digits =
    4)
(ctable <- cbind(ctable, "p value" = p))
```

Table 2:

	Value	Std. Error	t value	p value
UNEMPLOYED	0.196983424	0.0062094605	31.723114	0.0000
RETIRED	0.149432095	0.0564906830	2.645252	0.0082
DISABLED	-0.121698241	0.0278003426	-4.377581	0.0000
OTHER_EMP	0.105875083	0.0730957009	1.448445	0.1475
ppeducat	0.448982870	0.0296304055	15.152775	0.0000
union0	-0.125712220	0.0552735429	-2.274365	0.0229
white6	-0.248112956	0.0491833466	-5.044654	0.0000
male	-0.201135932	0.0381265758	-5.275479	0.0000
AGE	0.003473527	0.0023848264	1.456511	0.1453
pre_party1	-1.162072214	0.0400357488	-29.025864	0.0000
INCOME	0.001781918	0.0003965795	4.493217	0.0000
Year	0.058865588	0.0001148059	512.740008	0.0000
state	-0.001633945	0.0012222045	-1.336883	0.1813
1|2	118.184158533	0.0112448075	10510.109544	0.0000
2|3	118.660845411	0.0191759134	6188.015281	0.0000
3|4	119.113187201	0.0232719513	5118.315431	0.0000
4|5	119.991815895	0.0289024713	4151.610931	0.0000
5|6	120.603579530	0.0323543872	3727.580396	0.0000
6|7	121.257656034	0.0365344216	3318.997560	0.0000

We can see from the results that one unit change in `UNEMPLOYED` variable that is moving from "unemployed" to "employed" is associated with an increase of 0.197 log odds on average for a one step change of `path` variable which captures support for deportation on a 7-point scale ranging from 1 ('Return illegal immigrants to their native countries') to 7 ('Create a pathway to U.S. citizenship for illegal immigrants').
So, we find sufficient evidence to say that unemployed respondents oppose the deportation of unauthorised immigrants.

Model: Effect of economic shocks on support for deportation of unauthorised migrants

```
-
# Table 2 (author)
models_2 <- list(
  "(1)" = lm(dep_d ~ LOST_JOB,
             data = data,  subset = (samp == 1)),
  "(2)" = lm(dep_d ~ LOST_JOB + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + logINCOME + state,
             data = data,  subset = (samp == 1)),
  "(3)" = lm(dep_d ~ LOST_JOB + RETIRED + DISABLED + OTHER_EMP + factor(
    ppeducat) + logINCOME + Year + state,
             data = data,  subset = (samp == 1)),
  "(4)" = lm(dep_d ~ LOST_JOB + income_shock2 + RETIRED + DISABLED + OTHER_EMP
     + factor(ppeducat) + logINCOME + state,
```

```
              data = data,   subset = (samp == 1)),
  "(5)" = lm(dep_d ~ LOST_JOB + income_shock2 + FOUND_JOB + RETIRED + DISABLED
    + OTHER_EMP + factor(ppeducat) + logINCOME + state,
              data = data,   subset = (samp == 1)))
```

N.B.: *The script is truncated and contains more information on table formatting which can be found in the* ***R*** *script file.*

Table 3:
Effect of economic shocks on voters' support for the deportation of unauthorized immigrants

	(1)	(2)	(3)	(4)	(5)
Lost job	0.0673+ (0.0421)	0.0743+ (0.0412)	0.0685* (0.0417)	0.0756+ (0.0412)	0.0750+ (0.0413)
Income drop				0.0556** (0.0193)	0.0558** (0.0193)
Found job					-0.0207 (0.0416)
Individual FE		Yes	Yes	Yes	Yes
Year FE			Yes	Yes	Yes
Observations	9620	9620	9620	9620	9620
Adjusted R-squared	0.000	0.051	0.057	0.052	0.052
RMSE	0.49	0.48	0.48	0.48	0.48
Std.Errors	HC2	HC2	HC2	HC2	HC2

$+ p < 0.1$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Notes: *Outcome variable is a binary indicator that equals 1 if respondents support deporting unauthorized migrants and 0 otherwise. All regressions control for respondents' level of education, level of income (logged), and employment status. Robust standard errors in parentheses.*

Across different model specifications we see that if respondent has lost job recently or experienced a drop in income (either personal or family), it affects opposition to unauthorised immigration.

Respondents who recently lost their job are 7.5 percentage points more supportive of deporting unauthorised immigrants. Again, a major income drop (of at least 25 per cent) is associated with a 5.5 percentage points increase in opposition to unauthorised immigration.

We also see that if the respondent has recently found a job, it is negatively associated with support for deporting authorised immigration. However, the coefficient is not statistically reliable.

Next, I run the multinomial ordered logit model with the 7-point scale dependent variable.

```
—'
# Running the ordered multinomial model
multinom_or_2 <- polr(path ~ LOST_JOB + income_shock2 + FOUND_JOB + RETIRED +
    DISABLED + OTHER_EMP + factor(ppeducat) + logINCOME + state,
                     data = data,  subset = (samp == 1), Hess = T)

summary(multinom_or_2) #Producing the output

# Calculating the -pvalue
ctable <- coef(summary(multinom_or_2))
p <- round(pnorm(abs(ctable[, "t value"]), lower.tail = FALSE) * 2, digits =
    4)
(ctable <- cbind(ctable, "p value" = p))
```

Table 4:

	Value	Std. Error	t value	p value
LOST_JOB	-0.213567659	0.151907476	-1.4059062	0.1598
income_shock2	-0.207933736	0.069856838	-2.9765695	0.0029
FOUND_JOB	0.133809587	0.153516189	0.8716318	0.3834
RETIRED	0.246179562	0.044447214	5.5386950	0.0000
DISABLED	-0.034218629	0.085938449	-0.3981760	0.6905
OTHER_EMP	0.029195483	0.076193952	0.3831732	0.7016
factor(ppeducat)2	0.289677605	0.105699855	2.7405677	0.0061
factor(ppeducat)3	0.749595032	0.108924429	6.8817899	0.0000
factor(ppeducat)4	1.379924562	0.108846389	12.6777247	0.0000
logINCOME	0.008965511	0.023801613	0.3766766	0.7064
state	-0.003784855	0.001160226	-3.2621718	0.0011
1|2	-0.428223520	0.142333975	-3.0085826	0.0026
2|3	0.017343994	0.142232843	0.1219409	0.9029
3|4	0.426003191	0.142231108	2.9951478	0.0027
4|5	1.220687717	0.142668735	8.5560983	0.0000
5|6	1.778897021	0.143251141	12.4180304	0.0000
6|7	2.383304486	0.144104814	16.5386875	0.0000

We can see from the results that one unit change in `income_shock2` variable that is experiencing a major income drop (of at least 25 per cent) is associated with a decrease of 0.207 log odds on average for a one step change of `path` variable which captures support for deportation on a 7-point scale ranging from 1 (‘Return illegal immigrants to their native countries’) to 7 (‘Create a pathway to U.S. citizenship for illegal immigrants’).

The coefficient for recent `LOST_JOB` and `FOUND_JOB` is not statistically reliable.

Model: Effect heterogeneity by respondent characteristics

```r
–’–
# Table 3 (author)
models_3 <- list(
  "(1)" = lm(dep_d ~ LOST_JOB + low_educ +  union0 + white6 + male + copcimm10M +
                    Unemployment_rateM + pre_pid7 + AGE + INCOME + FOUND_JOB + RETIRED +
                    DISABLED + OTHER_EMP + factor(Year) + factor(countyfips), data = data),
  "(2)" = lm(dep_d ~ LOST_JOB*low_educ + union0 + white6 + male + copcimm10M +
                    Unemployment_rateM + pre_pid7 + AGE + INCOME + FOUND_JOB + RETIRED +
                    DISABLED + OTHER_EMP + factor(Year) + factor(countyfips), data = data),
  "(3)" = lm(dep_d ~ LOST_JOB*union0 + low_educ +  white6 + male + copcimm10M +
                    Unemployment_rateM + pre_pid7 + AGE + INCOME + FOUND_JOB + RETIRED +
                    DISABLED + OTHER_EMP + factor(Year) + factor(countyfips), data = data),
  "(4)" = lm(dep_d ~ LOST_JOB*copcimm10M + low_educ +  union0 + white6 + male +
                    Unemployment_rateM + pre_pid7 + AGE + INCOME + FOUND_JOB + RETIRED +
                    DISABLED + OTHER_EMP + factor(Year) + factor(countyfips), data = data),
  "(5)" = lm(dep_d ~ LOST_JOB*Unemployment_rateM + low_educ +  union0 + white6 + male + copcimm10M +
                     pre_pid7 + AGE + INCOME + FOUND_JOB + RETIRED +
                    DISABLED + OTHER_EMP + factor(Year) + factor(countyfips), data = data),
  "(6)" = lm(dep_d ~ LOST_JOB*white6 + low_educ +  union0 + male + copcimm10M +
                    Unemployment_rateM + pre_pid7 + AGE + INCOME + FOUND_JOB + RETIRED +
                    DISABLED + OTHER_EMP + factor(Year) + factor(countyfips), data = data),
  "(7)" = lm(dep_d ~ LOST_JOB*male + low_educ +  union0 + white6 + copcimm10M +
                    Unemployment_rateM + pre_pid7 + AGE + INCOME + FOUND_JOB + RETIRED +
                    DISABLED + OTHER_EMP + factor(Year) + factor(countyfips), data = data))
```

N.B.: *The script is truncated and contains more information on table formatting which can be found in the* `R` *script file.*

Table 5:
Effect heterogeneity by respondent characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lost job	0.0879* (0.0403)	0.0598 (0.0487)	0.0952* (0.0417)	0.1431+ (0.1333)	0.1598+ (0.1391)	-0.0181 (0.0660)	0.0188 (0.0571)
Lost job x Low-skilled		0.0876 (0.0852)					
Lost job x Union member			-0.1054 (0.1561)				
Lost job x High % of foreign-born				-0.0920 (0.0806)			
Lost job x High unemployment rate					-0.1124 (0.0823)		
Lost job x White						0.1676* (0.0826)	
Lost job x Male							0.1361+ (0.0797)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8849	8849	8849	8849	8849	8849	8849
Adjusted R-squared	0.178	0.178	0.177	0.178	0.178	0.178	0.178
RMSE	0.44	0.44	0.44	0.44	0.44	0.44	0.44
Std.Errors	HC2	HC2	HC2	HC2	HC2	HC2	HC2

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: *Outcome variable is a binary indicator that equals 1 if the respondent supports deporting unauthorized migrants, and 0 otherwise. The linear probability models in columns 2–7 interact with unemployment shocks with indicator variables denoting the different groups of respondents. All regressions control for the constitutive terms of the interaction with job loss and age, income, employment status (retired, disabled or other) and partisanship. Robust standard errors in parentheses.*

We can see from the above table that there is no evidence of heterogeneous effects across respondents (who recently lost their jobs) differentiated by skill level or union membership. Also, no evidence is found in case of such respondents belonging to counties with higher percentage of foreign-born or unemployment rate. However, we do find some evidence that white respondents who have recently lost their jobs are 16.76 percentage points more opposed to unauthorised immigration. Furthermore, male respondents who have recently lost their jobs are 13.61 percentage points more opposed to unauthorised immigration.

Conclusion

From the research, we find that labour market factors like unemployment rate and counties with high proportion of foreign-born do not affect opposition towards unauthorised immigrants. However personal economic factors like recent job loss or income shock (of at least 25%) is associated with negative sentiment towards unauthorised immigrants and support their deportation.

Furthermore, from the heterogeneity model we observe that white respondents and male respondents who have faced recent job loss are more likely to support deportation of unauthorised immigrants.

On doing the replication of key results, I was able to confirm similar results as originally reported by the authors.
Moreover, as part of my contribution to the research, when I used the original 7-point scale dependent variable, I was able to find that majority of the trends remained the same (as with the authors work), just that the effects of `UNEMPLOYED` variable was found to be different (in Model 1).

Replication limitations

The authors used STATA to run the regression models. However, as part of my academic requirement, I had to use `R` for analysis. The original codes were therefore, rewritten in `R` for the replication exercise. I notice that while the broad trends and estimates are unchanged, there is marginal change in the estimation of standard errors.

The replication gave me a good opportunity to brush up my knowledge on STATA and implement same analysis in `R`.