Supplemental Appendix For

U.S. Federal Reserve Policies Can Cause Political Instability By Raising Bread Prices

Contents

This appendix proceeds in two parts. The first part reports the data and variables used in our mediation analyses, as well as our identification strategy and sensitivity of the underlying parameters. The second part list summary statistics on all variables, as well as plots of the sensitivity analyses discussed in the first part.

Data, Variables, and Methods

The sample used to compile Figures 1 and 2 in the main text relies on monthly-level data on money supply, food price indexes, and social unrest globally for each month between January 2000 and December 2011.[1] Our first dependent variable is designed to capture – for theoretical reasons – events specifically reflecting food stress-borne civil mobilization and unrest to ensure accurate identification of our relationship(s) of interest (see, e.g., Smith, 2014). Therefore, to measure food-related events, we operationalize our dependent variable, *Food riots*$_t$, using the global-month food riots data created by Bellemare (2015). These data were compiled using "all news stories in English between January 1990 and December 2011 containing at least five occurrences of the terms 'cereal,' 'commodity,' 'food,' 'grain,' or 'staple,' and their plural forms and at least five occurrences of the terms 'demonstration,' 'mob,' 'protest,' 'riot,' 'strike,' 'unrest,' or 'violence' and their plural forms" (2015, 8) downloaded from LexisNexis. A total of 14,635 food riot incidents were reported over the January 2000–December 2011 period.

To create our more general *Social conflict*$_t$ dependent variable, we relied on the Nonviolent and Violent Campaigns and Outcomes (NAVCO) 3.0 dataset (Chenoweth, Pinckney and Lewis, 2017). NAVCO 3.0 is a CAMEO-based data collection effort of major nonviolent and violent resistance campaigns and events measured at the event-day level. NAVCO 3.0 assembles over 100,000 hand-coded observations of nonviolent and violent methods in 21 countries around the world between 1991 and 2012. Important with respect to our focus on the Arab Spring, NAVCO 3.0 heavily sampled from the Middle East and Africa. At the same time, this means that a large portion of the events captured are incidents directly related to food prices. To ensure that we broaden our empirical operationalization of social conflict, and considering that some campaigns have both violent and nonviolent elements, we include all events recorded in NAVCO 3.0 rather than reducing it to its violent or nonviolent components. Overall, a total of 847 social conflict events were recorded within our Jan. 2000- Dec. 2011 period, which corresponds to the period covered by our *Food riots*$_t$ variable.

Our mediating variable – i.e., the variable channeling the impact of our key explanatory variable (M2 USD supply, as discussed below) on the dependent variable – are food prices, both aggregated and of specific food groups. Again, we follow Bellemare (2015) and use the food price indicators from the Food and Agricultural Organization's (FAO) food price index. The FAO's aggregate food price index is a monthly indicator of the global food prices, covering five food groups (meat, dairy, cereals, oils and fats, and sugar) representing 55 commodities. To create this aggregate index, the FAO takes the average of these five food

[1]This temporal choice was determined by both the first availability of money supply data and the final recording of food riots in Bellemare's (2015) data.

groups and weights them using each group's export share for 2002–2004. Additionally, recall that our argument assumes that the prices of specific staples are more likely to be affected by changes in USD supply. Here, we specifically expect the relatively inealstic prices of cereals (e.g., wheat, barley, corn) to be sensitive to the Fed's monetary policies, and hence to have the greatest impact on civil unrest due to the reasons discussed in the previous section (Messer and Cohen, 2007; Hendrix and Haggard, 2015; Koren, 2018). Accordingly, we also include a global-month indicator – created by the FAO using the same methods used to create the general food price indicators – denoting the aggregate prices of commodities included under 'cereals.' In contrast, we expect that the prices of food commodities, especially meat, are more elastic (Gallet, 2010). Correspondingly they will not be noticably affected by domestic U.S. monetary policies, and hence will not mediate these policies' impacts on civil unrest. To this end, we also construct a global-month indicator of meat-commodities prices to serve – in effect – as a 'placebo' test for our theory. The range of each price index – aggregate food, cereals, and meat, respectively – over the January 2000–December 2011 period was 85.1 $\Leftrightarrow$ 240.1, 80.2 $\Leftrightarrow$ 267.7, and 84.5 $\Leftrightarrow$ 189.7.

Because our theory focuses on the global impacts of the U.S. Federal Reserve's (Fed) monitory policy on food-related conflict, our key explanatory variable must capture the impacts of such policies in a way that effectively translates to civil unrest through shaping food prices. As we explained in the previous section, by influencing the global supply of USD, domestic Fed policy has the capacity to directly shape food prices, especially with respect to cereals. To capture these policy impacts, we operationalize our key independent variable as the percent (%) change in money supply during a given month compared with the same month the previous year. Over the January 2000–December 2011 period, $\%$ *Change in money supply*$_t$ thus have a mean of 6.3%, and a range of 1.7% $\Leftrightarrow$ 10.5%. The sample size in for our main analyses below – 144 monthly observations from January 2000 to December 2011 inclusively – was ultimately determined by the fact that the Fed only started reporting money supply changes in January 1999 and our reliance of a one year lag.

A key contribution this study makes is in not only theorizing but also empirically identifying the impact of change in USD money supply on food prices, and – by extension – food riots. Accordingly, we rely on a mediation analysis approach originally suggested by Baron and Kenny (1986) and extended by Imai, Keele and Tingley (2010). Briefly, mediation analysis assumes that the key explanatory variable (in our case, % change in money supply) impacts our dependent variable (food riots) only by affecting a mediating variable (food prices). Accordingly, we estimate the following system of equations to identify the relationship between Fed-mandated money supply, food prices, and civil unrest:

$$\mathbf{f_t} = \beta_0 + \beta_1 \mathbf{m_t} + \beta_2 \mathbf{c_{t-1}} + \beta_3 \mathbf{s_t} + \beta_t \mathbf{T_t} + \beta_\phi \phi_\mathbf{t} + \epsilon_t \tag{1}$$

$$\mathbf{c_t} = B_0 + \gamma_1 \mathbf{f_t} + B_1 \mathbf{m_t} + B_2 \mathbf{c_{t-1}} + B_3 \mathbf{s_t} + B_t \mathbf{T_t} + B_\phi \phi_\mathbf{t} + E_t \tag{2}$$

Here, $\mathbf{m_t}$ is our key explanatory variable: a vector measuring change in USD money supply in a given month from the past year; $\mathbf{f_t}$ is our mediator: a vector denoting the index of global food, cereal, or meat, prices within a given month; $\mathbf{c_t}$ is the dependent variable, namely a vector measuring the global count of food riots or social conflict events occurring in a given month, and $\mathbf{c_{t-1}}$ its lag; $\mathbf{s_t}$ is a binary vector measuring the existence of the 2007-2008 global economic crisis; $\mathbf{T_t}$ and $\phi_\mathbf{t}$ are the time trend and month fixed effects, respectively; and ϵ_t and E_t are the respective robust error terms. Not that we differed from Bellemare (2015) in not including the 2010-11 crisis dummy considering that our argument specifically highlights the crisis originated in domestic Fed policies and the resulting inflation. Including a dummy would hence introduce a large degree of autocorrelation and will go against our theoretical argument as well as our ability to test a moderated relationship. If our hypothesis is correct, then two conditions must be met:

i $\beta_1 > 0$, $\gamma_1 > 0$. The explanatory variable should noticeably increase food prices, and food prices should noticeably increase civil unrest.

ii $B_1 = 0$. The only channel by which our explanatory variable should impact food riots is by impacting food prices.

It is possible for either one of these conditions to occur independently. So, for example, changes in meat prices (our placebo) can still increase the frequency of food riots, but be unaffected by Fed monetary policies, and vice versa. Yet, neither of these can be considered as confirming our *mediated* hypothesis. Moreover, in relying on the method by Imai, Keele and Tingley (2010), we add a third necessary condition for confirming our hypothesis, namely that the underlying sensitivity of our results to unobserved confounders is not high.

Sensitivity Analyses

A major advantage of the method used here is that it offers "sensitivity analysis of causal mediation effects without reference to any specific statistical model" (Imai, Keele and Tingley, 2010, 1). Specifically, Imai, Keele and Tingley (2010) provide a way for researchers to quantify the degree to which any unobserved confounders that may effect the results (i.e.,

Table A1: Causal Mediation Analysis Estimates

	Food riots*$_t$*			***Social conflict****$_t$*		
	Cereal	*Food*	*Meat*	*Cereal*	*Food*	*Meat*
$ACME_t$	2.639**	0.491	0.105	0.109***	-0.047	-0.050
	(0.003 ⇔ 6.01)	(-1.051 ⇔ 2.40)	(-0.721 ⇔ 1.03)	(0.017 ⇔ 0.24)	(-0.186 ⇔ 0.07)	(-0.156 ⇔ 0.03)
ADE_t	-3.327*	-1.197	-0.783	0.012	0.166	0.173
	(-6.841 ⇔ 0.17)	(-3.749 ⇔ 1.35)	(-3.428 ⇔ 1.91)	(-0.359 ⇔ 0.38)	(-0.163 ⇔ 0.50)	(-0.169 ⇔ 0.50)
Total Effect$_t$	-0.688	0.706	-0.678	0.121	0.118	0.122
	(-3.588 ⇔ 2.25)	(-3.690 ⇔ 2.30)	(-3.428 ⇔ 2.11)	(-0.246 ⇔ 0.49)	(-0.245 ⇔ 0.47)	(-0.230 ⇔ 0.46)
Prop. Mediated$_t$	-0.888	0.014	0.017	0.385	-0.071	-0.123
	(-26.114 ⇔ 29.55)	(-7.557 ⇔ 7.03)	(-3.216 ⇔ 2.85)	(-7.085 ⇔ 7.98)	(-4.773 ⇔ 4.81)	(-4.266 ⇔ 4.32)
Observations	144	144	144	143	143	143

95% Credible intervals in parentheses. Each model was estimated using 10,000 simulations.
*** p<0.01, ** p<0.05, * p<0.1

violate the assumption of sequential ignorability). We conduct these sensitivity analysis in Figures A1– A6 With respect to these sensitivity analyses, note that any interpretation of how sensitive any underlying findings are is relative – there is no clear 'cutoff point.' Accordingly, we estimate the degree to which our findings with respect to food prices are sensitive to unobserved confounders by comparing variations in the mediation effects across different values of the sensitivity parameter ρ to values obtained in other studies that rely on observational (as opposed to purely experimental) data.

To this end, Figure A1 first evaluates the sensitivity of our only statistically significant mediated relationship with respect to food riots. Here, we find that our values are robust over the range of $0.3 \leq \rho \leq 0.6$, suggesting our finding are reasonably robust compared with other observational data studies (see, e.g., Sales, 2017). Moving on, we see similar results with respect to the underlying sensitivity of the mediated relationship when social conflict is concerned in Figure A4. That the sensitivity of our results is medium but not high is not expected. Theoretically, it is highly unlikely that high levels of robustness can be achieved considering the integrated nature of the international political economy and the potential impact of environmental factors.

Summary Statistics and Additional Plots

Table A2: Summary Statistics, January 2000 - December 2011

	Min	**Median**	**Mean**	**Max**	**Std. Dev.**
Food riots$_t$	24	85	101.632	433	64.312
Social conflict$_t$	1	4	5.923	28	5.334
Cereal prices$_t$	80.2	111.95	139.894	267.7	56.105
Food prices$_t$	85.1	122.55	139.323	240.1	47.413
Meat prices$_t$	84.5	121.2	126.287	189.7	29.262
% Change in money supply$_t$	1.7	6.05	6.180	10.5	2.006

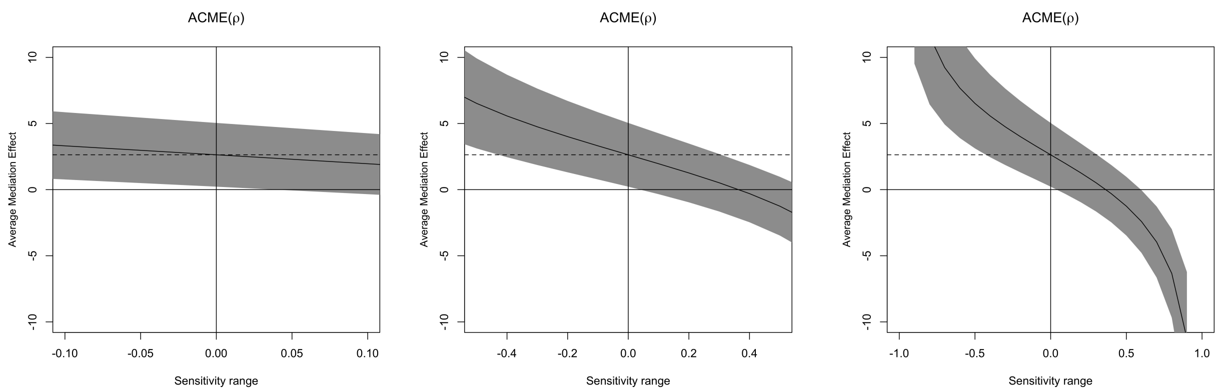

Figure A1: Sensitivity analyses – *Cereal prices*$_t$'s impact on *Food riots*$_t$

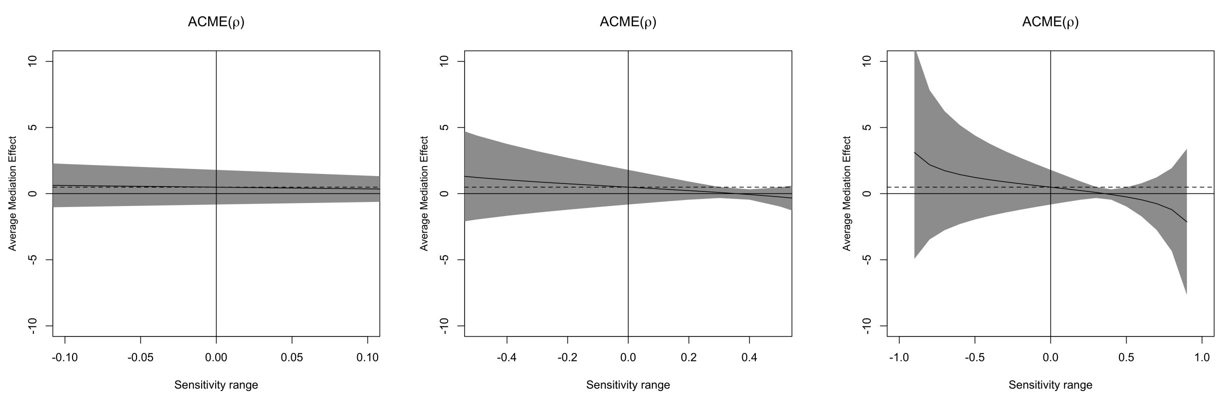

Figure A2: Sensitivity analyses – *Food prices*$_t$'s impact on *Food riots*$_t$

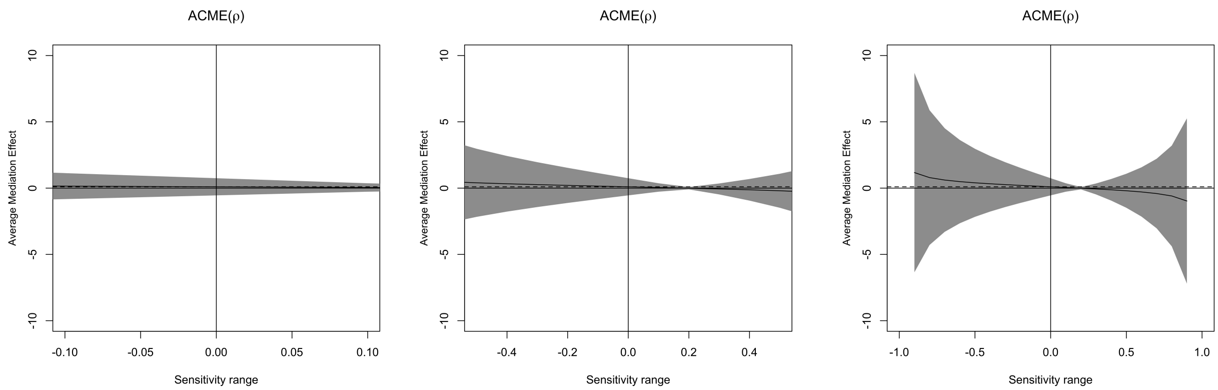

Figure A3: Sensitivity analyses – *Meat prices$_t$*'s impact on *Food riots$_t$*

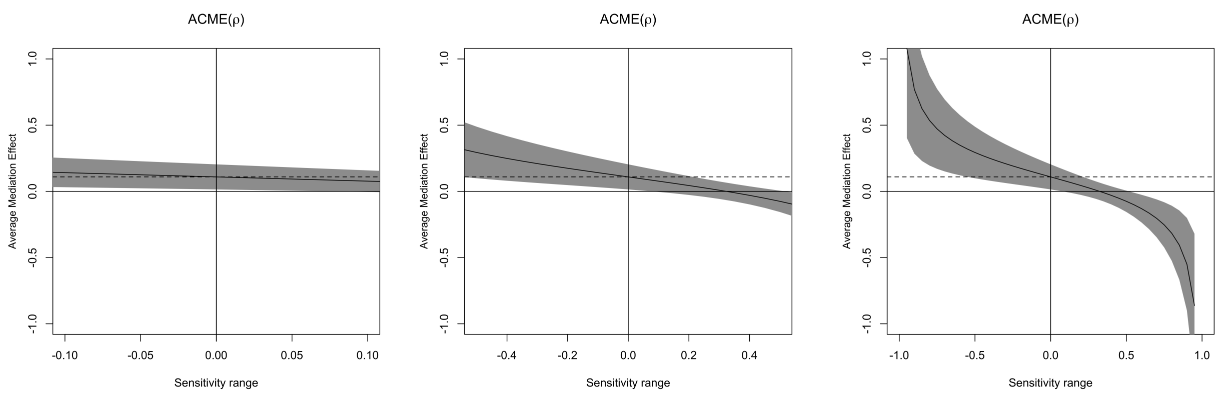

Figure A4: Sensitivity analyses – *Cereal prices$_t$*'s impact on *Social conflict$_t$*

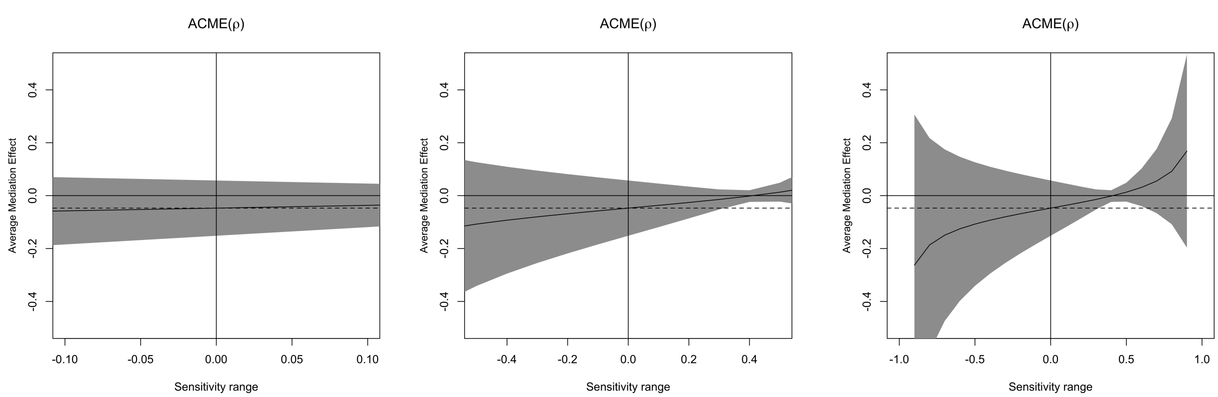

Figure A5: Sensitivity analyses – *Food prices$_t$*'s impact on *Social conflict$_t$*

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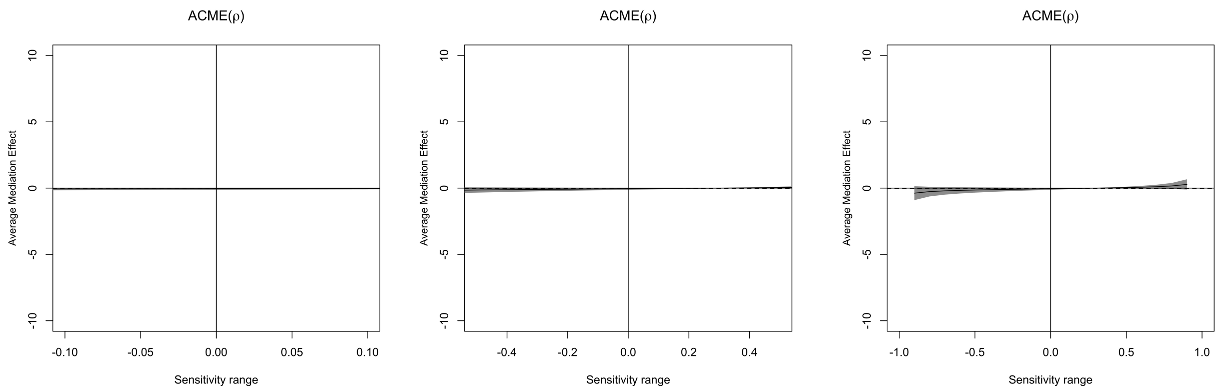

Figure A6: Sensitivity analyses – *Meat prices$_t$*'s impact on *Social conflict$_t$*

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