Food prices and social unrest: *Local* impact across Asia and Africa

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Abstract

Using a novel dataset disaggregated at city level in a monthly frequency, I empirically test the linkage between food prices and incidents of urban social unrest for 43 cities in Asia and Africa for the period 2000 to 2008. Using shocks in prices in international markets as exogenous instruments in order to account for endogeneity (reverse causality in particular), I find that sudden shocks in prices of the corresponding staple food commodity, that is most important locally, significantly affects the occurrence of a spontaneous riot or demonstration. The finding is consistent with anecdotal evidence in the wake of the food

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crisis of 2008 and is also in line with the triggering of spontaneous collective action eventually culminating in the Arab Spring of 2011. In line with the assumptions and theoretical model developed, I find no corresponding evidence for organized riots and demonstrations.

1 Introduction

Given its importance in the personal domain, food is one of the few commodities that evokes a self-righteous feeling of ensuring justice, fairness and empathy by policy-makers and researchers alike. Questions on ensuring food security and impacts of and on policies have been given ample justice. It is then natural to consider possible eventualities—states of world—when ensuring food security becomes a challenge. In wake of contradicting viewpoints over time (Swinnen, 2011), there is a need for deeper insights in academic discourse into the implications of changes in food prices and access to food (thereby welfare) for different sections of the society.

The food crisis of 2008 has since spawned a great deal of academic literature on the impact of food prices in general and the food crisis in particular. In view of the concurrent world-wide increase in events of social disturbances hyped up all the more by the media (figure 1), it remains to be seen whether or not this could be a spurious correlation. This is keeping in mind the diversity of societies worldwide, the society itself being a complex and dynamic entity.

The strength of this study lies in its focus. Narrowing down to incidents of unrest in *urban* areas we fix our attention on the section of population that is primarily net food consumer. Moreover, both the theoretical exposition, which is based on applied utility theory as well as the empirical analysis based on identification using instrumental variable (IV) technique using local prices prevalent in the market (read city) are directed to understanding the effect of *shock* in food prices on triggering *spontaneous* collective action in the form of riots and demonstrations.[1]

The present study contributes to research on social implications of food prices, in particular on unraveling the specific way food price shocks (change in *levels* as opposed to variance) are related to particular kinds of incidents of social unrest (spontaneous riots or demonstrations). In order to account for endogeneity, I use international food price shocks as IVs. The international food price shocks are the shocks in the key international (export) market price of the corresponding local food item which itself is chosen to be the one most important for an average urban resident of the city.[2] Reasonably so, as long as it's one's own consumption bundle that matters in terms of utility, agents should have no reason to protest for changes in prices in international markets.[3]

To give an idea of the magnitudes involved, the results indicate that a sudden doubling up of prices (100% change) over previous months' levels increases the probability of having a spontaneous riot or demonstration by around 23%.

I would navigate the study by keeping the reader abreast of related academic literature on the effect of economic shocks on society. Then move on to the conceptual mechanisms behind collective action highlighting the concept of 'thresholds'. Following this I would apply basic utility theory to justify

[1]For the purpose of our study, the word 'protest' can be treated synonymously with riots and demonstrations.

[2]As explained later, this importance is decided on the basis of a fixed criteria incl. dietary energy supply etc.

[3]As far as simple correlations are concerned, shocks in international price series are uncorrelated with the outcome (incident of unrest) while being positively correlated (significantly at a level of 10%) with the endogenous variable, the shock in local food prices. We will see that the tests for weakness of the instruments (based on first-stage regression) are passed.

the subsequent empirical analysis. The results of the empirical analysis are subject to robustness checks and further study before the final conclusion.

2 Background

Economic shocks have long been linked to unrest and violence. Most of the literature on the relationship between economic shocks and social unrest has focused on the economic causes of civil war (Blattman & Miguel, 2010; Easterly & Levine, 1997; Elbadawi & Sambanis, 2002). The greed aspect of the landmark 'greed vs grievance' model as propounded by Collier and Hoeffler (2004) to explain the occurrence of civil war, includes the economic causes in the form of opportunity costs of the agents. There is a strong negative association between civil war and economic development but the direction of causality is often unclear. While poor economic performance may lead to conflict, the reverse relationship is equally credible, and this complicates the analysis.[4] Dube and Vargas (2013) study changes in commodity prices and their effect on revolutionary movements, specifically focusing on international prices of coffee and oil and their differential impact on revolutionary incentives in Colombia. Studying the effect of government economic policies on social unrest in particular, Ponticelli and Voth (2011) find that austerity and budget cuts led to increased levels of social unrest and instability over the period 1919-2009. Möller (2011) provides a general cause and effect mechanism to relate economic hardships with incentives to engage in anti-government action and finds significant effects in democracies where it is easier to resolve collective action owing to low costs.

As a matter of fact, there is a large literature on the political economy

[4] An exception is Miguel, Satyanath, and Sergenti (2004), who instrument for economic decline using rainfall shocks (weak IV) and establish a causal link between economic hardship and the incidence of civil war.

of food policies (see Swinnen (2011) for a recent review). An important insight from this literature is that changes in market prices trigger political pressure by those hurt by the changes in order to induce governments to respond to protect them through policies. Such political pressure may take different forms, including transferring funds to political campaigns or demonstrations and riots. The resulting (endogenous) government response is well-documented(see e.g. de Gorter and Tsur (1991) and Swinnen (1994) for theory; and Anderson, Hayami, and et al (1986); Gardner (1989); Swinnen, Banerjee, and de Gorter (1994) for empirical evidence).

Notice that demonstrations and riots may have both benefits and costs. The general public may receive utility from expressing their grievances in demonstrations as they may consequently lead to government action corresponding to its preferences This is in line with the argument of Acemoglu and Robinson (2001) that transitory economic shocks can give rise to a democratic window of opportunity. However, countries seeking to reduce the political cost from rising food prices by altering trade restrictions at their national border (e.g. the imposition of export restrictions or reducing import protection) may initially succeed in dampening increases in domestic food prices, but the more countries revert to such actions, the more these actions become collectively self-defeating, reducing the role that global trade can play in dampening fluctuations in international prices (Anderson & Nelgen, 2010). Moreover, insulatory trade policies might lead to decreased welfare of the poor at the global level, thereby challenging their efficacy vis-a-vis other schemes such as conditional cash transfers (Anderson, Ivanic, & Martin, 2013). At the same time, demonstrations can turn violent, leading to casualties, destroying private and public property, and looting. Riots may divert domestic and foreign investment, decreasing growth and income in the long run, and when riots occur in important food or oil producing countries, they may in turn lead to short-term increases in commodity prices.

Historically, food shortages have sparked social unrest. While the most famous is indeed the French Revolution ("Let them eat cake"), other events include the 1684 Moscow Salt Riot, the 1713 Boston bread riot, the 1837 New York City Flour Riot, and the 1918 Rice Riots in Japan. In 2008, high food prices triggered riots from Haiti to Bangladesh to Egypt and causing mass social tensions even in high-growth countries like China and India. In 2011, several North African countries fell prey to riots and mass demonstrations, and again these protests occurred in a climate of rising food prices.

There are a few recent empirical studies on the relationship between international food prices and social unrest. Hendrix, Haggard, and Magaloni (2009) study the link between food prices and social unrest for the period 1961-2006 in 55 major cities in 49 Asian and African countries. The authors find that producers riot more easily with a price decrease than consumers do with a price increase.[5] In addition, they find that the impact of food prices on riots depends on regime type, with riots upon food price changes more frequently occurring in hybrid regimes than in democratic or repressive regimes. Arezki and Bruckner (2011) examine the effects of variations in international food prices on democracy and intra-state conflict using panel data for 120 countries during 1970-2007. They find a negative effect of food price increases on political institutions in Low Income Countries. In addition, increases in food prices significantly increase the incidence of civil conflict as well as the number of anti-government demonstrations and the number of riots. Finally Bellemare (2014) uses monthly data and exploits natural disasters as instrumental variables to isolate the causal relationship between food prices and political unrest at the international level. His results imply that between January 1990 and January 2011 food price increases have led to increased political unrest even as increases in food price volatility has been associated with their decrease. However, taking into account heterogeneity (in his case

[5] Compare Deaton (1989)'s finding of Thai rural households benefiting from high prices.

one might presume at the country level) both for the dependent variable (unrest) and independent variable (food prices) might be important to avoid the Simpson's paradox and thereby deepen the insight into the already careful analysis (Pearl, 2014).

The current study offers a new insight into the literature and contributes in more than one way. Unlike Hendrix et al. (2009) and Arezki and Bruckner (2011), I use monthly data (including that for the food price crisis). The two working papers analyze annual data series from respectively the periods 1961-2006 and 1970-2007. Arezki and Bruckner (2011) report that a one standard deviation increase in the food price index increases the number of anti-government demonstrations and riots by about 0.01 standard deviations. Statistically, the use of monthly rather than annual time series is expected to yield more accurate estimates in the sense of having lower variance due to larger number of data points. Also, it allows to capture within-year fluctuations in prices, which, due to the impact of weather and pest related shocks may be high, even after taking into account the usual seasonal fluctuations (Peterson & Tomek, 2005). Next, as noted by (Schneider, 2008) and in (*Crop Prospects and Food Situation*, 2008) the relationship between food price shocks and social unrest as well as the policy responses is often instantaneous, justifying the use of high frequency time series.[6] Moreover, to my knowledge, this study is the first attempt in literature to study the question at the local level down to the city both for the explained and the explanatory variables.

More recently, there have been a couple of notable studies on links between food-related issues and political instability. Nunn and Qian (2012) looks at how US food aid is causally linked to fueling civil wars in recipient countries (using data until 2006). In order to account for endogeneity, they

[6] Covered comprehensively `http://www.fao.org/docrep/010/ai470e/ai470e05.htm#COG`

ingeniously use US wheat production and tendency to receive aid. Carter and Bates (2012) very meaningfully underlies the importance of government policy bias towards urban consumers to pacify instances of civil conflict caused by food price shocks. According to them, political instability (in the form of civil wars) is related to food price shocks unless government policies (to circumvent urban unrest in the form of riots and demonstrations) is taken into account.

But as emphasized earlier, looking at a richer, high-frequency monthly data enables us to take a closer look at the mechanisms involved by taking into account various complexities such as possibility of substitution of consumption goods and spontaneity of incidents. Food price shocks, by their very nature inherent are unexpected, sudden deviations from the natural trend. In view of this, what can be expected in the short-run, at the most is a spontaneous expression of discontent in the form of collective action, perhaps facilitated by social networking and advances in media technologies. Civil wars and conflicts of the sort require both funding and organisation and are likely to be the results of accumulated grievances, which may be triggered by a 'sparky' incident.

3 Theoretical model

Building on the conceptual framework as detailed in the appendix, let us prepare the ground for empirical predictions. We consider below a threshold-based model that not only addresses the collective action problem, but also the beliefs of the protestor on the outcome of the protest upon her participation.

Let the utility function of a typical urban-dwelling agent take the following form:

$$U(q_f, q_n) = q_f^a . q_n^{(1-a)} \tag{1}$$

where q_f is the the quantity of food consumed and q_n is the quantity of non-food item at prices before the unexpected shock, $a \in (0, 1)$.[7]

As derived in the appendix, we can write the (optimal) utility loss, ΔU from a sudden change in food prices Δp_f as

$$\Delta U = [(1-a)/p_n]^{(1-a)} \cdot [a/p_f]^a \cdot q_f \cdot \Delta p_f \tag{2}$$

Hence the utility loss (gain), ΔU is directly proportional to the positive (negative) price shock. [8]

Let us study the considerations of an agent on the brink of taking a decision whether or not to protest in the event of a food price shock. There are *expected* costs of protesting, that might include possibility of arrest etc., which are are most likely to decrease with increasing expected co-participants, given by N^e. These can be most simply be expressed as $c(N^e) = k/(N^e)$ with the parameter, k ($k > 0$), capturing the costs of coordination.[9] Given the costs associated with protesting (and perhaps even greater loss if the protest is unsuccessful), there exists the traditional coordination problem due to incen-

[7]Indeed, this is a simplification. As would be clear in the empirical investigation, 'food' should be thought of as the most important or in a sense dearest food item. While we term the second good as 'non-food' items for pedagogical reasons undoubtedly less important food items can be thought of as being included in this group.

[8]For any continuous and strictly increasing (on $\mathbb{R}^+_{\not\approx}$) utility function $U(q_f, q_n)$, $v(\mathbf{p}, y)$ is decreasing in $\mathbf{p}$ where $\mathbf{p}$ is the price vector.

[9]There is considerable anecdotal evidence to suggest the role played by social networking sites such as Facebook and Twitter in facilitating protests and mass campaigning. It is the reason why governments in Egypt or Turkey have resorted to banning/blocking them during times of unrest. See for example this report by the Guardian `http://www.theguardian.com/world/2011/jan/26/egypt-blocks-social-media-websites`.

tives to free-ride Olson (1965).[10] The parameter γ is a measure of a relative decrease in utility from not having participated in a successful protest due to reputational or integrity concerns, as in Kuran (1989). Based on her belief about the government's capacity to repress, each agent has a threshold K_i, which is the minimum number of participants needed for the protest to be successful. Hence, a protest is expected to be successful if $N^e \geq K_i$. Based on the above considerations, we have the following pay-off matrix.

Table 1: Payoff matrix

	$N^e < K_i$	$N^e \geq K_i$
Not protest	$-\Delta U$	$(1-\gamma) \cdot \Delta U$
Protest	$-(k/N^e) - \Delta U$	$\Delta U - (k/N^e)$

Let F(.) denote the cumulative distribution function of the thresholds, K_i in the population.[11] Therefore as shown in the appendix, an agent would participate in a protest if the following inequality holds good,

$$\gamma \cdot F(N^e) \cdot \Delta U \geq (k/N^e) \tag{3}$$

From 2 and 3, one can see that for positive (negative) price changes, the incentive to engage in collective action should increase (decrease). Rearranging terms, we can write 3 as

$$F(N^e) \cdot N^e \geq \frac{k}{\Delta U \cdot \gamma} \tag{4}$$

As the left hand side of 4 is increasing in N^e, that (minimum) value of N^e that solves for the equality can be thought of as the threshold in the sense

[10]For the sake of tractability we define a 'successful' protest as one in which the government responds by taking policy measures to reverse the price increase.

[11]Note that the threshold in our model subsumes the informational cascades of Lohmann (1993, 1994, 2000) as detailed in the previous section so that it is taken into account while attributing success to the protest based on the expected number of participants.

of Granovetter (1978), as the minimum number of fellow participants needed to spur an agent to participate in the protest. Our model gels well with the conceptual framework considered above too. Food price shocks lower the Granovetter threshold, thereby inciting moderates. Moreover better communication technologies and increased social network membership is in line with reducing the costs of coordination ($\downarrow k$), its role in the decision-determining inequality concurring well with anecdotal evidence on their role in facilitating social unrest.

4 Empirics

In this section I empirically test the prediction that sudden food price spikes can tilt decision-making in favour of spontaneous protests.[12]. As shown in the previous section, food price changes can change the incentives to engage in collective action. In this section, we set about to verify the existence of this relationship empirically.

Note that 2 can be re-written in terms of relative price change as

$$\Delta U = [(1-a)/p_n]^{(1-a)} \cdot [p_f]^{1-a} \cdot a^a \cdot q_f \cdot \frac{\Delta p_f}{p_f} \tag{5}$$

Equation 5 generates empirical predictions in terms of relative change (read shocks) in food prices, so that the condition for protesting, 3 is more easily satisfied in response to a (relative) food price shock. This being a cross-national study, representing (real) price shocks in terms of relative changes from the trend has an advantage of ease of common interpretation of coefficients as shown later, independent of local currency units.

[12]While I have used the term 'protests', the reader could think of it as mass collective action and includes events like spontaneous demonstrations and violent riots

4.1 Variables and Data

The aggregated data set consist of data from a number of sources. Table 2 specifies the datasets and main features of the variables.

Dependent Variable My measure of an incident of urban social unrest is an an indicator variable, whether or not an incident of riot or demonstration took place in a given month from January 1990 till September 2010, in any of the 43 cities in 37 countries [13] [14]. The USDAA categorises events of social unrest ranging from civil war to armed conflict. These are listed in table 3 along with the event category codes. For the purposes of analysing the research question, I take two sets of categories–one consists of 'spontaneous violent riot' and 'spontaneous demonstration' (PTYPE=51 & 62). The other consists of 'organised violent riot' and 'organised demonstration' (PTYPE=50 & 60). In the main specification that follows, the dependent variable (denoted as the dependent variable, E_{ijmy}) takes the value of 1 if there was an occurence of a spontaneous riot or demonstration and 0 otherwise.

Independent Variables The variable, the coefficient of which is of main interest for our research question is the sudden food price shock. I define it to be the relative deviation of current price level of the most important crop (the criteria of selecting the most important crop for a city is explained in the appendix), from the (moving) average over the previous four months.[15] Table 4 lists the food commodity selected

[13] The Urban Social Disturbances in Asia and Africa (USDAA) dataset, which is itself sourced from the Keesing's Record of World Events, actually covers 55 cities in 49 countries since 1960. Refer to (Urdal, 2008) for more details on the dataset.

[14] If either one of endtime or starttime are not known, shortest duration of event (occurrence in that month only) is assumed. However, events in our categories of interest seldom last longer for a month so in our analysis, incidence coincides with onset

[15] Reason for choosing the deviation from the average price from the previous 4 months:

for each city as per the criteria as explained in the appendix. Hence, symbolically, if $p_{i,m}$ is the price of the most important food item in local currency unit for a city i in month m, food price shock for the month m is determined as

$$\left(\frac{\Delta p}{p}\right)_{i,m} = \frac{p_{i,m} - \overline{p}_{i,m}}{\overline{p}_{i,m}}$$

where

$$\overline{p}_{i,m} = \frac{\sum_{k=1}^{4} \cdot p_{m-k,i}}{4}$$

I make use of country-level covariates (which are at yearly frequency), that include democracy indicator, population (total with percentage of urban population or urban population separately), per capita income levels and to take into account the role played by information exchange and communication, internet penetration and cellphone subscriptions, the latter two being the number of users/subscribers.[16]

As explained later, I make use of exogenous shocks in prices of international food commodities (defined exactly the same way as for local prices–i.e. relative deviation of current price level from the average price in the previous four months), as IV for consistent estimation.

The average duration of a cropping cycle is 3-5 months for most staples. I also control for seasonal effects in the ensuing analysis by taking dummies for four-month periods. Hence it is the change in prices over and above the 'natural' change from one season to the next, that is internalized by the consumer.

[16]From Cheibub, Gandhi, and Vreeland (2010), a regime is considered a democracy if the executive and the legislature is directly or indirectly elected by popular vote, multiple parties are allowed, there is de facto existence of multiple parties outside of regime front, there are multiple parties within the legislature, and there has been no consolidation of incumbent advantage (e.g. unconstitutional closing of the lower house or extension of incumbent's term by postponing of subsequent elections). Transition years are coded as the regime that emerges in that year.

The values taken up by this variable is the price shock in any of the six commodities in table 5, corresponding to the most important local crop.

4.2 Descriptive statistics

Table 6 displays the cities in our sample that experienced some kind of an incidence of disturbance and for which the corresponding monthly price shock of the main food item is known. Table 7 shows for the cities that experienced the two kinds of events, namely spontaneous and organised, the average price shocks during the two scenarios. During periods of spontaneous social disturbances the food price shocks were on an average almost three times higher than food price changes when these disturbances were not recorded. At the same time, notice that relative food price shocks were lower on average when organized events were recorded.

Table 8 compares the country-level covariates between the countries that experienced spontaneous incidents of social unrest and those that did not do so over the period 1990-2010.[17] Notable differences between the countries in whose major cities which spontaneous social disturbances did take place are in terms of real income and democracy. Incidents of spontaneous social unrest tend take place to be in a high-income and more democratic environment. In view of its exponential growth in the recent years, starting from nil in the 1990s, figure 3 shows the exponential trend in internet penetration over the years.

Table 9 displays the summary statistics of the international price series used for creating the instrumental variable (the relative deviation).

[17]Countries experiencing incidents of social disturbance might inherently be different due to, among others political, cultural or embedded socio-economic factors.

4.3 Empirical strategy and specification

Our purpose of this section of the study is to estimate the causal impact of shocks in relative prices on occurence of incident of spontaneous riots or demonstrations in order to lay firm basis for the foregoing theoretical model and assumptions and conceptual framework. Use of local prices is both consistent with theory and intuition as well as provides statistical spatial and temporal variation as shown in table 10. However as Carter and Bates (2012) argue, local prices are subject to intervention by government as an instrument of preemptively appeasing the urban populace.[18] This lends support to the use of (exogenous) international price shocks as IV for consistent estimation in the possible presence of reverse causality.

$$E_{ijmy} = \alpha_{0i} + \alpha_1 \cdot \left(\frac{\Delta p_f}{p_f}\right)_{im} + \alpha_2 \cdot y + \alpha_3 \cdot X_{jy} + \alpha_4 \cdot s + \epsilon_{ijmy}$$

Here, the left hand side is an indicator variable for occurrence of an event in city i in country j in month m and year y.

The coefficient of interest is α_1, s is the season fixed effect (separate dummies for January-April, May-August and September to December), y being the year fixed-effects. The data structure is of a panel form with city-month as a unit of observation. α_{0i} are the city level fixed effects. X_{jy} is the vector of country-level covariates varying annually. They include the binary indicator of democracy, population of the country to take into account the size effect, urban population as a percentage of total population internet penetration (as measured by number of internet users per 100 of the country's population) and as additional check for improved communication, cellphone subscriptions (per 100 of the population).

In order to account for the serial-correlation within the panels and possible correlation across countries in a particular year, robust estimation by

[18]This is even at the cost to the exchequer, the gains being political.

clustering at two-level (country-year level) was peformed (Arellano, 1987). As Schaffer (2005) notes, however, with clustering the possibility of the covariance matrix of orthogonality conditions being not of full rank increases. In this situation efficient estimation is not feasible and the solution is to "partial" out exogenous regressors from all the other variables (other regressors and excluded instruments), so that the corresponding coefficients are not calculated. Nevertheless the coefficients of rest of the variables are unaffected. For efficiently estimating the coefficient of interest namely that on the relative price shock, it was observed necessary to "partial out" the democracy indicator (besides the usual dummies controlling for varying intercepts for different years, countries and seasons) or the total population as needed.

For consistent estimation, I employ panel-IV estimation (controlling for fixed-effects as mentioned above) using standard two-stage least squares with the instruments being the relative changes in the international market price of the selected food item. Results of further diagnostic tests are reported in the following section.

5 Results

5.1 First stage

The first stage estimates are shown in table 11 with the columns corresponding to the different specifications. The international food price shocks are significantly correlated with the corresponding local food price shocks. The test statistics for underidentification and weak identification, the Angrist-Pischke (AP) first-stage chi-squared and F statistic, respectively indicate the relevance of our instrument.[19]

[19]Note that I take the shock in international prices corresponding to the same time period as the shock in local prices. The transmission rate argument does not bite too much as the main urban cities, which are generally the chief consumers of imported goods

5.2 Second stage

Column 1 of table 12 provides the estimation results of our main specification but using simple OLS regression with fixed effects.[20] Comparing with column 2 (which provides the final estimates for the 2-SLS regression), one finds that failure to take into account endogeneity can lead to biased estimates to the extent that the sign of the coefficient of interest is reversed.

The results indicate that a positive 100 percent change (shock) in price of the staple food crop significantly increases the probability of incidence of a spontaneous riot or demonstration by almost 20-25 percent and the size and significance levels are consistent with regard to different specifications. Among other covariates that affect the incidences of spontaneous events of unrest are population of the country and cellphone subscription rate, and both do so negatively which is counterintutive. As a first guess, larger countries might have more diffused population and greater number of cities than represented in the sample. Due to the country covariates being far more aggregate than the level of analysis, drawing mechanism-based long conclusions is a non-trivial task.

5.3 Robustness checks

In order to check for robustness of above results, I also perform exactly the same analysis using only positive shocks for prices (both in explanatory and the dependent variable), that would take the value of zero in case of negative shocks as well as the reverse i.e., taking the negative shocks (positive being zero). The results as shown in table 13 are consistent with the view that the urban centers are chiefly food consumers (that positive food price

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are more integrated with the international markets (to the extent being subject to govt. policies) than the interior regions.

[20] Clustering, however is possible at one level, that at the country level being more meaningful

shocks should increase discontent and vice-versa), albeit the association with positive food price shock is not significant, but still the magnitude agrees well with earlier results.[21] Estimation using organised riots or demonstrations as the dependent variable yields insignificant results thereby underlining the fore-mentioned need to focus on the appropriate event of political instability and validating our theoretical assumptions on substitutability in response to a sudden shock in food prices.

6 Conclusion

It is an artifact of Engel's Law that people from low-income countries would spend a major share of their incomes for food consumption. This paper studies the role played by food prices in instilling grievances and inducing incidents of urban social unrest for 43 cities in Asia and Africa. Being motivated by the much media-hyped events of 2008 which concurred with the food crisis, I find an important role for "shocks" in local food prices in leading to spontaneous incidents of riots and disturbances. Sudden deviations in prices of a basic necessity as food in our case can play a major role in shaping the decision to participate in collective action as shown in the model, for a typical urban-dweller, who most likely would happen to be a food-consumer.

As far as policy implications are concerned, much less is known about the direct relationship between food price changes and unrest and its exact form. Besides providing a political economic justification for enacted policies both in anticipation, as well as measures of response, better insights in the impact of food prices on social unrest is valuable, not only because it helps to understand real world events, but also because it may allow assess the real cost and benefits of food price changes. This study is a step in that direction that focuses on a particular class of agents (urban-dwellers) and specific kind

[21]Interestingly, this *is* significant if the population is not logged.

of incidents of unrest (spontaneous riots and demonstrations).

References

Acemoglu, D., & Robinson, J. A. (2001, September). A theory of political transitions. *American Economic Review*, *91*(4), 938-963. Retrieved from http://ideas.repec.org/a/aea/aecrev/v91y2001i4p938-963.html

Anderson, K., Hayami, Y., & et al. (1986). *The political economy of agricultural protection: East asia in international perspective.* Allen and Unwin:London.

Anderson, K., Ivanic, M., & Martin, W. J. (2013, October). Food Price Spikes, Price Insulation, and Poverty. In *The Economics of Food Price Volatility* (p. 311-339). National Bureau of Economic Research, Inc. Retrieved from http://ideas.repec.org/h/nbr/nberch/12818.html

Anderson, K., & Nelgen, S. (2010). How do governments respond to food price spikes? lessons from the past. *Journal of International Commerce, Economics and Policy (JICEP)*, *1*(02), 265-285. Retrieved from http://ideas.repec.org/a/wsi/jicepx/v01y2010i02p265-285.html

Arellano, M. (1987, November). Computing robust standard errors for within-groups estimators. *Oxford Bulletin of Economics and Statistics*, *49*(4), 431-34. Retrieved from http://ideas.repec.org/a/bla/obuest/v49y1987i4p431-34.html

Arezki, R., & Bruckner, M. (2011, March). *Food Prices, Conflict, and Democratic Change* (School of Economics Working Papers No. WP/11/62). IMF. Retrieved from http://ideas.repec.org/p/adl/wpaper/2011-04.html

Attanasio, O., Maro, V. D., Lechene, V., & Phillips, D. (2013). Welfare consequences of food prices increases: Evidence from rural Mexico. *Journal of Development Economics*, *104*(C), 136-151. Retrieved from http://ideas.repec.org/a/eee/deveco/v104y2013icp136-151.html

Bellemare, M. (2014, June). Rising Food Prices, Food Price Volatility, and Social Unrest. *American Journal of Agricultural Economics*, To appear.

Blattman, C., & Miguel, E. (2010). Civil war. *Journal of Economic Literature*, *48*(1), 3-57. Retrieved from http://www.aeaweb.org/articles.php?doi=10.1257/jel.48.1.3 doi: 10.1257/jel.48.1.3

Booth, S. L., Sallis, J. F., Ritenbaugh, C., Hill, J. O., Birch, L. L., Frank, L. D., ... Hays, N. P. (2001). Environmental and societal factors affect food choice and physical activity: Rationale, influences, and leverage points. *Nutrition Reviews*, *59*(3), S21–S36. Retrieved from http://dx.doi.org/10.1111/j.1753-4887.2001.tb06983.x doi: 10.1111/j.1753-4887.2001.tb06983.x

Carter, B., & Bates, R. H. (2012). Public policy, price shocks, and civil war in developing countries.

Cheibub, J., Gandhi, J., & Vreeland, J. (2010, April). Democracy and dictatorship revisited. *Public Choice*, *143*(1), 67-101. Retrieved from http://ideas.repec.org/a/kap/pubcho/v143y2010i1p67-101.html

Collier, P., & Hoeffler, A. (2004). Greed and grievance in civil war. *Oxford Economic Papers*, *56*(4), 563-595. Retrieved from http://oep.oxfordjournals.org/content/56/4/563.abstract doi: 10.1093/oep/gpf064

Crop prospects and food situation (No. 3). (2008, July).

Deaton, A. (1989, Supplemen). Rice Prices and Income Distribution in Thailand: A Non-parametric Analysis. *Economic Journal*, *99*(395), 1-37. Retrieved from http://ideas.repec.org/a/ecj/econjl/v99y1989i395p1-37.html

de Gorter, H., & Tsur, Y. (1991). Explaining price policy bias in agriculture: The calculus of support-maximizing politicians. *American Journal of Agricultural Economics*, *73*(4), pp. 1244-1254. Retrieved from http://www.jstor.org/stable/1242452

De Mesquita, E. B. (2010, August). Regime change and revolutionary entrepreneurs. *American Political Science Review*, *104*, 446–466. Retrieved from http://journals.cambridge.org/article_S0003055410000274 doi: 10.1017/S0003055410000274

Dube, O., & Vargas, J. F. (2013). Commodity Price Shocks and Civil Conflict: Evidence from Colombia. *Review of Economic Studies*, *80*(4), 1384-1421. Retrieved from http://ideas.repec.org/a/oup/restud/v80y2013i4p1384-1421.html

Easterly, W., & Levine, R. (1997, November). Africa's growth tragedy: Policies and ethnic divisions. *The Quarterly Journal of Economics*, *112*(4), 1203-50. Retrieved from http://ideas.repec.org/a/tpr/qjecon/v112y1997i4p1203-50.html

Elbadawi, I., & Sambanis, N. (2002). How much war will we see? explaining the prevalence of civil war. *The Journal of Conflict Resolution*, *46*(3), pp. 307-334. Retrieved from http://www.jstor.org/stable/3176229

Gardner, B. (1989). *Price supports and optimal spending on agricultural research* (Working Paper 88-01). Deptt. of Agricultural Economics, University of Maryland.

Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology*, *83*(6), pp. 1420-1443. Retrieved from http://www.jstor.org/stable/2778111

Hendrix, C., Haggard, S., & Magaloni, B. (2009, February). *Grievance and*

Opportunity: Food Prices, Political Regime and Protests.

Kaempfer, W. H., & Lowenberg, A. D. (1992, June). Using threshold models to explain international relations. *Public Choice*, *73*(4), 419-43. Retrieved from http://ideas.repec.org/a/kap/pubcho/v73y1992i4p419-43.html

Klosko, G., Muller, E. N., & Opp, K. D. (1987). Rebellious collective action revisited. *The American Political Science Review*, *81*(2), pp. 557-564. Retrieved from http://www.jstor.org/stable/1961968

Kuran, T. (1989). Sparks and prairie fires: A theory of unanticipated political revolution. *Public Choice*, *61*(1), 41-74.

Lohmann, S. (1993). A signaling model of informative and manipulative political action. *The American Political Science Review*, *87*(2), pp. 319-333. Retrieved from http://www.jstor.org/stable/2939043

Lohmann, S. (1994). Information aggregation through costly political action. *American Economic Review*, *84*(3), 518-30. Retrieved from http://EconPapers.repec.org/RePEc:aea:aecrev:v:84:y:1994:i:3:p:518-30

Lohmann, S. (2000). Collective action cascades: An informational rationale for the power in numbers. *Journal of Economic Surveys*, *14*(5), 655–684. Retrieved from http://dx.doi.org/10.1111/1467-6419.00128 doi: 10.1111/1467-6419.00128

Miguel, E., Satyanath, S., & Sergenti, E. (2004, August). Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of Political Economy*, *112*(4), 725-753. Retrieved from http://ideas.repec.org/a/ucp/jpolec/v112y2004i4p725-753.html

Möller, M. (2011). *Economic voting and economic revolutionizing? The economics of incumbency changes in European democracies and revolutionary events in the Arab World* (CIW Discussion Papers No. 10/2011). University of Münster, Center for Interdisciplinary Economics (CIW). Retrieved from http://ideas.repec.org/p/zbw/ciwdps/102011.html

Morris, S., & Shin, H. S. (2000, September). *Global Games: Theory and Applications* (Cowles Foundation Discussion Papers No. 1275R). Cowles Foundation for Research in Economics, Yale University. Retrieved from http://ideas.repec.org/p/cwl/cwldpp/1275r.html

Muller, E. N., & Opp, K.-D. (1986). Rational choice and rebellious collective action. *The American Political Science Review*, *80*(2), pp. 471-488. Retrieved from http://www.jstor.org/stable/1958269

Nunn, N., & Qian, N. (2012). Aiding conflict: The unintended consequences of us food aid on civil war. *NBER Working Paper Series*.

Olson, M. (1965). *The logic of collective action* (First ed.). Cambridge: Harvard University Press.

Opp, K.-D. (1988). Grievances and participation in social movements. *American Sociological Review*, *53*(6), pp. 853-864. Retrieved from http://www.jstor.org/stable/2095895

Pearl, J. (2014). Understanding simpson's paradox. *The American Statistician*, *68*, 8-13.

Peterson, H. H., & Tomek, W. G. (2005, November). How much of commodity price behavior can a rational expectations storage model explain? *Agricultural Economics*, *33*(3), 289-303. Retrieved from http://ideas.repec.org/a/bla/agecon/v33y2005i3p289-303.html

Ponticelli, J., & Voth, H.-J. (2011). *Austerity and anarchy: Budget cuts and social unrest in europe, 1919-2009* (Working Paper). Center for Economic Policy Research. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1899287

Schaffer, M. E. (2005, November). *Xtivreg2: Stata module to perform extended iv/2sls, gmm and ac/hac, liml and k-class regression for panel data models.* Statistical Software Components, Boston College Department of Economics. Retrieved from `http://ideas.repec.org/c/boc/bocode/s456501.html`

Schneider, M. (2008). *"we are hungry!" a summary report of food riots, government responses, and states of democracy in 2008* (Tech. Rep.). Development Sociology: Cornell University.

Seale, J., Jr., Regmi, A., & Bernstein, J. (2003, October). *International evidence on food consumption patterns* (Tech. Rep. No. 1904). USDA. Retrieved from `http://www.ers.usda.gov/publications/tb1904/tb1904.pdf`

Swinnen, J. (1994). A positive theory of agricultural protection. *American Journal of Agricultural Economics*, *76*(1), 1-14.

Swinnen, J. (2011). The right price of food. *Development Policy Review*, *29*(6), 667–688. Retrieved from `http://dx.doi.org/10.1111/j.1467-7679.2011.00552.x` doi: 10.1111/j.1467-7679.2011.00552.x

Swinnen, J., Banerjee, A., & de Gorter, H. (1994). Economic development, institutional change and the political economy of agricultural protection: An empirical study of belgium since the 19th century. *American Journal of Agricultural Economics*, *76*(1), 1-14.

Urdal, H. (2008). *Urban social disorder in asia and africa: Report on a new dataset* (Tech. Rep.). International Peace Research Institute (PRIO).

van Jaarsveldt, L. (2011). *Are social networking sites effective platforms for political engagement?* Unpublished master's thesis, National Chengchi University.

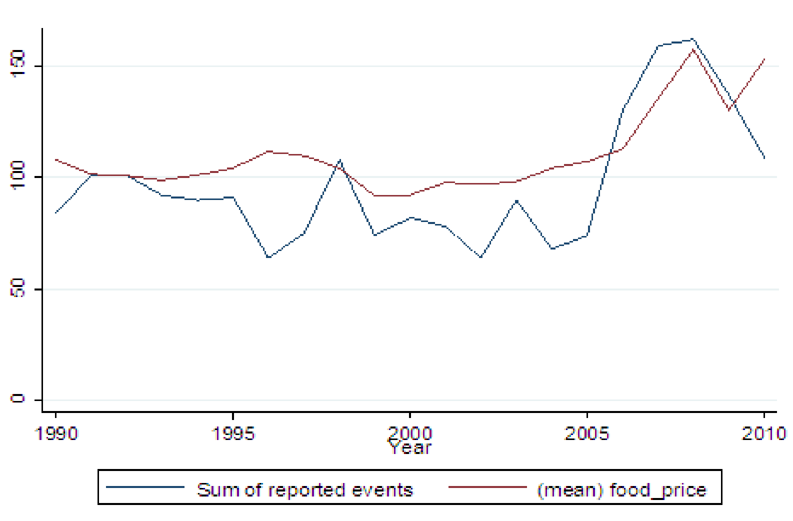
Verba, S., Schlozman, K. L., & Brady, H. E. (2000). Rational action and political activity. *Journal of Theoretical Politics*, *12*(3), 243-268. Retrieved from `http://jtp.sagepub.com/content/12/3/243.abstract` doi: 10.1177/0951692800012003001

Yin, C.-C. (1998). Equilibria of collective action in different distributions of protest thresholds. *Public Choice*, *97*(4), pp. 535-567. Retrieved from

http://www.jstor.org/stable/30024447

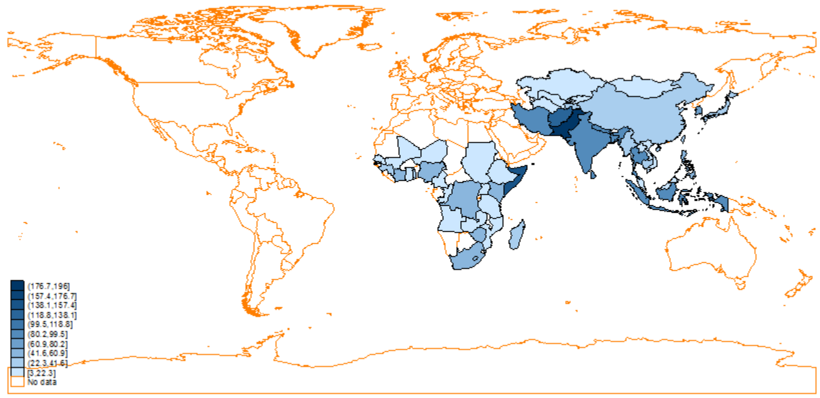
A Figures

Figure 1: Event reportage and international food price index correlation



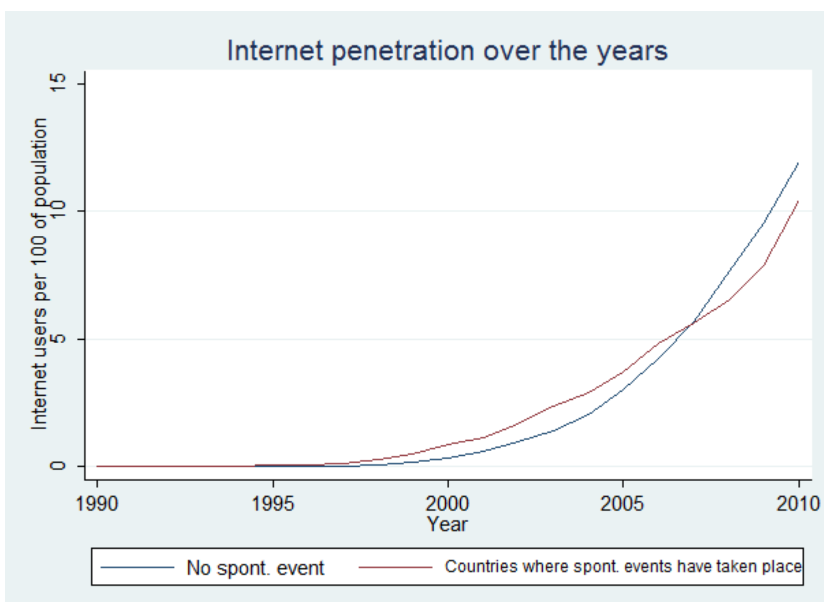
Source: FAO, Food price index calculated by export weighted average of 6 commodity price indices, USDAA dataset for events

Figure 2: Spatial coverage of all events of PRIO'S Urban Social Disturbance in Asia and Africa dataset



Note: The intensity of the shade indicates the number of events over the period 1990-2010.

Figure 3: Internet penetration over the years



Source: WDI indicators

B Tables

Table 2: Variable sources and features

Variable	Source	Spatial coverage	Temporal coverage	Frequency
Urban Social Disturbances	USDAA, PRIO, Oslo	55 cities (49 countries)	1960-2010	Event-based
Local food prices	FAO GIEWS database	43 markets (in common with USDAA)	1990-Present (unbal-anced)	Monthly
Total population	WDI 2010	190 countries	1960-2010	Annual
Urban population (as p.c. of total)	WDI 2010	190 countries	1960-2010	Annual
Internet penetration	WDI 2010	177 countries	1960-2010	Annual
Cellphone subscription rate	WDI 2010	177 countries	1960-2010	Annual
Percapita GDP (constant, 2000)	WDI 2010	248 countries	1960-2010	Annual
Index of democracy	QoG database, U of Gothenberg	202 countries	1960-2008	Annual
International food prices	FAO GIEWS database	13 Export price series	2000-Present	Monthly

Table 3: Event categories in the USDAA dataset

PTYPE	Event description
10	General Warfare
20	Inter-communal warfare
30	Armed battle/clash
31	Armed attack
40	Pro-govt terrorism(Repression)
41	Anti-govt terrorism
42	Communal terrorism
50	Organized violent riot
51	Spontaneous violent riot
60	Organized demonstration
61	Pro-govt demonstration
62	Spontaneous demonstration

Table 4: Local food price series used in the analysis

Country	Price series selected	Retail (R)/Wholesale(W)	Real(R)/Nominal(N)	Location
Afghanistan	Bread	R	R	Kabul
Bangladesh	Rice	W	N	Dhaka
Cambodia	Rice	W	N	Phnom Penh
Cameroon	Maize	R	N	Yaonde
China (for both Beijing and Lhasa)	Wheat	R	N	NA
DRC	Cassava	R	N	Kinshasa
Ethiopia	Sorghum	W	N	Addis Ababa
Ghana	Maize	R	R	Accra
Guinea	Imported rice	R	N	Conakry
India	Rice	R	R	Patna
	Wheat	R	R	Delhi
	Wheat	R	R	Mumbai
Indonesia	Rice	R	R	NA
Kazakhstan	Bread	R	R	Almaty
Kenya	Maize	W	N	Nairobi
Kyrgyzstan	Bread	R	R	Bishkek
Laos	Glutinous Rice Grade 1	R	N	NA
Madagascar	Imported Rice	W	R	NA
Mali	Imported Rice	W	N	Bamako
Mongolia	Wheat	R	R	Ulaan Bator
Mozambique	Maize	R	N	Maputo
Myanmar	Rice	R	N	NA
Nepal	Rice	R	R	Kathmandu
Niger	Imported rice	R	R	Niamey
Nigeria	Maize	W	R	Kano
Pakistan	Wheat flour	R	R	Lahore
	Wheat flour	R	R	Karachi
Philippines	Regular rice	R	R	Manila
Senegal	Imported Rice	R	R	Dakar
Somalia	Sorghum	R	N	Mogadishu
South Africa	Wheat	W	R	Randfontain
Sri Lanka	White Rice	R	R	Colombo
Sudan	Sorghum	W	R	Khartoum
Tajiskistan	Bread	R	R	Dushanbe
Tanzania	Maize	W	R	Dar es Salaam
Thailand	25% broken rice	W	R	Bangkok
Togo	White Maize	R	R	Lome
Uganda	Maize	W	R	Kampala
Vietnam	Rice	R	R	Hanoi
	25 % broken rice	R	N	Dong Thap
Zambia	White Maize	R	R	NA
Zimbabwe	Maize	R	N (USD)	Harare

Note: NA stands for National Average.

Table 5: City-wise international price series selected for creating IV

City	Instrumenting international price (Export), USD/kg
Accra	USA: Gulf - Maize (US No. 2 Yellow)
Addis Ababa	USA: Gulf - Sorghum (US No. 2 Yellow)
Almaty	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Antananarivo	Thailand: Bangkok - Rice (Thai 100% B)
Bamako	Thailand: Bangkok - Rice (Thai 100% B)
Bangkok	Thailand: Bangkok - Rice (25% broken)
Beijing	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Bishkek	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Calcutta	Thailand: Bangkok - Rice (Thai 100% B)
Colombo	Thailand: Bangkok - Rice (Thai 100% B)
Conakry	Thailand: Bangkok - Rice (Thai 100% B)
Dakar	Thailand: Bangkok - Rice (Thai 100% B)
Dar es Salaam	USA: Gulf - Maize (US No. 2 Yellow)
Delhi	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Dhaka	Thailand: Bangkok - Rice (Thai 100% B)
Dushanbe	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Hanoi	Thailand: Bangkok - Rice (Thai 100% B)
Harare	USA: Gulf - Maize (US No. 2 Yellow)
Islamabad	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Jakarta	Thailand: Bangkok - Rice (Thai 100% B)
Johannesburg	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Kabul	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Kampala	USA: Gulf - Maize (US No. 2 Yellow)
Karachi	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Kathmandu	Thailand: Bangkok - Rice (Thai 100% B)
Khartoum	USA: Gulf - Sorghum (US No. 2 Yellow)
Kinshasa	USA: Gulf - Maize (US No. 2 Yellow)
Lagos	USA: Gulf - Maize (US No. 2 Yellow)
Lhasa	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Lomé	USA: Gulf - Maize (US No. 2 Yellow)
Lusaka	USA: Gulf - Maize (US No. 2 Yellow)
Manila	Thailand: Bangkok - Rice (Thai 100% B)
Maputo	USA: Gulf - Maize (US No. 2 Yellow)
Mogadishu	USA: Gulf - Sorghum (US No. 2 Yellow)
Mumbai	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Nairobi	USA: Gulf - Maize (US No. 2 Yellow)
Niamey	Thailand: Bangkok - Rice (Thai 100% B)
Phnom Penh	Thailand: Bangkok - Rice (Thai 100% B)
Rangoon	Thailand: Bangkok - Rice (Thai 100% B)
Saigon	Thailand: Bangkok - Rice (25% broken)
Ulan Bator	USA: Gulf - Wheat (US No. 2 Soft Red Winter)
Vientiane	Thailand: Bangkok - Rice (Glutinous 10%)
Yaounde	USA: Gulf - Maize (US No. 2 Yellow)

Table 6: Spontaneous incidents recorded by city

City	No. of incidents recorded
Antananarivo	2
Bangkok	5
Bishkek	2
Calcutta	3
Colombo	2
Conakry	3
Dakar	1
Delhi	8
Dhaka	17
Harare	1
Islamabad	2
Johannesburg	1
Kabul	3
Kampala	3
Karachi	10
Kathmandu	4
Khartoum	2
Lagos	1
Lomé	3
Manila	6
Maputo	3
Mogadishu	2
Nairobi	2
Niamey	3
Rangoon	2
Ulan Bator	1
Yaounde	1
Total	93

Table 7: Average relative price shocks in cities with incidents of unrest in alternative situations

	Observations	Mean Relative price shock	Std Dev
Panel A			
Spontaneous event	93	0.044	0.219
No spontaneous event	2380	0.015	0.149
Panel B			
Organised event	108	0.011	0.117
No organized event	2365	0.017	0.154

Table 8: Descriptive statistics of country-level yearly covariates

	Countries experiencing spont. events of disturbance			Countries not experiencing spont. events of disturbance		
	Obs	Mean	Std Dev.	Obs	Mean	Std. Dev
Urban population (percent)	525	32.527	13.186	273	30.994	11.883
GDP per capita (constant, USD, year 2000)	462	643.516	700.011	270	488.737	480.186
Democracy indicator (Binary)	474	0.409	0.492	242	0.178	0.383
Internet penetration (users/100 of population)	418	2.739	4.598	213	2.916	5.954
Cellphone subscribers (users/100 of population)	524	10.857	20.657	270	12.015	24.364

Table 9: Summary statistics of international price series (USD/kg) used for generating IV

Market of origin	Crop	Obs	Mean	Std. Dev.	Min	Max
USA: Gulf	Sorghum (US No. 2 Yellow)	148	0.149595	0.061077	0.08	0.3
USA: Gulf	Maize (US No. 2 Yellow)	148	0.148716	0.065996	0.08	0.32
USA: Gulf	Wheat (US No. 2 Soft Red Winter)	148	0.178987	0.070293	0.09	0.4
Thailand: Bangkok	Rice (Glutinous 10%)	148	0.507703	0.251294	0.27	1.1
Thailand: Bangkok	Rice (25% broken)	148	0.318378	0.157683	0.14	0.87
Thailand: Bangkok	Rice (Thai 100% B)	148	0.366149	0.182543	0.17	0.96

Table 10: Summary statistics of relative price shocks

City	Obs	Mean	Std. Dev.	Min	Max
Kabul	92	-0.0041	0.070824	-0.19242	0.231037
Dhaka	164	-0.00739	0.075295	-0.17305	0.23991
Phnom Penh	73	-0.02634	0.102338	-0.3578	0.194853
Yaonde	83	-0.02147	0.055269	-0.20198	0.13199
China (NA)	37	-0.01724	0.021006	-0.07297	0.03706
Kinshasa	61	0.006416	0.293231	-0.44434	1.828859
Addis Ababa	146	-0.01845	0.091181	-0.35844	0.196809
Accra	46	0.005394	0.214406	-0.4375	0.789474
Conakry	29	-0.05208	0.138227	-0.30631	0.388889
Delhi	143	0.003675	0.048596	-0.12572	0.151429
Mumbai	143	0.001652	0.041635	-0.10113	0.217199
Kolkata	143	-0.00172	0.065865	-0.20488	0.249358
Almaty	71	-0.00341	0.04855	-0.25762	0.066365
Nairobi	74	-0.00301	0.155817	-0.3023	0.550287
Laos (NA)	247	-0.02819	0.11398	-0.33296	0.594118
Madagascar (NA)	71	0.00357	0.059994	-0.19148	0.163765
Bamako	74	-0.00524	0.07451	-0.15323	0.285714
Ulan Bator	59	0.005913	0.093852	-0.21316	0.252225
Maputo	222	-0.0076	0.187811	-0.35972	0.837255
Myanmar (NA)	63	-0.02201	0.048181	-0.16451	0.073828
Kathmandu	81	0.003595	0.111116	-0.31475	0.452668
Niamey	143	-0.00069	0.04538	-0.11891	0.179232
Kano (Lagos)	100	0.017134	0.159076	-0.35678	0.516444
Karachi	90	0.003988	0.083315	-0.28484	0.28703
Lahore	90	0.000839	0.062821	-0.16777	0.204776
Manila	143	0.002549	0.043114	-0.20392	0.166902
Randfontain (Jo'berg)	144	-0.00462	0.11491	-0.25211	0.386961
Dakar	59	-0.00667	0.081434	-0.35594	0.135213
Colombo	58	-0.00275	0.079038	-0.22561	0.219307
Mogadishu	193	0.021409	0.272176	-0.65587	1.124969
Khartoum	123	0.030684	0.162166	-0.31322	0.75
Dushanbe	35	-0.00999	0.063258	-0.25	0.0375
Dar es Salaam	72	0.038401	0.191616	-0.3375	0.566667
Bangkok	144	-0.00194	0.087053	-0.4606	0.266341
Lome	131	0.023916	0.234612	-0.45535	1.319782
Kampala	72	0.056647	0.276202	-0.38333	0.944444
Hanoi	37	-0.01905	0.084528	-0.17348	0.146505
Zambia (NA)	93	0.029299	0.17554	-0.18088	0.669176
Harare	64	0.009918	0.36594	-0.65741	1.431034
Dong Thap (Saigon)	50	-0.00098	0.164537	-0.28472	0.474246
Bishkek	83	-0.0021	0.055554	-0.3278	0.094031
Indonesia (NA)	48	-0.01342	0.031748	-0.08882	0.046573

Note: NA stands for National Average.

Table 11: First-stage results

	(1)	(2)	(3)	(4)
Dependent variable-Local food price shock	Model 1	Model 2	Model 3	Model 4
International food price shock	0.167***	0.167***	0.171***	0.168***
	(0.040)	(0.040)	(0.038)	(0.038)
Democracy	PO	PO	PO	PO
Country population, logged	-0.002		0.284	0.287
	(0.498)		(0.571)	(0.579)
Percentage of country population urban	0.001		0.000	0.000
	(0.004)		(0.004)	(0.004)
Urban population of country, logged		-0.028		
		(0.188)		
Real income (per capita GDP, 2000 USD), logged	0.134	0.132	0.193	0.195
	(0.135)	(0.112)	(0.173)	(0.166)
Internet users (per 100 of population)	0.001	0.001	-0.000	
	(0.003)	(0.002)	(0.004)	(0.001)
Cellphone subscribers (per 100 of population)			0.001	0.001
			(0.001)	(0.001)
Observations	2,226	2,226	2,215	2,227
AP Chi-sq (1)	19.99	19.61	23.01	22.43
(Underid)				
P-val	0.0000	0.0000	0.0000	0.0000
AP F (1,8)	17.64	17.32	20.30	19.80
(Weak id)				
Stock-Yogo weak ID test critical value for single endogenous regressor				
10% maximal IV size	16.38	16.38	16.38	16.38

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

PO stands for Partialled Out

All estimates rounded off to 3 significant digits

Table 12: Regression results

	(1)	(2)	(3)	(4)	(5)
Dependent variable-Spont. Event	OLS	Model 1	Model 2	Model 3	Model 4
Local food price shock	-0.053***	0.219*	0.225*	0.214*	0.213*
	(0.019)	(0.113)	(0.116)	(0.117)	(0.114)
Democracy	-0.020	PO	PO	PO	PO
	(0.512)				
Country population, logged	-0.506	-0.484		-0.911*	-0.915*
	(0.372)	(0.433)		(0.526)	(0.534)
Percentage of country population urban	-0.004	-0.003		-0.002	-0.002
	(0.005)	(0.006)		(0.006)	(0.006)
Urban population of country, logged			-0.102		
			(0.148)		
Real income (per capita GDP, 2000 USD), logged	0.350	0.005	0.064	-0.070	-0.072
	(0.096)	(0.099)	(0.096)	(0.084)	(0.085)
Internet users (per 100 of population)	-0.002	-0.002	-0.002	0.000	
	(0.002)	(0.002)	(0.001)	(0.001)	
Cellphone subscribers (per 100 of population)				-0.001**	-0.001**
				(0.001)	(0.001)
Constant	Yes	Yes	Yes	Yes	Yes
City-fixed Effects	Yes	Yes	Yes	Yes	Yes
Seasonal dummies	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,329	2,226	2,226	2,215	2,227

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

PO stands for Partialled Out

All estimates rounded off to 3 significant digits

Cluster-robust standard errors reported, clustered by country for OLS and country-year for Models 1-4

Table 13: Robustness checks (Second stage-results)

	(1)	(2)	(3)
Dependent variables →	Spont. event	Spont. event	Org. event
Local food price shock			-0.211
			(0.175)
Positive local food price shock	0.211		
	(0.224)		
Negative local food price shock		-0.490*	
Democracy	PO	PO	-0.034
			(0.037)
Country population, logged	-0.446	-0.581	-0.363
	(0.372)	(0.484)	(0.309)
Percentage of country population urban	-0.002	-0.004	-0.008***
	(0.006)	(0.007)	(0.002)
Real income (per capita GDP, 2000 USD), logged	0.022	-0.001	0.032
	(0.077)	(0.110)	(0.093)
Internet users (per 100 of population)	-0.002*	-0.003	-0.003
	(0.001)	(0.002)	(0.003)
Constant	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Seasonal dummies	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Observations	2,226	2,226	2,226

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

PO stands for Partialled Out

All estimates rounded off to 3 significant digits

Cluster-robust standard errors reported, clustered country and year

C Derivation of expression for utility change in terms of change in price of food

Given the utility function in 1, let us derive the expression for utility loss when there is a food price shock, Δp_f. The budget constraint is

$$p_f \cdot q_f + p_n \cdot q_n = y \tag{6}$$

where y is the income, p_i and q_i are the prices and quantities of commodity $i \in \{f, n\}$, where f and n denote food and non-food, respectively.

Standard utility maximization subject to budget constraint entails finding the stationary points of the following Lagrangian with λ as the Lagrangian multiplier. Writing the Lagrangian and subsequently substituting the functional form of the utility function, we have

$$\mathcal{L}(q_f, q_n, \lambda) = U(q_f, q_n) - \lambda(p_f \cdot q_f + p_n \cdot q_n - y) \tag{7a}$$

$$\mathcal{L}(q_f, q_n, \lambda) = q_f^a . q_n^{(1-a)} - \lambda(p_f \cdot q_f + p_n \cdot q_n - y) \tag{7b}$$

Taking the partial derivatives with respect to each of the arguments, we have the following first order conditions:

$$\frac{\partial \mathcal{L}}{\partial q_f} = 0 = a q_f^{a-1} \cdot q_n^{1-a} - \lambda p_f \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial q_n} = 0 = (1-a) q_f^a \cdot q_n^{-a} - \lambda p_n \tag{9}$$

FOC with respect to λ is just the budget constraint, 6.

Eliminating λ from 8 and 9, we obtain the optimal quantities $q_f^\star$ and $q_n^\star$ as

$$q_f^\star = a \cdot (y/p_f) \tag{10a}$$

$$q_n^\star = (1-a) \cdot (y/p_n) \tag{10b}$$

Now, from 7 we have

$$\lambda^\star = \frac{\left.\frac{\partial U}{\partial q_f}\right|_{q_f^\star, q_n^\star}}{p_f} = \frac{\left.\frac{\partial U}{\partial q_n}\right|_{q_f^\star, q_n^\star}}{p_n}$$

Substituting for the above optimal quantities into the expression for the partial derivative of the utility function in 1 yields the optimal value of the Lagrangian multiplier.

$$\lambda^\star = [(1-a)/p_n]^{(1-a)}.[a/p_f]^a \tag{11}$$

Minimum expenditure at prices $\mathbf{p}$ and maximum utility (as given by the indirect utility function) that can be achieved at prices $\mathbf{p}$ and income y is equal to income y. Or in the language of mathematics,

$$e(\mathbf{p}, v(\mathbf{p}, y)) = y = p_f \cdot q_f^\star + p_n \cdot q_n^\star \tag{12}$$

Supposing that there is a change in food price levels, Δp_f, the change in the expenditure function (or the cost of living) can be expressed as a second order Taylor series expansion.

$$\Delta e = q_f^\star \cdot \Delta p_f + 0.5 \cdot \sigma_{ff} \cdot [\Delta p_f]^2 \tag{13}$$

In the above equation, we make use of the Shephard's Lemma and the fact that the Hicksian (compensated) demand at the optimal utility level is the Marshallian demand itself. σ_{ff} is the derivative of the Hicksian demand of food with respect to the price of food and is the relevant diagonal element of the substitution matrix (own-price substitution effect). Now, the substitution matrix is negative semi-definite and $\sigma_{ff} \leq 0$, the impact on costs of living thus being cushioned by the possibility of substitution. However, the focus of our analysis on the most important food commodity in the diet as well as on short-term impact using high-frequency data allows us to make an important assumption; we assume negligible substitution which allows us to proceed without second term in the last in equation 13.[22] [23]

$$\Delta e \approx q_f^{\star} \cdot \Delta p_f \tag{14}$$

By definition of minimum expenditure function, 14 represents the amount of transfer needed to keep the agent at the earlier utility level in the new scenario of changed price levels. In other words it is the utility loss expressed in monetary terms. To calculate the actual utility loss, we make use of the interpretation of the Lagrangian multiplier as the 'shadow price' or the change in marginal utility with respect to relaxing or tightening the budget constraint.

Change in optimal utility level can be approximated by the following expression,

$$\Delta U = \lambda^{\star} \cdot \Delta e \tag{15}$$

where e is the minimum expenditure.

[22]Not to mention the fact that it is more coherent with the idea of a spontaneous event

[23]Seale, Jr., Regmi, and Bernstein (2003) uses a two-stage demand estimation technique to estimate the slutsky term for own-price elasticities of food commodities for the long-term at constant real income (closest number available to get a sense of magnitude of σ_{ff} for our purposes). Overall for 91 countries, it is around -0.15 for bread and cereals which is at the higher end considering other food commodities. As Booth et al. (2001) note, dietary habits are not trivially broken.

Substituting for e from 14 and the value of the Lagrangian multiplier from 11 leads us to 2.[24]

$$\Delta U = [(1-a)/p_n]^{(1-a)} \cdot [a/p_f]^a \cdot q_f \cdot \Delta p_f \tag{2}$$

D Derivation of inequality 3

Inequality 3 on which an agent bases her decision whether or not to protest is obtained by weighing the expected pay-offs from following each of the two strategies i.e. protesting or not. Given cumulative distribution function, F(.) of the thresholds K_i as defined in section 3 above, the probability of a successful protest is $P[N^e \geq K_i] = F(N^e)$. Hence the probability of an unsuccessful protest is given by $1 - F(N^e)$. The expected pay-offs from each of the two decisions is obtained using the entries in 1. Given the parameters, we have

$$\begin{aligned}\text{Expected payoff from not protesting} = (1 - F(N^e)) \cdot (-\Delta U) \\ + F(N^e) \cdot (1-\gamma) \cdot \Delta U\end{aligned} \tag{16}$$

$$\begin{aligned}\text{Expected payoff from protesting} = (1 - F(N^e)) \cdot (-\frac{k}{N^e} - \Delta U) \\ + F(N^e) \cdot (\Delta U - \frac{k}{N^e})\end{aligned} \tag{17}$$

Based on 16 and 17, the agent will protest if the following holds good,

$$\begin{aligned}(-\Delta U) + p(\Delta U) + p(\Delta U) - \gamma p(\Delta U) \leq -\frac{k}{N^e} - (\Delta U) + p \cdot \frac{k}{N^e} \\ + p(\Delta U) + p(\Delta U) - p(\frac{k}{N^e})\end{aligned} \tag{18}$$

[24]Note that we could derive exactly the same result using the Envelope Theorem. However the above proof is more intutive.

where p represents $F(N^e)$

Simple cancellation of terms leads us to 3.

E More on generation of local and international price series

Local food price series The most important requirement in order to address our question of interest is to find in a sense, the 'dearest' food commodity (in terms of habits or preferences and access the latter, the idea being the 'closest' series to the ultimate urban food consumer. The food items for which the local prices were selected are based on a number of criteria.[25] More or less in decreasing order of relevance, these are the following. [26]

- Dietary Energy Supply

  It is the percentage of energy supply provided by the food crop in the average diet.

- Urban consumption pattern

  This was an important criteria that determined the exceptions to the DES. If the chiefly urban crop was second in terms of DES but the difference wasn't significantly large, then its price series was selected.

- Retail vs wholesale

  Retail being preferred to wholesale.

- Processed

[25]These are at the country level sourced from the FAO.

[26]I also corroborated the available information by interviewing nationals from sampled countries.

For instance bread is preferred over wheat

- Imported vs local

  Prices of the imported item are chosen over local prices as primary consumers for the imported item tend to be urban residents. Besides, it lends further relevance to the instrument.

- Market location

  The price prevailing at closest market to the city for which unrest data was available (but according to the preferences of the latter). E.g. Prices of rice in Patna for Kolkata and that of maize in Kano for Lagos.

Exceptions were only made in case of missing values and highly significant correlation.

International food price series The instrumental variables used for the estimation of effects of price shocks were the corresponding international prices of the local food item selected previously (taking into account the preferences in the dietary habits of the populace). Amongst the many choices 6 series were selected as these shared a great amount of correlation with similar crops exported from other countries but had the least missing values. An exceptional case is that of Kinshasa where cassava is selected as the relevant local crop (DES criterion) but due to good correlation with local maize prices, the instrumenting series is that of (shocks) in international maize prices.

F Conceptual framework

This addendum aims to provide a conceptual framework based on thresholds in the sense of Granovetter (1978).

F.1 Understanding protests: How *thresholds* matter for the domino effect

The discussion in sections 1 and 2, points towards the fact that changes in food prices imply a negative welfare impact for at least a part of the population in the sense of Attanasio, Maro, Lechene, and Phillips (2013). This likely generates grievances, in particular material or economic grievances stemming from relative or absolute deprivation, both in the temporal sense as well as spatially or across individuals, especially if the impact is heterogenous. The theory of protest movements focuses on the coordination or collective action problem. It is well documented that economic theory, assuming self-interested rational individuals, predicts an undersupply of collective action due to the classic free-ridership problem (Olson, 1965). At the same time, the frequent occurrence of mass demonstrations and protests contradicts this basic economic insight. This has led to two strands of literature that try to reconcile this apparent contradiction.

The general framework for analysing the origin and subsequent propagation of collective action is based on models of threshold and critical mass. While the literature focuses on mass action for revolutions or regime change, these can be easily extended to study protest movements. A threshold is defined as the minimal proportion (or number, as per the context) of the population who must be perceived as protesting before an individual decides to join the protest. Applications of the threshold model to explain collective action are varied. Granovetter (1978) examines the effect of small disturbances in the initial threshold distribution on riots. Kaempfer and Lowenberg (1992) discuss the how external shocks can influence group incentives (as well as the change in critical mass) to engage in collective action. They base their comparative static framework by explicitly including in the protestors' utility function, probability of success, cost of participation, reputational utility and opportunity costs of contributing effort to interest group objective. Kuran (1989) studies ex-ante unpredictability of revolutions based on a model of 'preference falsification' as follos. Political movements cannot be explained by models based on rational preferences alone and, instead, a person places value on the act of political expression itself (e.g. (Opp, 1988; Klosko, Muller, & Opp, 1987; Muller & Opp, 1986; Verba, Schlozman, & Brady, 2000)). Even as Kuran (1989) explains spontaneous revolutions, a number of features translate directly when it comes to protests in the case of protests. Essentially, in her decision to protest, a person i makes a trade-off between two costs. On the one hand, a person who privately opposes the regime, but fails to express her opinion publicly, has an internal cost (the so-called preference falsification). This cost increases with the level of private discontent, x_i, but can be removed when the person decides to express herself, i.e. participate in the protest movement. However, on the other hand, the public expression of one's private opinion comes with a cost, e.g. the risk of being persecuted for outspokenness, and/or facing government security forces or hostile supporters of the government. Importantly, this external cost at the time of decision to participate or not falls with the size of the (perceived) public opposition, which is denoted by S. Considering both the internal and external cost, i's publicly revealed preference depends on S and x_i. For each person i with internal cost stemming from corresponding level of discontent, x_i, there exists a value of S for which the external cost falls below her internal cost and i publicly expresses her opinion. This switching value can be referred to as person i's public opposition threshold T_i. [27] Hence, even in a heterogeneous society in which people differ in their private preferences and public opposition thresholds T_i, mass protest can occur because a minor change in x_i for one or more individuals can increase the size

[27] And, vice versa, for each individual i and a given level of S, there exists a level of discontent x_i for which the internal cost exceeds the external cost.

in S and set in motion a process in which the value of S reaches the public opposition threshold of an increasing number of individuals. In the words of (Kuran, 1989) "a suitable shock would put in motion a bandwagon process that exposes a panoply of social conflicts, until then largely hidden" (p.42).

Consider the following example. Imagine a 10-person society featuring a threshold sequence, $\langle T_i \rangle_{i=1\cdots10}$ with $T_i \leq T_{i+1}$, $T_1 = 0$ and $T_{10} = 10$ meaning that person 1 will always express her opinion publicly and person 10 will never do so (needs 10 other people, excluding herself). For the other eight persons in society having 'interior' thresholds, the decision will depend on the relation between perceived opposition S and the threshold T_i. Assume for example that $T_2 = 2$ then person 2 will express her opinion publicly if $S \geq 2$, in other words if at least 2 people are expected to join apart from herself.[28] A price shock can mobilize person 2 only if the shock increases person 2's discontent (x_2, in our notation in the previous paragraph sufficiently to lower her threshold value T_2 from 2 to 1. The the price shock has two effects—directly lowering thresholds and indirectly facilitating the domino effect (in this case making it easier for person 3 to join in once 2 has joined). Thus, whether or not a price shock leads to protests depends on the size of the price shock, the initial distribution of the threshold sequence and the impact of the price shock on the threshold sequence. As in (Yin, 1998), the c.d.f. of normally distributed thresholds can be represented by a logistic function

$$G(T_i) = [(1 + exp(-\lambda(T_i - \mu))]^{-1} \tag{19}$$

Where μ is the mean (location) parameter $\in (0,1)$ which is the average threshold level of the population; and λ is a dispersion (or scale) parameter $\in (0,\infty)$. The inverse of λ is a measure of the spread of the distribution.

[28]Here an individual threshold, T_i is the proportion of total population of co-participants needed to instigate a person to protest.

F.2 Role of information in protests

While there are models based on uncertain and stochastic shocks to pay-offs leading to coordination as in global games (Morris & Shin, 2000), models based on information aggregation and updating of beliefs by potential joinees based on their observations of actions by other strategic actors are familiar in the theoretical literature for modelling revolutions and regime change. For example De Mesquita (2010) shows how (strategic) violent acts by revolutionary vanguards might lead non-participants to believing that the support for the revolution is more than what it seems and decrease their perceived costs of participation (or less stringent thresholds). The dynamic informational cascade theory (Lohmann, 1993, 1994, 2000) belongs to a strand of literature that has developed several theories on how collective action can emerge from rational behaviour at the level of the individual. It is particularly relevant in our case, since it highlights the role of information streams and signalling, allowing us to formulate hypotheses on the role of online communication in present-day mass mobilization.

Let us first highlight a number of distinctive features of the Lohmann model and then integrate these into the framework of the previous section to illustrate how a dynamic theory of informational cascades can yield new insights. The most important distinctive feature of Lohmann's theory is that an individual's action not only contributes to overturning the status quo in a given period (because, as in Kuran's model, it makes the number of people taking costly action exceed a critical threshold), but it also signals the actor's information about the status quo (the quality of a policy, regime, etc) and influences other people's decisions to act or abstain. This signaling function of an action makes an individual action non-negligible in overturning the status quo, which explains why rational individuals that care about overturning the status quo engage in costly collective action. There are explicit gains in overturning the status quo, in addition to the x_i (in the Kuran framework), the internal cost stemming from preference falsification. This is of course also a positive function of discontent with the current status quo;now the trade-off results from a rational calculus apart from a feeling of psychological discomfort.

Turning back to the examples above, upon the shock ΔP, person a protestor takes the costly action of publicly revealing her preferences, not because doing so reliefs her from her psychological discomfort, but because she knows that her action can set in motion a protest movement that can change the status quo. However, as discussed, it could be the case that for a given threshold distribution (e.g. in the case of subsequent threshold in the sequence being far larger) it is not sufficient for mass mobilization to unfold. At this point, the signaling function of an action comes into play. The subsequent protestor having this high value of threshold observes the action of the initial protestor and updates her (imperfect) observation about the pros and cons of the status quo, affecting the value of her threshold. Concurrently, other people having higher threshold values observe the action of person 2 and may also update their perception of the status quo. If the signal is strong enough, the shock ΔP may put in motion the bandwagon in populations which might be otherwise impermeable to protests. This examples illustrates that, if mass behaviour results as a by-product of rational behaviour of a decentralized mechanism of information aggregation and updating, even small shocks can gain momentum.

An important note to make is that the strength of the signal, i.e. the value attached to the information, depends on the type of the sender. For example, moderates will attach less importance to signals send by extremists than to signals send by other moderates because moderates know that the preferences of extremists may not be in line with their own preferences. In the words of Lohmann (2000) "The participation of moderates (actors who generate reliable informational cues) is crucial for the success of a social movement, but the (uninformative) turnout of 'extremists' is discounted." Because of this feature, the impact of group heterogeneity is not monotonous. In fact: "Overall, the maximum degree of information revelation is associated with the degree of group heterogeneity that maximizes the number of activist moderates."

Now that we have illustrated the basic insights of Lohmann's complex model (in an admittedly simplistic way), we are ready to hypothesize about the possible impact of mass media and online (political) communities. Firstly, both mass media and online communities allow the public to take notice of the signals sent, whereas otherwise many signals may be blocked by those that benefit from a status quo. Second, both may be instrumental in coordinating action in the sense that the former reduces information asymmetries and the latter is a tool in enhancing the simultaneity of turnout, e.g. by agreeing on the timing and location of turnout. Such coordination is important because a mass demonstration takes place when sufficient people lower their thresholds. Thirdly, online communities play an additional role by allowing individuals to signal their perception of the status quo at a very low cost. This new form of signalling is a double-edged sword. On the one hand, it lowers the value of the signal because receivers know that the risks of signalling are much lower. On the other hand, it increases the number of senders, and importantly, especially among the moderates, who otherwise might have found the cost of signaling too high. In sum, this discussion highlights the role of online networking as a tool that can significantly contribute to the power of informational cascades. van Jaarsveldt (2011) empirically shows how social networking sites play a significant role in online political engagement and information seeking both by political parties (supply side) and the voters (demand side).