Rising Food Prices, Food Price Volatility, and Social Unrest*

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March 6, 2014

Abstract

Can food prices cause social unrest? Throughout history, riots have frequently broken out, ostensibly as a consequence of high food prices. Using monthly data at the international level, this paper studies the impact of food prices – food price levels as well as food price volatility – on social unrest. Because food prices and social unrest are jointly determined, data on natural disasters are used to identify the causal relationship flowing from food price levels to social unrest. Results indicate that for the period 1990-2011, food price increases have led to increases in social unrest, whereas food price volatility has not been associated with increases in social unrest. These results are robust to alternative definitions of social unrest, to using real or nominal prices, to using commodity-specific price indices instead of aggregated price indices, to alternative definitions of the instrumental variable, to alternative definitions of volatility, and to controlling for non-food-related social unrest.

Keywords: Food Prices, Price Volatility, Food Riots, Social unrest

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* I am indebted to two anonymous reviewers, Gani Aldashev, Chris Barrett, Samuel Bazzi, Chris Blattman, Ed Carr, Jeff Conroy-Krutz, Kim Yi Dionne, Jay Hamilton, Rasmus Heltberg, Scott Irwin, Marc Jeuland, Anirudh Krishna, Ken Lee, Jean-François Maystadt, Gabriel Power, Joe Ritter, Cyrus Samii, and Satoru Shimokawa for their helpful suggestions. I also thank seminar audiences at the Center for Global Development, NC State, the University of Illinois at Urbana-Champaign, and UC Davis as well as conference participants at the December 2011 MGAPE meeting and the 2012 Midwest International Economic Development Conference. This work would not have been possible without the excellent research assistance of Kevin Fishner and Laura Paul.

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1. INTRODUCTION

Can food prices cause social unrest? Throughout history, riots have often broken out in areas with high concentration of poor households, ostensibly as a consequence of high food prices. Since the turn of the millennium, the world has experienced two major food crises, which were both associated with food riots. The first food crisis took place in 2008. Although food prices increased by 3 percent between January 2007 and December 2008, they increased by 51 percent between January 2007 and March 2008. This rise in food prices was associated with food riots in several developing and emerging countries across Africa, Asia, Europe, and the Americas (Schneider, 2008; Bush, 2010; Paarlberg, 2010; Berazneva and Lee, 2011), going so far as to cause Haitian prime minister Jacques-Édouard Alexis to resign (Collier, 2008).[1]

The second food crisis, which began at the end of 2010 and saw food prices increase by 40 percent between January 2010 and February 2011, has culminated in the summer of 2011 with famine in the Horn of Africa. Once again, a rapid rise in food prices was associated with social unrest throughout the world, which does raise the broader question of whether food prices can, in fact, cause social unrest.[2] Figure 1 plots the relationships between the main measure of social unrest used in this paper and the FAO's food price index, which a measure of the price of food worldwide, a relationship that is positive, and thus suggestive of a potentially causal relationship.[3]

To further complicate the relationship between food prices and social unrest, there is some confusion among policy makers and commentators about what is the precise mechanism through which food prices may cause social unrest. For some, rising food prices (i.e., increases in the price of food) cause social unrest. Economists have long known (see, for example, Deaton, 1989) that

[1] The expression "social unrest" is used throughout this paper to designate instance of social unrest that are or appear related to food. This is not only limited to food riots, as the main dependent variable used in this paper also includes food-related social movements other than food riots: demonstrations, mobs, protests, strikes, unrest, or episodes of violence.

[2] Although some have associated the Arab Spring – a series of events that began with riots in Algeria and in Tunisia in early January 2011 and which led to the collapse of the Ben Ali regime in Tunisia and of the Mubarak regime in Egypt – with food prices (Ciezadlo, 2011), an anonymous reviewer pointed out that the Arab Spring began with an incident with a policewoman that led to a suicide, and angered people because of the arrogance and corruption of the state, not because food was too expensive. The protesters were apparently calling for dignity, democracy, and jobs, not cheaper food.

[3] A precise definition of how "social unrest" is defined in this paper is provided in section 4, when discussing how each variable retained for analysis was measured.

an increase in the price of a commodity, although it increases the welfare of the households who are net sellers of that commodity (i.e., households whose production exceed their consumption of that commodity), decreases the welfare of the households who are net buyers of the same commodity (i.e., households whose consumption exceed their production of that commodity), and there are numerous instances of social unrest associated with rising food prices throughout history (Rudé, 1964; Walton and Seddon, 1994; Schneider, 2008; Bush, 2010).

For others, food price volatility (i.e., increases in the uncertainty surrounding food prices) is the culprit. A senior analyst at the Brookings Institution noted in March 2011 that “the crux of the food price challenge is about price volatility rather than high prices per se ... It is the rapid and unpredictable changes in food prices that wreak havoc on markets, politics and social stability” (Kharas, 2011). In that spirit, the FAO convened its High-Level Panel of Experts on Food Security and Nutrition at the end of 2010 with the explicit goal of exploring the causes and consequences of food price volatility.

Given that food prices occupy a place of increasing importance in the global policy discourse, this paper takes a closer look at the relationship between food prices and social unrest. More specifically, this paper looks at two research questions. First, it looks at whether the relationship between food price levels and social unrest is causal. Because food prices and social unrest are jointly determined, however, the prevalence of natural disasters is used as an instrumental variable in an attempt to exogenize food price levels relative to social unrest. The idea behind this empirical setup is that an unpredictable shock to the supply and demand of food that occurs in one part of the world can affect world food prices, and a change in world food prices makes it more or less likely to observe food riots in other parts of the world in the short term (Lofchie, 1975). Second, this paper compares the differential impacts food price levels and food price volatility have on social unrest in an attempt to contribute to the debate between those who argue that rising food prices cause social unrest and those who argue that food price volatility causes social unrest.

Using monthly data at the global level, the empirical results indicate that for the period 1990-2011, rising food prices have led to increased social unrest, whereas food price volatility – here, the coefficient of variation (i.e., standard deviation divided by mean) of the food price series over the previous three or six months – has not had the posited effect on social unrest.[4] In fact, in the best of cases, food price volatility is actually associated with *de*creases in social unrest. In the worst of cases, there is simply no statistically significant relationship between food price volatility and social unrest. This is not to say that food price volatility is desirable; food price volatility today can lead to decreased output – and thus higher food prices – in the future (Clapp, 2009; Naylor and Falcon, 2010). But it does mean that it is difficult if not impossible to make the case that food price volatility causes social unrest.

This paper is part of a growing literature at the intersection of economics and political science studying the determinants of riots (DiPasquale and Glaeser, 1998; Bohlken and Sergenti, 2010), but it is perhaps closest in spirit to a working paper by Arezki and Brückner (2011), who look at the relationship between food prices and political instability. The analysis in this paper differs from that of Arezki and Brückner in an important way, however: this paper relies on monthly food price data, whereas Arezki and Brückner use annual food price data. The advantage of using monthly data is that this allows capturing short-term (i.e., month-to-month) price fluctuations. This is important given that people are more likely to react to short-term (i.e., monthly) changes in food price levels and volatility than they are to react to long-term (i.e., annual) changes in price levels and volatility. In addition, this study looks at the impact of food price volatility, whereas Arezki and Brückner's does not. As such, and also because both papers rely on different identification strategies, the analyses in both papers are complementary.

Given increasingly integrated world food markets, ever higher volumes of food commodities are being traded. This means that food prices are increasingly correlated, and so episodes of rising food prices – which are expected to occur more frequently given the threat to agricultural productivity posed by climate change (Lobell et al., 2011; Burke and Emerick, 2013; Massetti et al., 2013) – will be increasingly correlated across countries. Thus, if there is a causal relationship between food prices and social unrest, this could ultimately mean that episodes of social unrest will occur simultaneously across countries, which means that food prices have the potential to

[4] Though Jin and Kim (2012) show that the coefficient of variation can amplify the measurement of food price volatility when food price series are nonstationary, the unit root tests conducted below indicate that using the coefficient of variation is an adequate measure of volatility in this context.

cause irreversible damage to the health of affected populations by depriving them of nutrients and causing them to be malnourished (Haddad et al., 1999; Webb, 2010) as well as to be a destabilizing geopolitical force. Of course, the results in this paper do not imply that food prices are the only cause of food riots. Goldstone (1982) notes that food riots usually break out when high food prices are accompanied by widespread unemployment, and food riots certainly appear more likely in a poor city like Lagos than they are in a wealthy city like New York City. Likewise, the results in this paper do not imply that rising food prices inevitably cause social unrest, nor do they imply that rising food prices are the only cause of social unrest. Rather, the objective of this paper is to show that food prices can cause social unrest while remaining agnostic about the precise mechanism through which they do so, and to show that food prices are *one* of the causes of social unrest.

2. FOOD RIOTS THROUGHOUT HISTORY

Throughout history, food-related social unrest has been frequent. Food riots are thought to have helped bring about the French Revolution (Rudé, 1964), the fall of the Confederate States of America (Smith, 2011), the Russian Revolution (Wade, 2005), and the fall of the British Raj in India (Arnold, 1979). Although there are several studies of food riots in the historical and sociological literatures, there are few quantitative studies. In order to put the empirical results in this paper in their proper context, what follows is an overview of food riots in modern and contemporary history.[5]

The earliest such study is Rudé's (1964) investigation of social movements – food riots, labor disputes, and political protests – in France and England between 1730 and 1848. Rudé begins with the "disastrous harvest and famine of 1709" (p.19) in France and goes on to discuss how bad harvests and other natural disasters in 1787 "stirred the whole countryside into a renewed outbreak of rebellion, which played a vital part in the revolutionary crisis of 1789" (p.20) that marked the beginning of the French Revolution. Between 1709 and 1789, however, food riots occurred in France as a consequence of bad harvests and subsequent shortages in 1725, 1740, 1749, 1768,

[5] For a survey of the social science literature on riots broadly defined, see Wilkinson (2009).

1775, and 1785. Yet until the French Revolution, food riots were not political in nature.[6] Rather, rioters targeted farmers, merchants, and traders in an effort to force a decrease in food prices. This phenomenon is known to historians as *taxation populaire* (Tilly, 1971), i.e., a situation in which farmers, merchants, and traders are made to pay a "tax to the people" by forgoing some profit or incurring a loss as a consequence of the price ceiling imposed by rioters.

In England where, as a consequence of the Industrial Revolution, a greater share of the population was composed of net consumers of food than in relatively more rural France, Rudé notes that "[o]f some 275 disturbances that [he has] noted between 1735 and 1800, two in every three" (p.35) were food riots. Moreover, food riots tended to break out more often in the north and west than in the south and east of England given that food – more specifically, grain – was exported from the latter to the former.

A discussion of more recent food riots can be found in Walton and Seddon (1994), who study the impact of the International Monetary Fund's (IMF) structural adjustment programs on the economies of the developing world between 1970 and the early 1990s. According to Walton and Seddon, even though food riots had largely disappeared from the political landscape after the middle of the 19th century, they reappeared in the 1970s as a consequence of an increasingly integrated world economy in which local food prices were increasingly determined by the international political economy.

Walton and Seddon note that with the exception of Ceylon's *hartal* in 1953, in which countrywide food riots broke out in response to the government eliminating rice subsidies, there were only few food riots between the middle of the 19th century and the 1970s,[7] and the few that occurred were local, sporadic events.[8] The mid-1970s saw a resurgence of food riots, however, as Walton and Seddon count 146 food riots across 39 countries in response to austerity policies

[6] Citing Clark (1976), Walton and Seddon (1994) note that before the French Revolution, "there was no question of overthrowing the government or established order, of putting forward new solutions, or even of seeking redress of grievances by political action" (p. 29).

[7] See Taylor (1996) for a study of some of the food riots that broke out in the first half of the 20th century.

[8] The food riots of 2001 in Argentina (Auyero and Moran, 2007) were also local in the sense that they did not occur in a context where food riots broke out in several countries.

imposed by the IMF's structural adjustment policies between 1976 and 1992. What began in Peru in July 1976 and Egypt in January 1977 peaked in the mid-1980s and ended in India in February 1992 and Nepal in April 1992. Walton and Seddon's volume includes also case studies of food riots in Latin America, Africa, as well as in the Middle East and North Africa.

The "classical" food riots studied by Rudé (1964) often took place in the countryside and involved the rural poor (i.e., individuals and households who, even though they might have produced some food themselves, remained net buyers of food). By contrast, the "modern" food riots studied by Walton and Seddon (1994) almost always took place in cities and involved the urban poor and the working class (i.e., individuals and households do not produce any food, and who are thus a lot more dependent on food purchases than rural households). Classical and modern food riots also differ in their targets: whereas the targets of classical food riots were local food producers suspected of price gouging and grain merchants suspected of speculating, the targets of modern food riots were supermarkets, government institutions, and symbols of foreign affluence such as luxury hotels.

It is still too early for the history of recent food riots to have been written, but Schneider (2008) provides an overview of the riots that took place across Africa, Asia, Latin America, and the Middle East during the food crisis of 2008. For each of the 25 countries in which there were food riots, Schneider provides a description of the rioting that took place, of the government's response to social unrest, and of the state of democracy. Bush (2010), for his part, displays a great deal of foresight in his discussion of the consequences of the 2008 food riots in the Middle East and North Africa by pointing to the fact that the Mubarak regime in Egypt was likely to collapse as a consequence of unsustainable food policies, a year before it actually did so. Lastly, Berazneva and Lee (2011) conduct an empirical investigation of the 2007-2008 food riots in Africa and find a positive correlation between food riots and poverty, but their analysis cannot make a causal statement.

3. EMPIRICAL FRAMEWORK

The contribution of this paper lies in the way it identifies the impact of food prices on social unrest. This section thus discusses the equations to be estimated and the identification strategy used here to establish the causal impact of food prices on social unrest.

The first equation to be estimated in this paper is

$$y_t = \alpha_1 + \beta_{1f} f_t + \beta_{1\sigma}\sigma_t + \beta_{1y} y_{t-1} + \beta_{1m} m_t + \beta_{1\tau}\tau_t + \epsilon_{1t}, \tag{1}$$

where the unit of observation t is a given month, y_t denotes the level of food-related social unrest in month t; f_t denotes the food price level; σ_t denotes three-month coefficient of food price variation in food price volatility, i.e., the standard deviation of the food price series divided by the mean of the price series over the months t, $t-1$, and $t-2$;[9] y_{t-1} denotes social unrest in the previous month in order to account for the potential carryover of media stories from one month to the next; m_t is a vector of monthly indicator variables; τ_t is a time trend, and ϵ_t is an error term with mean zero.

Because food riots tend to occur in poor countries, where the average diet consists mainly of cereals, equation 1 is initially estimated twice: once for an index of the overall price of food in real terms (which controls for the general price level, and so it controls income levels since most people's income is derived from their wage, which are the price of labor), and once for an index of the price of cereals, also in real terms. Though this provides a first robustness checks on the empirical results, four additional robustness checks are conducted using specific price indices for maize, rice, soybeans, and wheat. If food prices are exogenous to social unrest, coefficients β_{1f} and $\beta_{1\sigma}$ respectively represent the average treatment effects (ATE) of food prices on social unrest

[9] The coefficient variation is thus a measure expressing the food price volatility as a percentage of the food price level. A three-month food price coefficient of variation of zero would thus mean that the food price index has remained constant over the last three months. A robustness check is conducted in section 5 which relies instead on six-month coefficients of food price variation, i.e., the standard deviation of the food price series divided by the mean of the food price series over the months t to $t-5$. An additional robustness check is conducted in section 5 which relies on implied rather than historical volatility. That is, on the coefficient of variation of food prices over the next three months rather than over the last three months. Implied volatility is used under the assumption that people are forward-looking and have rational expectations. A previous version of this paper used the three-month standard deviation instead of the three-month coefficient of variation as its measure of volatility, without any qualitative change to the results.

and the ATE of food price volatility on social unrest. Appendix A discusses the results of unit root tests for the variables used in equation 1 as well as of tests of serial correlation.[10]

As was discussed in the introduction, the primary objective of this paper is to assess whether food prices cause social unrest. Because social unrest and food prices are jointly determined, however, the next section discusses the identification strategy used in this paper to make a causal statement about the impact of food prices on social unrest.

(a) Identification Strategy

Food prices cannot be argued to be exogenous to social unrest in equation 1. Therefore, a great deal of thought must be given to how to make a causal statement about the impact of food prices on social unrest.

Before doing so, however, it is worth pointing out that the specification in equation 1 does not assume that there is perfect price transmission from (global) food prices to (local) food riots, i.e., that local price movements perfectly track global price movement. In fact, a test of the null hypothesis H_0: $\beta_{1f} = 0$ against the alternative hypothesis H_A: $\beta_{1f} \neq 0$ is itself a test of whether prices are integrated enough from the global to the local level so as to make increases in global food prices cause food riots at the local level. In order to ensure that any rejection of the null does not simply happen by happenstance, the test just described is run several times in this paper, for several different definitions of the dependent variable, for several different definitions of food prices, and for several different specifications of the core regression in equation 1, as described below.

The identification strategy used to do so in this paper relies on the use of an instrumental variable (IV), i.e., a variable that is correlated with food prices but arguably uncorrelated with the

[10] A reviewer pointed out that the presumed causal relationship considered here, from food prices to food riots, would lend itself nicely to process tracing, a methodology whose aim is "to generate and analyze data on the causal mechanisms, or processes, events, actions, expectations, and other intervening variables, that link putative causes to observed effects" (Bennett and George, 1997). While that method would allow precisely identifying which causal mechanisms makes people riot when food prices increase, such an analysis is beyond the scope of this paper. This paper is concerned with whether there is a causal relationship flowing from food prices to food riots rather than with the precise causal mechanism through which such a relationship operates.

error term in equation 1. Recall that an IV must satisfy two requirements. First, it must be correlated with food prices. This is easily ascertained with statistical tests – in effect, tests of the null hypothesis that the instrument is weak – the results of which are shown in section 5. Second, it must only affect social unrest through food prices, a requirement that is also known as meeting the exclusion restriction. Because one cannot test this latter assumption, this section discusses its validity in this context.

The variable used to identify the causal relationship between food prices and social unrest in this paper is the number of natural disasters – all droughts, earthquakes, epidemics, episodes of extreme temperature, floods, insect infestations, mass movements (both dry and wet),[11] storms, volcanic eruptions, and wildfires – in a given month. That droughts, episodes of extreme temperature, floods, insect infestations, and storms constitute shock to the supply and demand of food should be relatively uncontroversial. Earthquakes, epidemics, mass movements, volcanic eruptions, and wildfires are included because they are also included in the official definition of "natural disaster" provided by the Center for Research on the Epidemiology of Disasters' (CRED), where the natural disasters data used in this paper come from.[12] Therefore, it would be ill-advised to drop types of natural disasters arbitrarily and exclude them from the count of natural disasters used here. Besides, earthquakes, epidemics, mass movements, volcanic eruptions, and wildfires can all depress economic growth, which leads to reduced incomes and thus to a decreased demand for food.

The identifying assumption is thus that natural disasters are uncorrelated with ϵ_2 in the equation

$$y_t = \alpha_2 + \beta_{2f}\hat{f}_t + \beta_{2\sigma}\sigma_t + \beta_{2y}y_{t-1} + \beta_{2m}m_t + \beta_{2\tau}\tau_t + \epsilon_{2t}, \tag{2}$$

where $\hat{f}_t$ is the predicted value of f_t obtained from the first-stage regression of food prices on natural disasters and all the control variables in equation 2, which is such that

[11] Mass movements are hazards such as landslides, rockfalls, subsidences, and other instances of debris, land, or snow falling down a mountainside. The dry/wet distinction is made to distinguish between geophysical and hydrological hazards.

[12] Robustness checks are conducted in section 5 which rely on a narrower definition of natural disaster.

$$f_t = \alpha_3 + \beta_{3n} n_t + \beta_{3\sigma} \sigma_t + \beta_{3y} y_{t-1} + \beta_{3m} m_t + \beta_{3\tau} \tau_t + \nu_{3t}, \qquad (3)$$

where n_t is the number of natural disasters in period t, ν_t is an error term with mean zero, and all other variables are defined as above. Just as in the case of equation 1, equations 2 and 3 are estimated six times (once for food, once for cereals, and once each for maize, rice, soybeans, and wheat) so as to provide a robustness check on the overall results. If the instrument is valid and effectively exogenizes food prices relative to social unrest, the coefficient β_{2f} is the local average treatment effects (LATE) of food prices on social unrest, i.e., the increase in the extent of social unrest (as measured by the dependent variable) due to food prices *in those months where natural disasters induce a change in food prices* (Angrist and Pischke, 2009).

One might also wish to use the number of natural disasters in period t as an instrument for food price volatility in addition to instrumenting for the food price level, and thus to run an additional first-stage regression like equation 2 with σ_t as the dependent variable. But this would be what Wooldridge (2002, p.236) refers to as a "forbidden regression," since each endogenous variable requires its own instrument. It is thus because there is only one instrument available in this case that the empirical results on the impact of food price volatility on social unrest cannot be argued to be causal.

How are natural disasters a good IV for food prices in the context of equations 2 and 3? Within a given month, natural disasters constitute unpredictable shocks to both the supply of and demand for food.[13] Although the use of rainfall as an IV has recently been questioned due to the predictable nature of rainfall (see the discussion of Miguel et al., 2004 in Sovey and Green, 2011 and in Sarsons, 2011), the natural disasters used in this paper are unpredictable. Indeed, although some of the natural disasters included in the IV are certainly more likely in certain seasons (e.g., droughts, episodes of extreme temperature, and floods), the presence of monthly dummies in

[13] Although natural disasters are usually conceived of as shocks to the supply of food (Del Ninno et al., 2003), the fact that natural disasters can kill or displace large numbers of people makes them equally – if not more – likely to also affect the demand for food. Indeed, there are many more consumers of food than there are producers of food, and so exposure to natural disasters should affect consumers of food disproportionately more than they affect producers of food.

equations 2 and 3 eliminates the predictability of natural disasters by controlling for seasonality. In other words, while it is true that droughts are more likely in the summer, and thus a priori (somewhat) predictable within a given year, natural disasters should be unpredictable once the month is controlled for. Similarly, the inclusion of a time trend should control for increases in the number of food riots, food prices, food price volatility, and the number of natural disasters due to the passage of time. The inclusion of a time trend should thus control for the fact that the number of natural disasters has risen sharply between 1900 and 2010, along with the number of people affected and the estimated value of the damages caused by those same disasters (CRED, 2011).

Even though it is not possible for social unrest to cause natural disasters, could a natural disaster occur early in a given month and influence the degree of social unrest later on in the same month through a variable other than food prices? The World Bank (2010, p.49), for example, notes that disaster relief is often used by those who oversee its distribution as an additional weapon in civil conflicts. Likewise, Polman (2010) provides several examples where relief, assistance, and the efforts of nongovernmental organizations were captured by specific groups and used as weapons in civil conflicts. Additionally, the Indonesian government used some of the assistance it received after the tsunami of December 2004 to pacify some of the Free Aceh Movement insurgents, in which case disaster relief was used to foster peace rather than conflict (World Bank, 2010, p.49). Such occurrences, however, are highly unlikely given that the median lag on emergency shipment of relief aid is more than four months (Barrett and Maxwell, 2005).

Likewise, natural disasters could lead to job losses via destroyed capital, which would make it easier to recruit disaffected and disenfranchised populations as combatants in civil conflict. Once again, it is unlikely that this compromises the empirical results. Indeed, for this to happen, it would need to be the case that a natural disaster directly leads to social unrest in the same country as the one in which it takes place, which would in turn require that that region or country is a price maker, i.e., that it has enough market power so as to significantly affect food or cereal prices worldwide. This is not impossible, but it is highly unlikely given the scope of the data, the fact that world markets are well integrated and that only few countries have enough market power to significantly affect the price of food, and the short time frame (i.e., one month) of each observation.

Although it is possible that, within a given month, a natural disaster occurs that influences the degree of social unrest within the same month through a variable other than food prices, the dependent variable used in this paper makes this unlikely. Indeed, the main dependent variable only measures instances of food-related social unrest, and not of protests, demonstrations, riots, strikes, etc. related to other resources, so the likelihood that n_t is correlated with ϵ_{2t} is very low.

An anonymous reviewer pointed out that because natural disasters constitute shocks to both the demand for and the supply of food, the effect of the IV on the endogenous variable might not be monotonic. When the effect of an IV on the endogenous is non-monotonic, one must assume homogeneous treatment effects, otherwise the LATE theorem might not hold. Appendix B shows that the assumption of homogeneous treatment effects is likely to hold here, and so the remainder of this paper proceeds under that assumption.

Lastly, one might argue that equations 1 and 2 omit income as a control variable, which might compromise the identification of the causal impact of the level of food prices on social unrest. The core results in this paper, however, rely on real food prices, which control for the general price level (and thus for income, given that people's income is largely derived from their wage, which is the price of their labor).

The next section gives a precise definition of the dependent variable as well as precise definitions of the variables of interest, the IV, and the control variables, along with a discussion of descriptive statistics.

4. DATA AND DESCRIPTIVE STATISTICS

The data used in this paper come from several sources that are either open to the public or open to anyone with an institutional subscription. The measure of social unrest used as the dependent variable is a proxy for actual food-related social unrest. It comes from a LexisNexis Academic search of 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. The "at least five occurrences" criterion was applied to each component of the search for two reasons. First and foremost, this was done in an effort to weed out false positives (e.g., news items such as articles about food worker strikes in the hotel industry). Second, LexisNexis imposes an upper bound of 3,000 the returns of any given search, which means that to accurately count all the news stories about food-related social unrest (and not just those satisfying the "at least five" criteria above) in a given month, one would have to split the month into ten-, five-, and sometimes three-day intervals. This variable will hereafter be referred to interchangeably as the number LexisNexis stories about food-related social unrest, as food-related social unrest, or more simply as "social unrest."

To gauge the robustness of the results, three additional specifications of the dependent variable are used. The first comes from a LexisNexis Academic search of all news in English between January 1990 and December 2011 containing at least five occurrences of the term "food" and its plural and at least five occurrences of the term "riot" and its plural. The second is a similar count of news stories about food riots, but using the Factiva database instead of LexisNexis. The main difference between LexisNexis and Factiva lies in the scope of the media outlets covered by each database, with Factiva focusing on business publications. The third is a measure of the prevalence of food riots in Africa obtained from the Social Conflict in Africa Database (SCAD) collected by Hendrix and Salehyan (2012). Additional robustness checks are conducted by looking at which proportion of all Factiva stories about social unrest are stories about food riots, in order to ensure that the results in this paper are not spurious because they are due to increases in non-food-related social unrest.

It is possible that, as food prices rise, journalists and news reports start looking for stories of food-related social unrest. Even if that were the case, the identification strategy outlined above would account for this. Indeed, with such a reverse causality problem, the variation in natural disasters would still be exogenous to (the number of news stories about) social unrest. This is because it is unlikely that a natural disaster occurring in one part of the world would lead journalists and news reporters to look for stories of food-related social unrest in the same part of the world; after all, the link between natural disasters and conflict is only a recent discovery in the social sciences (Hsiang et al., 2011). And if it is unlikely that a natural disaster occurring in one part of the world would lead to journalists and news reporters to look for stories of food-related social unrest in the same part of the world, it is even more unlikely that a natural disaster occurring in one part of the world would lead journalists and news reporters to look for stories of food-related social unrest elsewhere in the world, as is effectively the setup of the data used in this paper.

The number of news sources covered by LexisNexis can vary between time periods as news outlets move in and out of the database. The way LexisNexis appears to add and drop sources, however, is such that once a source is included, all of its electronically available records are searchable. In other words, it is not the case that if a newspaper is included in LexisNexis starting on January 1, 2012, only the articles published after that date by that newspaper will be available on LexisNexis. Rather, all of its electronically available articles are included in LexisNexis after January 1, 2012, and none are available before that date. Because each LexisNexis count of news stories used in this paper was collected within the span of a few days, it is thus highly unlikely that this influences the news counts. This is why robustness checks are conducted below which look at alternative definitions of the dependent variable and which look at Factiva in addition to LexisNexis.

The food prices used as the variables of interest are the FAO's food price index and the FAO's cereal price index.[14] The FAO's food price index is a monthly indicator of the price of food worldwide that covers five food groups (meat, dairy, cereals, oils and fats, and sugar) representing 55 commodities.[15] To come up with an aggregate food price index, the FAO takes the average of the five food groups and weights them using group-specific export shares for the period 2002-2004. The size of the sample used for analysis in this paper – 264 monthly observations from January 1990 to December 2011 inclusively – was ultimately determined by the fact that the FAO only started recording food prices in January 1990.

In addition, robustness checks are conducted with specific primary commodity price series collected by the IMF and which are also publicly available. These include a maize price index (US

[14] The indices used in this paper are deflated (i.e., real) measures. Robustness checks conducted with nominal food price indices during preliminary work leave the qualitative results unchanged. Those are not shown for brevity, but are available upon request.

[15] Although the FAO will introduce fish and seafood as an additional category in its food price index sometime in 2012 (Tveterås et al., 2012), the estimates in this paper omit fish and seafood.

No. 2 corn, FOB Gulf of Mexico, in US$ per metric ton), a rice price index (5 percent broken milled white rice, Thailand nominal price quote, US$ per metric ton), a soybeans price index (US soybeans, Chicago soybean futures contract first contract forward, US$ per metric ton), and a wheat price index (No.1 hard red winter wheat, ordinary protein, FOB Gulf of Mexico, US$ per metric ton). The difference with the FAO food and cereals price indices, however, is that the IMF prices series are only available in nominal terms.

The natural disaster data used to construct the IV come from the CRED EM-DAT database, which was used by Strömberg (2007) to study the relationship between natural disasters and economic development. Instead of arbitrarily selecting which types of natural disasters to include, this paper retains all types of natural disasters: droughts, earthquakes, epidemics, episodes of extreme temperature, floods, insect infestations, mass movements (both dry and wet), storms, volcanic eruptions, and wildfires. A natural disaster is included in the EM-DAT database only if it satisfies at least one of the following criteria:[16]

1. At least ten persons are killed;
2. At least 100 persons require immediate assistance, are displaced, or evacuated;
3. A state of emergency is declared by public officials; or
4. Public officials call for international assistance.

In the empirical application below, a natural disaster is recorded in the month when it began in order to focus on unpredictable shocks to the supply and demand of food. A disaster that unfolded in the current month but which began in an earlier month is thus not recorded as having occurred in the current month. For example, a volcanic eruption beginning on April 15 and ending on July 13 is only recorded as having occurred in April. Natural disasters whose beginning month was coded as “00” (i.e., unknown) in the EM-DAT database were simply dropped from the data

[16] More information on the EM-DAT data can be obtained http://www.emdat.be/explanatory-notes.

because it was impossible to ascribe them to a specific month. This implicitly assumes that these "month-zero" occur at random.

Turning to the descriptive statistics in table 1, the average month sees about 69 mentions of food-related social unrest in the English-language media on LexisNexis. This figure masks a considerable amount of heterogeneity, however, as the number of such mentions ranges from three in February 1990 to 433 in April 2008. Likewise, the average month sees about four mentions of food riots specifically in the English-language media on LexisNexis, and a little less than one mention of food riots specifically in the English-language media on Factiva. As one would expect, the average monthly proportion of Factiva social unrest stories that are about food is small, at about 1 percent. Looking at the number of food riots in the SCAD data, which focuses on Africa, there are very few food riots over the period 1990-2011, with an average of 0.06 food riots per month. In fact, the number of food riots recorded in the SCAD is either zero or one, which will allow estimating linear probability models when dealing with that dependent variable.

The FAO food price index was equal to roughly 112 on average in real terms, with a minimum of 90.2 in January 2000 and a maximum of 168 in December 2010. Likewise, the FAO cereal price index also averaged about 112 between January 1990 and December 2011. The food and cereals price indices were similarly volatile between January 1990 and December 2011, as the average three-month coefficient of variation for each price index was equal to 2 percent, and the average six-month coefficient of variation for food was equal to 3 percent and the average six-month coefficient of variation for cereals was equal to 4 percent. In other words, on average, the food and cereals price indices varied by 2 percent over a three-month period, and they varied respectively by 3 and 4 percent over a six-month period. The IMF price indices average 131 for maize, 325 for rice, 600 for soybeans, and 176 for wheat. The average three-month coefficients of variation for maize, rice, and soybeans were all equal to 3 percent, but the price of wheat was more volatile, given its three-month coefficient of variation of 4 percent.

Natural disasters most often take the form of floods and storms, with a monthly average of 11 floods and eight storms. At the other end of the natural disaster frequency spectrum, dry mass movements, insect infestations, volcanic eruptions, and wildfires occur on average less than once a month, with 0.09 dry mass movements, 0.11 insect infestations, 0.47 volcanic eruptions, and 0.97 wildfires per month. The average month sees about 31 occurrences of natural disasters.

Lastly, figures A1 and A2 in the appendix plot the standardized FAO food price index and volatility for the entire period considered in this paper, and then for the period 2006-2011, since that is when the bulk of the food riots in the data occurred. An anonymous reviewer suggested showing those plots in an effort to determine whether episodes of high food prices might be correlated with episodes of high volatility. Looking at figures A1 and A2, it looks as though there is no such systematic relationship.

5. ESTIMATION RESULTS

Before presenting and discussing estimation results for various specifications of equations 1 and 2, it is instructive to start by looking at some nonparametric evidence so as to check whether food prices and social unrest appear correlated at all. In that spirit, figures 2 to 5 plot time series for the IMF's maize, rice, soybeans, and wheat commodity price series, respectively, and for the count of LexisNexis news stories about food-related social unrest riots between January 1990 and December 2011. Figures 2 to 5 indicate that large spikes in food prices levels are often accompanied by a large spike in the count of news stories.

Obviously, figures 2 to 5 fail to control for confounding factors. The results in table 2 control for such confounding factors by including controls for the count of news stories in the previous month, a time trend, and a set of monthly dummy variables. The results in table 2 show that once those covariates are included, the food price level and the cereal price level are both positively associated with social unrest. Moreover, it appears that increases in food and cereal price volatility are negatively associated with social unrest.

Table 2 presents interesting associations between food prices and social unrest, but those associations are just that, and in no way do they imply that food prices actually cause social unrest. Table 3 attempts to make a causal statement about the impact of the food price level on social unrest by presenting estimation results in which natural disasters are used to instrument the food price level. In both cases, the IV is statistically significant at less than the 1 percent level. In fact, in both columns, the *F*-statistic on the IV far exceeds the threshold of 10 set by Stock and Yogo (2002) for an IV not to be considered weak, which is also true of all of the IV estimation results in this paper. In addition – and following Angrist and Pischke (2009) and Chernozhukov and Hansen (2008), who recommend running a diagnostic regression of the dependent variable on the IV– table A1 presents the results of a reduced-form regression of social unrest on the number of natural disasters in a given month. That the reduced-form relationship between the IV and the dependent variable is significant at the 1 percent level is evidence in favor of a causal relationship flowing from natural disasters to social unrest.

The results in table 3 indicate that increases in the level of food prices cause social unrest, and that increases in food price volatility are associated with decreases in social unrest. Although it is impossible to make a causal statement about the impact of food price volatility on social unrest, the negative association between food price volatility and social unrest in tables 2 and 3 is in line with theoretical results in the literature. Indeed, Turnovsky et al. (1980) show that a consumer is risk-loving (i.e., she benefits from price volatility) over the prices of all commodities encompassed by her utility function, and that consumers can be risk-loving over specific commodities (i.e., they can benefit from volatility in the price of specific commodities). Indeed, as Sandmo (1971) has demonstrated, the negative effects of food price volatility are largely felt by food producers who, by virtue of having to dedicate resources to food production long before the resolution of price uncertainty, cannot make profit-maximizing production decisions in the presence of food price volatility. Food consumers, however, can always adjust their food consumption bundle after the resolution of price uncertainty, and so for them, greater food price volatility (holding the food price level constant once again) means an increased likelihood of enjoying price discounts on food. Since it is food consumers – who are concentrated in urban areas, and who represent a large percentage of the population and most countries – rather than food producers – who are spread out over large rural areas, and who represent a small percentage of the population in most countries – who drive social unrest according to the historical literature on food riots discussed in section 2, the sign and significance of the estimated coefficient on food price volatility are not surprising.

The results in tables 2 and 3 indicate also that instances of food-related social unrest has been increasing over time, given the sign and significance of the linear time trend,[17] and given that the number of news stories about food riots in a given month is correlated with the number of news stories about food riots the previous month. The latter finding suggests that social unrest tends to carry over from month to month, but decreasingly so given that the estimated coefficient on the count of news stories in the previous month is less than one. Moreover, if one assumes that food prices are exogenous to social unrest, one can compare the ATE of food prices on social unrest with its LATE by comparing the results in tables 2 and 3. This comparison indicates that for those months when natural disasters have induced a change in food prices, the impact of food prices of social unrest has been stronger than in the average month.

The specifications in table 4 consider whether the results in table 3 are driven by the food crises of 2008 and 2010-2011. The results in columns 1 and 2 thus include a dummy variable equal to one if the year is 2008 and equal to zero otherwise. Likewise, the results in columns 3 and 4 include a dummy variable equal to one if the year is 2010 or 2011 and equal to zero otherwise. Only the dummy for 2010-2011 is positive and significant, and only in the specification focusing on cereals prices (column 4), with the qualitative results for food price levels and food price volatility remaining unchanged from table 3. This suggests that the core results in this paper are not driven by food crises. When including both the dummy for the 2008 food crisis and the dummy for the 2010-2011 food crisis (not shown), however, the food and cereals price levels, become significant only at the 25 percent level, although they remain of the right sign and magnitude. In other words, the causal relationship between food price levels and social unrest in this paper appears driven by the food crises of the last 10 years. Further, splitting the sample in two equal periods (i.e., 1990 to 2000, and 2001 to 2011; these results are not shown for brevity) provides further evidence that the causal relationship in table 3 is driven by the period 2001-2011.

Could the inclusion of food price volatility drive the result according to which food price levels appear to cause social unrest? The estimation results in table 5 answer that question in the negative

[17] Robustness checks were conducted for the core specifications which included instead a quadratic trend, a cubic trend, or a logarithmic trend. The results of those robustness checks are not shown given that they leave the qualitative results unchanged.

by showing that the estimated coefficient for the food price levels are still significant when food price volatility is omitted, in both the OLS and IV specifications.

Similarly, could excluding food price levels to only include food price volatility as a variable of interest explain the reasoning of some commentators, who have claimed that food price volatility causes social unrest? It cannot, as the estimated coefficients on both food and cereal price volatility in columns 1 and 2 of table 6 are not statistically different from zero at any of the conventional levels when the food and cereal price levels are omitted from their respective specification. Even if they were statistically significant, they would show a negative association between food price volatility and social unrest.

Finally, appendix C presents estimation results for several robustness checks. To ensure that the results in this paper are robust to alternative definitions of "natural disasters," and to ensure that the results are robust to the way various natural disasters can affect food prices, the results in table A2 progressively exclude specific types of natural disasters from the IV. In column 1, only droughts, episodes of extreme temperature, floods, and insect infestations are retained. Column 2 then drops insect infestations from that list. The empirical results are stable across these alternative definitions, for both food and cereal prices.

Following Angrist and Pischke (2009), the specifications in table A3 test whether social unrest Granger-causes food prices by including three food price lags as well as three food price leads. The null hypothesis of no Granger causation flowing from social unrest to food prices is such that the estimated coefficients for the price index in $t+1$, $t+2$, and $t+3$ should not be statistically significant, and indeed they are not, either jointly or individually. This is strengthened by the results in the second column of table A3, which show that social unrest also does not Granger-cause cereal prices.

The specifications in table A4 take a longer view of price volatility by considering six-month instead of three-month food and cereal price volatility. In this case, although the relationships between price volatilities and social unrest no longer appear statistically significant, the relationships between price levels and social unrest remain. In other words, if food price volatility exerts an impact on social unrest, it appears that it is short-term (i.e., three-month) and not longer-term (i.e., six-month) price volatility that matters.

Tables A5 and A6 reproduce the results in tables 2 and 3, which respectively presented estimation results for equations 1 (i.e., OLS) and 2 (i.e., IV) for the FAO food and cereals price indices, but for the IMF's commodity price series. Focusing on the IV results, maize, rice, soybeans, and wheat all seem to cause food-related social unrest, but their coefficients of variation are not significantly associated with social unrest (only the rice price volatility is positively and significantly associated with social unrest, but in the OLS specification in column 2 of table A5).

The dependent variable used so far is a count of LexisNexis stories about food-related social unrest. Because of the count nature of that variable (i.e., it consists only positive integers), some have suggested estimating count-data models instead of the linear regressions presented in equations 1 and 2. Table A7 shows the results of Poisson regressions, which take into consideration the count nature of the dependent variable. The results in table A7 show that taking into account the count nature of the dependent variable does not change the qualitative results in table 2 or in table A5.

What if one focuses purely on LexisNexis stories about food riots rather than on stories about food-related social unrest? Table A8 shows the result of narrowing down the definition of the dependent variable to consider only food riots. As it turns out, the core result – that food price levels cause social unrest – remains, but the statistically significant association between price volatilities and social unrest disappears. This suggests that price volatility is associated with changes in the extent of social unrest, but not with changes in the extent of food riots. A similar result obtains when using Factiva stories about food riots in table A9. Likewise, a similar result obtains when controlling for the total number of social unrest stories in the Factiva database by dividing the number of stories about food riots by the number of stories about social unrest in table A10.

Table A11 turns on its head the definition of price volatility used so far in this paper (i.e., the coefficient of variation of food prices over the last three months) by looking at implied food price volatility (i.e., the coefficient of variation of food prices over the next three months), under the assumption that people are forward-looking and have rational expectations. In that case, the core result that food price levels cause social unrest remains, as does the core result that food price volatility is associated with decreases in the extent of social unrest.

Tables A12 and A13 present OLS and IV estimation results for specifications looking at the determinants of the number of food riots in Africa, obtained from the SCAD data (Hendrix and Salehyan, 2012). Because this new dependent variable only takes values equal to zero or one, the specifications in tables A12 and A13 are linear probability models, and the estimated coefficients can directly be interpreted as the percentage change in the likelihood that a food riot will take place in a given month as a consequence of a one-unit increase in each explanatory variable. Looking at the results in table A13, a one-point increase in the FAO's food price index causes a 0.6-percent increase in the likelihood that a food riot will take place in Africa. The most extreme food price swings both took place in 2008, when the FAO's food price index spiked by 11.5 points between January and February and dropped by 17.8 points between September and October. Going by the estimated impact of the FAO's food price index in table A13, this means that the likelihood of observing a food riot in Africa increased by 6.9 percent in the former case but decreased by 10.7 percent in the latter case.

Lastly, in an effort to investigate whether there are threshold effects in the relationship between food prices and food riots, figure A3 shows the results of semiparametric specifications where the relationship between the food price index and food riots is allowed to be nonlinear via the use of splines. Specifically, equation 2 is then rewritten as

$$y_t = \alpha_2 + h(\hat{f}_t) + \beta_{2\sigma}\sigma_t + \beta_{2y}y_{t-1} + \beta_{2m}m_t + \beta_{2\tau}\tau_t + \epsilon_{2t}, \qquad (2')$$

where $h(\hat{f}_t)$ is simply a nonlinear function of the exogenized (as per the setup in equation 3) FAO food price index. Figure A3 shows those nonlinear relationships for splines with 3, 4, 5, and 6 knots, and the results in figure A3 indicate that the relationship between food prices and food riots is relatively flat over the conditioning domain. Moreover, the higher the degree of flexibility (i.e., the more knots are introduced in equation 2'), the flatter the relationship between food prices and food riots gets.

The empirical results above thus strongly suggest there is a robust causal relationship flowing from food price levels to social unrest. Likewise, the results suggest that food price volatility – often presumed to be the main culprit in causing social unrest when food prices spike – is, if anything, negatively correlated with social unrest, although this relationship cannot be argued to be causal, and it is not robust to alternative specifications of the core equation. This is in line with some recent research on food price volatility, which concludes that not only has food price volatility apparently not significantly increased in recent years (Gilbert and Morgan, 2010),[18] but that it has had counterintuitive effects on the welfare of households in developing countries. That is, holding the prices of food commodities constant, an increase in the volatility of the price of these same commodities decreases the welfare of households, but this welfare loss gets more – not less – pronounced as household income increases (Bellemare et al., 2013). In other words, wealthier households suffer more than poor households from an increase in food price volatility, holding food price levels constant. This is because wealthier households are more likely to be net producers than net consumers of food, and net producers must commit resources to production long ahead of realized prices (Baron, 1970; Sandmo, 1971; Barrett, 1996).

From a policy perspective, however, it is worth noting that, compared to a situation where the price of food fluctuates freely about its mean, any price stabilization policy that would successfully keep the price of food at that mean level or keep it at that mean level and allow it to fall below but not rise above that level would, by definition, reduce volatility to zero in the former case and significantly decrease it in the latter case. In reality, however, it might be very difficult to implement a policy like the one just described, and similar such price stabilization schemes tend to fail (see Bellemare et al., 2013).

[18] Likewise, Jacks et al. (2011) show that although commodity prices are more volatile than the prices of manufactured goods, commodity price volatility has not increased significantly over the last 300 years as a result of more integrated commodity markets.

The foregoing empirical results also raise an important question: Why is it that, after a period of relative calm after the early 1990s (Walton and Seddon, 1994), we have returned to a world of food riots? The answer to this question is beyond the scope of this paper, and an answer to it must necessarily remain speculative for the time being. But recall that after the oil crisis of the early 1970s, food prices steadily declined to hit historical lows in the early to mid-2000s (see figures 2 to 5). Given the empirical results just discussed, which show that people react so adversely to increase in prices as to be more likely to take to the streets when food prices rise, it is perhaps no surprise that the rapid and unexpected rise in food prices that took place in 2008 has meant that we have now returned to a world where food riots are a common occurrence.

6. CONCLUSION

Do food prices cause social unrest? The results in this paper indicate that the answer to this question is a qualified "yes." While rising food prices appear to cause food riots, food price volatility is at best negatively associated with and at worst unrelated to social unrest. These findings go against much of the prevailing rhetoric surrounding food prices. Indeed, whereas many in the media and among policy makers were quick to blame food price volatility for the food riots of 2008 and of 2010-2011, the empirical results in this paper indicate that rising food price levels are to blame and that increases in food price volatility may actually decrease the number of food riots. Additionally, specifications that focus on food price volatility at the expense of food price levels show that the latter is not statistically significantly related to the former. These findings are in line with those in the applied microeconomics literature on the impacts of rising food prices (Deaton, 1989) and of food price volatility (Bellemare et al., 2013). Moreover, the finding that increases in the level of food prices cause social unrest appears to be driven by the food crises of 2008 and of 2010-2011.

What are the implications of these findings for policy? First, policy makers should focus on curbing rising food prices, which appear to cause social unrest, rather than on curbing food price volatility, which is actually associated with decreases in social unrest. Many policies aimed at keeping prices low, however, are likely to also reduce the extent of volatility, however, as discussed at the end of the previous section. Still, the objective of keeping prices low would be best attained by policies aimed at increasing the supply of food will be the most helpful, whether this means investing in agricultural research aimed at increasing agricultural yields (Dorward et al., 2004), encouraging urban or peri-urban agriculture (Maxwell, 1995), liberalizing the international trade of agricultural commodities, increasing access to and the use of biotechnology in developing countries (Paarlberg, 2009), eliminating farm subsidies in industrialized countries, and so on.

Second, although it may be tempting to do away with consumer food price subsidies in the current context of budget austerity, policy makers should be very cautious when trying to eliminate such subsidies. In many developing countries, local political economy considerations lead to a systematic bias in favor of urban households when it comes to food policy, which pushes governments to subsidize the price of food in an effort to keep urban discontent at bay (Lipton, 1977; Bates, 1981; van de Walle, 2001).[19] Given that food riots almost always occur in urban areas, however, abandoning these food price subsidies may be ill-advised, especially since these policies often appear to have been put in place to avoid social unrest in the first place. In such cases, a better policy may be one that progressively – and slowly – abandons food price subsidies. This is especially so given that it is not at all unlikely that individuals exhibit loss aversion over food prices (Timmer, 2010), i.e., for equal-valued increases and decreases in food prices, the welfare losses caused by price increases are larger in magnitude than the welfare gains caused by price decreases.

[19] In fact, Carter and Bates (2011) show that in their data, once the policy response of governments to food price shocks is taken into account, the relationship between such shocks and civil conflicts disappears.

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Table 1. Descriptive Statistics, January 1990 to December 2011 (n=264)

Variable	Mean	(Std. Dev.)
Dependent Variables		
Count of LexisNexis Stories about Food-Related Social Unrest	69.63	(60.55)
Count of LexisNexis Stories about Food Riots	4.23	(12.11)
Count of Factiva Stories about Food Riots	0.89	(3.36)
Proportion of Factiva Riot Stories that Are about Food	0.01	(0.02)
Number of Food Riots in Africa (SCAD)	0.06	(0.24)
Food Prices Levels		
FAO Food Price Index (Real Terms)	112.22	(17.84)
FAO Cereals Price Index (Real Terms)	111.84	(26.31)
IMF Maize Price Index (Nominal Terms)	130.54	(51.85)
IMF Rice Price Index (Nominal Terms)	325.16	(143.76)
IMF Soybeans Price Index (Nominal Terms)	263.05	(91.69)
IMF Wheat Price Index (Nominal Terms)	175.83	(64.74)
Food Price Coefficients of Variation		
Food Historical Volatility (Three Months)	0.02	(0.01)
Cereals Historical Volatility (Three Months)	0.02	(0.02)
Food Historical Volatility (Six Months)	0.03	(0.02)
Cereals Historical Volatility (Six Months)	0.04	(0.03)
Maize Historical Volatility (Three Months)	0.03	(0.03)
Rice Historical Volatility (Three Months)	0.03	(0.03)
Soybeans Historical Volatility (Three Months)	0.03	(0.02)
Wheat Historical Volatility (Three Months)	0.04	(0.03)
Natural Disasters		
Drought	1.15	(1.27)
Earthquakes	2.31	(1.89)
Epidemics	3.86	(4.12)
Episodes of Extreme Temperature	1.34	(2.42)
Floods	11.09	(6.62)
Insect Infestations	0.11	(0.56)
Mass Movements (Dry)	0.09	(0.33)
Mass Movements (Wet)	1.46	(1.45)
Storms	8.06	(5.63)
Volcanic Eruptions	0.47	(0.70)
Wildfires	0.97	(1.32)
Count of Natural Disasters	30.92	(12.44)

Table 2. OLS Estimation Results for the Determinants of Social unrest, 1990-2011.

Variable	**(1)**	**(2)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.		
Food Price Index	0.686***	
	(0.160)	
Historical Volatility (Food, Three Months)	-368.382*	
	(201.490)	
Cereal Price Index		0.516***
		(0.111)
Historical Volatility (Cereals, Three Months)		-426.806***
		(136.977)
News Stories in the Previous Month	0.442***	0.440***
	(0.057)	(0.056)
Trend	0.248***	0.244***
	(0.042)	(0.042)
Constant	-149.750***	-125.552***
	(23.339)	(20.475)
Observations	262	262
Monthly Dummies	Yes	Yes
R-squared	0.702	0.708

Standard errors in parentheses

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

Table 3. IV Estimation Results for the Determinants of Social unrest, 1990-2011.

Variable	**(1)**	**(2)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.		
Food Price Index	0.990**	
	(0.402)	
Historical Volatility (Food, Three Months)	-478.098*	
	(242.834)	
Cereal Price Index		0.683**
		(0.272)
Historical Volatility (Cereals, Three Months)		-508.680***
		(183.567)
News Stories in the Previous Month	0.398***	0.408***
	(0.078)	(0.074)
Trend	0.238***	0.234***
	(0.044)	(0.044)
Constant	-173.887***	-135.383***
	(37.589)	(25.217)
Observations	262	262
Monthly Dummies	Yes	Yes
F-statistic (Weak Instrument Test)	46.79	50.13
R-squared	0.698	0.705

Standard errors in parentheses

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

Table 4. IV Estimation Results for Robustness Checks on the Determinants of Social unrest Controlling for Food Crises, 1990-2011.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.				
Food Price Index	0.971**		0.909*	
	(0.411)		(0.520)	
Historical Volatility (Food, Three Months)	-557.460**		-449.008*	
	(233.032)		(270.070)	
Cereal Price Index		0.678**		0.532*
		(0.287)		(0.293)
Historical Volatility (Cereals, Three Months)		-518.070***		-449.678**
		(168.598)		(187.941)
2008 Food Crisis Dummy	13.018	3.621		
	(13.354)	(15.432)		
2010-2011 Food Crisis Dummy			7.303	20.567**
			(14.826)	(9.813)
News Stories about Social Unrest, Previous Month	0.386***	0.404***	0.396***	0.397***
	(0.074)	(0.069)	(0.075)	(0.072)
Trend	0.242***	0.234***	0.235***	0.227***
	(0.045)	(0.045)	(0.043)	(0.044)
Constant	-171.983***	-134.893***	-164.571***	-118.237***
	(38.358)	(26.190)	(50.236)	(27.323)
Observations	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument Test)	47.06	52.71	31.81	42.12
R-squared	0.700	0.705	0.701	0.714

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. OLS and IV Estimation Results for Robustness Checks on the Determinants of Social unrest Omitting Price Volatility, 1990-2011.

Variable	(1)	(2)
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.		
Food Price Index	0.910**	
	(0.416)	
Cereal Price Index		0.618**
		(0.285)
News Stories about Social Unrest, Previous Month	0.416***	0.427***
	(0.078)	(0.075)
Trend	0.219***	0.211***
	(0.046)	(0.048)
Constant	-166.055***	-130.667***
	(38.175)	(25.874)
Observations	263	263
Monthly Dummies	Yes	Yes
F-statistic (Weak Instrument Test)	39.69	38.81
R-squared	0.695	0.691

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. OLS Estimation Results for Robustness Checks on the Determinants of Social unrest Omitting Price Levels, 1990-2011.

Variable	**(1)**	**(2)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.		
Historical Volatility (Food, Three Months)	-120.384	
	(199.735)	
Historical Volatility (Cereals, Three Months)		-173.349
		(130.751)
News Stories about Social Unrest, Previous Month	0.540***	0.540***
	(0.053)	(0.053)
Trend	0.271***	0.275***
	(0.043)	(0.043)
Constant	-95.193***	-95.116***
	(20.258)	(20.188)
Observations	262	262
Monthly Dummies	Yes	Yes
R-squared	0.680	0.682

Standard errors in parentheses

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

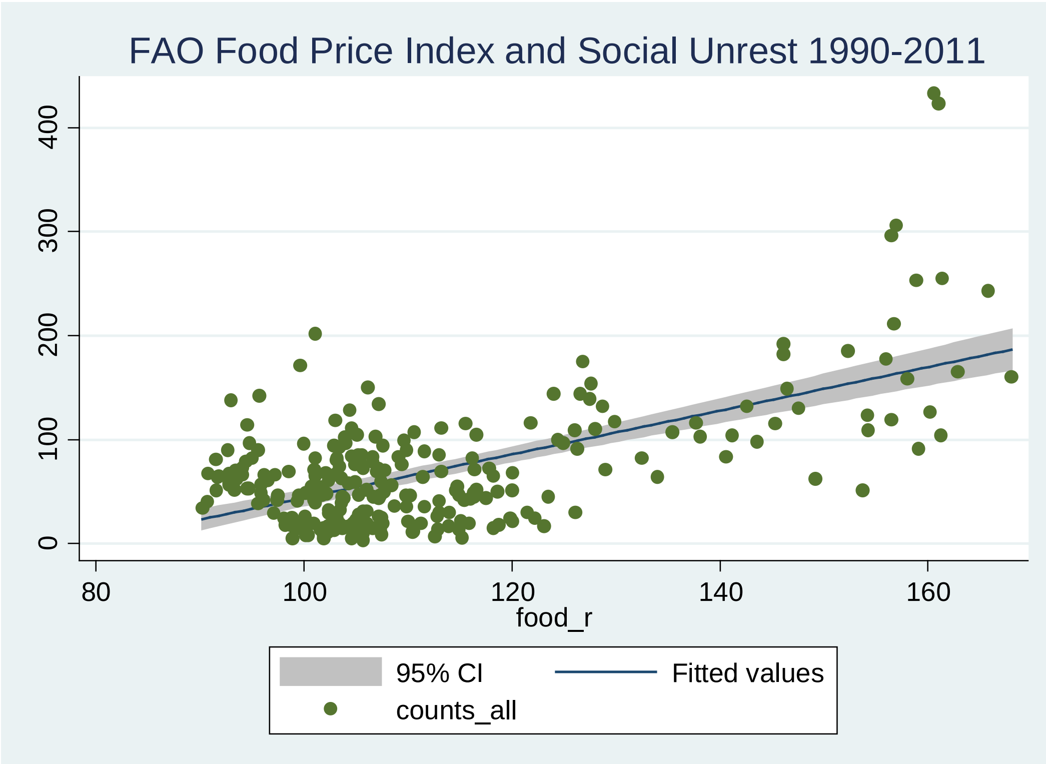

Figure 1. Linear Relationships between the FAO's Food Price Index and Social Unrest with 95% Confidence Interval, 1990-2011.

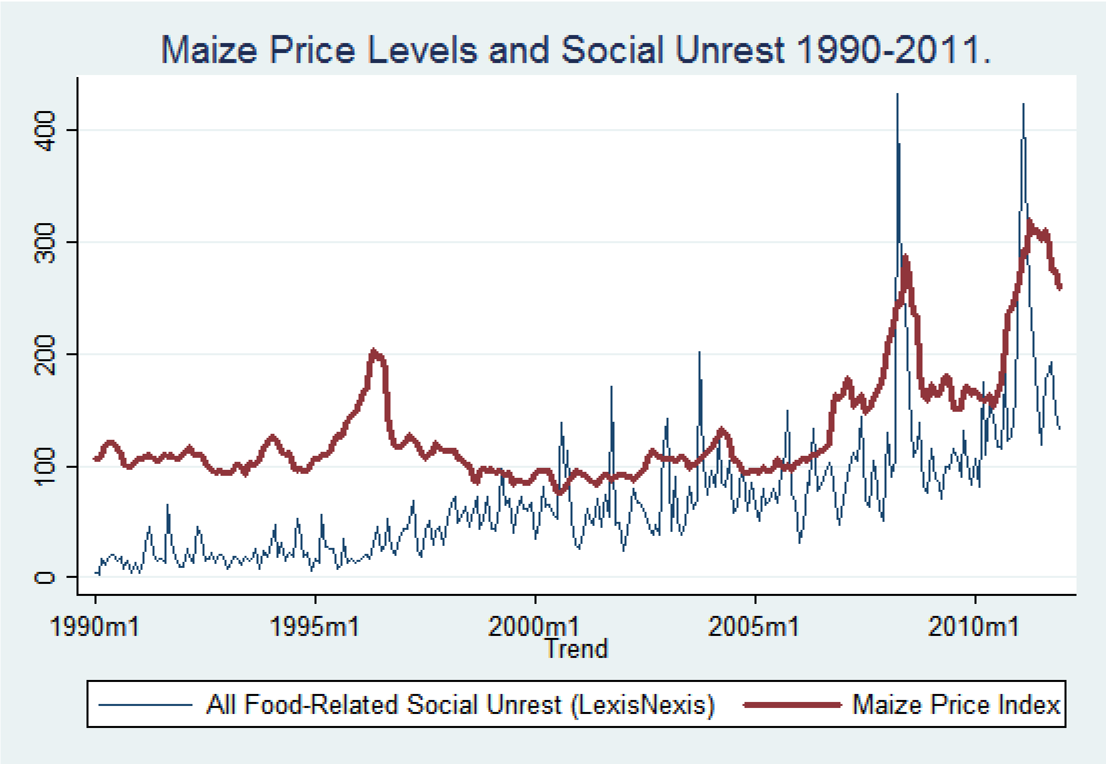

Figure 2. IMF Maize Price Index and Social Unrest, January 1990 to December 2011.

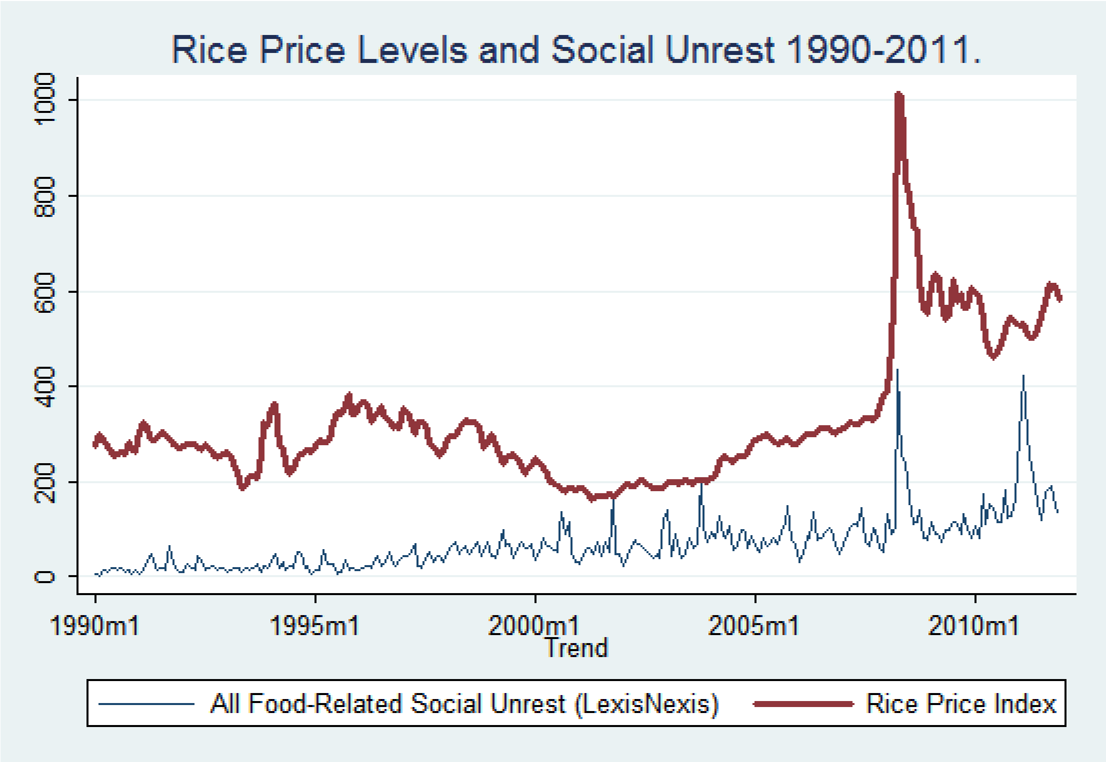

Figure 3. IMF Rice Price Index and Social Unrest, January 1990 to December 2011.

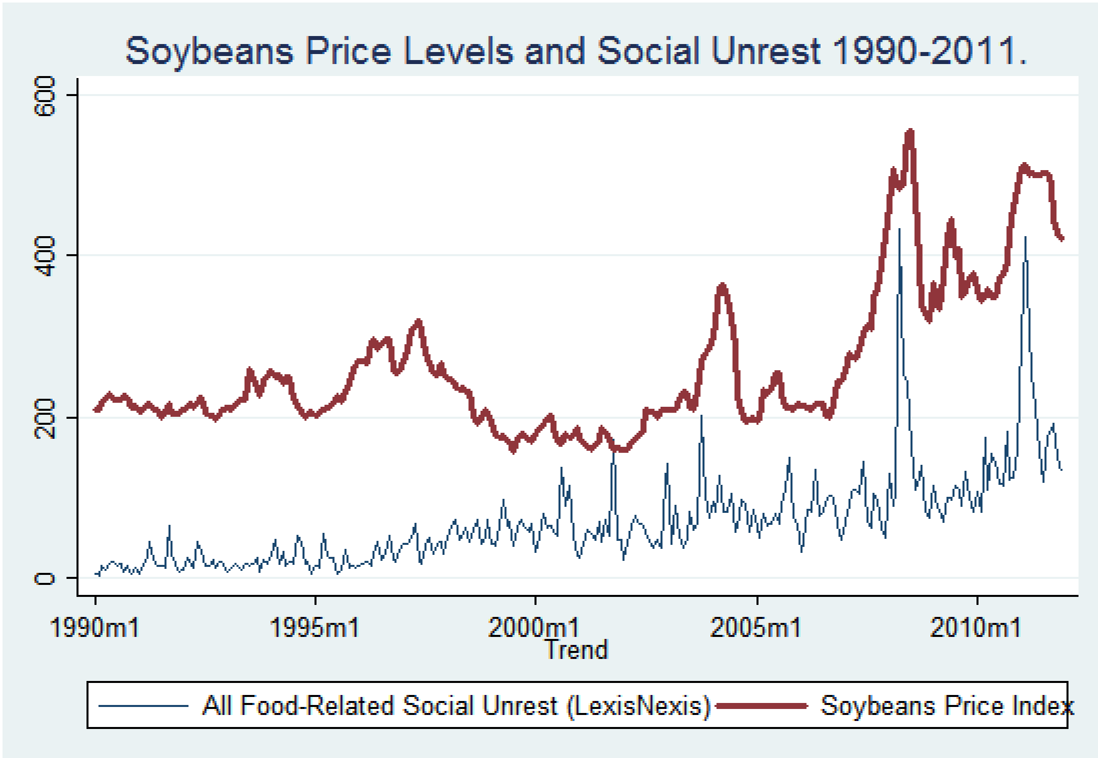

Figure 4. IMF Soybean Price Index and Related Social Unrest, January 1990 to December 2011.

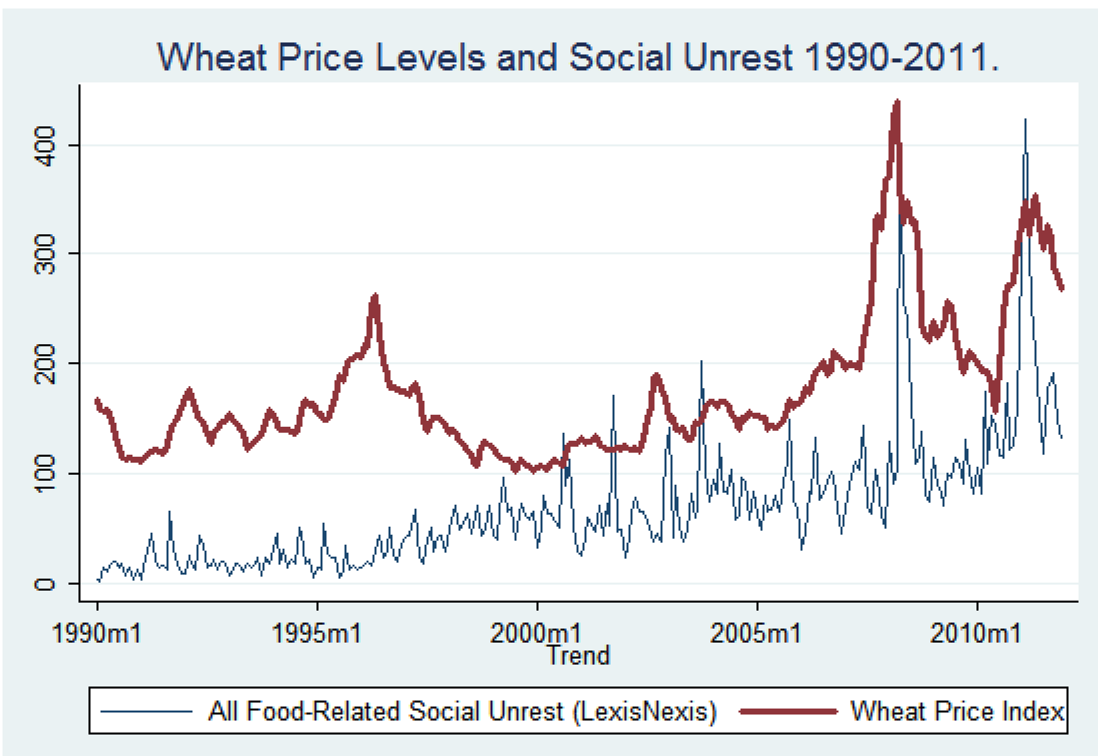

Figure 5. IMF Wheat Price Index and Social Unrest, January 1990 to December 2011.

FOR ONLINE PUBLICATION

Appendix

A. Time Series Tests

Augmented Dickey-Fuller tests below indicate that one can reject the presence of a unit root for the dependent variable as well as for the instrumental variable, but not for food prices. In an investigation of alternative specifications for unit root tests, however, Wang and Tomek (2007) show that food prices do not exhibit unit roots once structural breaks are accounted for. Likewise, in one of the tests they consider, Enders and Holt (2012) reject the presence of a unit root for all the commodities they consider except coffee, cocoa, and sugar. In the other test they consider, they fail to reject the null of stationarity for all commodities except cotton, oil, logs and coal. In other words, Enders and Holt's findings indicate that the bulk of the commodity price series they consider (maize, soybeans, wheat, sorghum, rice, and beef) are stationary.

Perhaps more importantly, in what follows, both Augmented Dickey-Fuller and Phillips-Perron tests (accounting for a trend in food prices because every regression in this paper indicates that there is a significant linear trend in food prices) reject the presence of a unit root in the *predicted* food and cereals price series used as variables of interest (i.e., food and cereal prices conditioned on natural disasters as an instrumental variable, as outlined below).[20] For this reason, all variables in equation 1 are expressed in levels. Moreover, because Durbin-Watson tests below show that the standard errors are not serially correlated, the usual standard errors are reported. Additionally, because the goal of this paper is to estimate the causal impact of the food price level on social unrest rather than to forecast the extent of future social unrest, this paper adopts a relatively simple empirical setup rather than more advanced time series techniques such as autoregressive integrated moving average (ARIMA) models, distributed lags model, error-correction models, and so on (Hamilton, 1994). This is not merely a matter of author preferences. The use of fancier time series techniques would weaken the identification strategy used to tease out causation from correlation in this paper, and the goal of this paper is to identify a causal relationship rather than to forecast social unrest or food prices.

[20] Similarly, DF-GLS tests with trend also allow rejecting the hypothesis that the predicted food price series exhibit a unit root.

Durbin-Watson test results indicate that the error terms in the first two columns of table 2 are not serially correlated. For column 1, the test statistic was equal to 2.02. Given the lower and upper critical values of the test, which were respectively equal to 1.67 and 1.92, this constitutes evidence that the error term is not serially correlated. For column 2, the test statistic was equal to 2.01, which similarly constitutes evidence that the error term is not serially correlated. In addition, the residual ϵ_{1t} from equation 1 was obtained both for the food price index regression of column 1 and for the cereals price index regression of column 2 and regressed on ϵ_{1t-1}, and then on ϵ_{1t-1}, ϵ_{1t-2}, and ϵ_{1t-3}. None of the estimated coefficients were statistically significant. The results of the Durbin-Watson tests and of these regressions of the residuals on their lagged values both indicate that Newey-West standard errors are not necessary.

Moreover, Dickey-Fuller (DF) tests indicate that one can reject the null hypothesis of a unit root in the dependent variable (with a DF test statistic of -5.76, this is below the 1 percent critical value of -3.46), food and cereal price volatility (with DF test statistics of -7.08 and -8.23), and the instrumental variable (with a DF test statistic of -10.24), but one cannot reject the null for the food and cereal price levels (with DF test statistics of -1.82 and 2.14, since this is above the 1 percent critical value of -3.46). As was mentioned above, however, Wang and Tomek (2007) find that structural breaks in food prices account for their apparent nonstationarity. For this reason (the time trend and monthly dummies should account for such structural breaks), and because this paper is interested in the impact of food price levels themselves on social unrest and not in the impact of the month-to-month changes in food price levels on social unrest, all the variables in this paper are expressed in levels.

B. Heterogeneous vs. Homogeneous Treatment Effects

Wooldridge (2002, p. 85) notes that the only two requirements for an IV are that (i) it be exogenous to the dependent variable, and that (ii) it be partially correlated with the endogenous variable once the other covariates are taken into account. In other words, the first-stage instrumenting regression is a reduced-form regression, and it should not be given a structural interpretation.

Moreover, Angrist and Pischke (2009, pp. 150-167) note that one can add that a third requirement, namely that (iii) the IV have a monotonic impact on the endogenous variable in case there are heterogeneous treatment effects. When assumptions (i), (ii), and (iii) are satisfied, one can estimate the local average treatment effect (LATE), the effect of the treatment (here, a change in the food price level) on compliers (here, those months in which food prices changed as a result of natural disasters). Without assumption (iii), IV estimates are not guaranteed to estimate a weighted average of individual causal effects, and the LATE theorem does not hold.

An alternative interpretation is to assume homogeneous treatment effects, which is what is assumed in this paper. Indeed, Angrist and Pischke (2009) note that

> [I]f the compliant subpopulation associated with two or more instruments are very different, yet the IV estimates they generate are similar, we might be prepared to adopt homogeneous effects as a working hypothesis. This revives the overidentification idea but puts it at the service of external validity (p. 167).

The plausibility of the heterogeneous treatment assumption was explored here by looking at all the components of the IV – drought, earthquakes, epidemics, episodes of extreme temperature, floods, insect infestations, mass movements (dry), mass movements (wet), storms, volcanic eruptions, and wildfires – piecewise. For each case where the IV had an F-statistic above 13 in the first stage (i.e., each case where the IV was not weak, as per Stock and Yogo, 2002), a comparison was made with the estimated coefficients for the price of food and for the price of cereals in their respective regressions.

For the FAO food price index, the only two natural disasters for which the F-statistic was above 13 were epidemics and floods, with associated coefficients for the price of food in the second-stage regression of 0.995 and 1.54 (recall the estimated coefficient of 0.990 in the case where the sum of all natural disasters is used as an IV in table 3). For the FAO cereals price index, the only two IVs for which the F-statistic was above 13 were also epidemics and floods, with associated coefficients for the price of food in the second-stage regression of 0.899 and 1.04 (recall the estimated coefficient of 0.683 in the case where the sum of all natural disasters is used as an IV in table 3).

In both cases, the coefficients are close to one another. This becomes especially obvious once one interprets those as marginal effects of 0.995, 1.54, or 0.989 (for the price of food) or 0.899. 1.04, or 0.683 (for the price of cereals) additional LexisNexis news stories about food riots, from a mean number of such stories of about 70 over the period 1990-2011. Doing the same thing for all of the four IMF nominal commodity prices and comparing the natural disaster that has the highest F-statistic in a first-stage regression with the count of natural disasters yields similar results, which are not shown for brevity but are available upon request.

C. Robustness Checks: Additional Figures and Tables

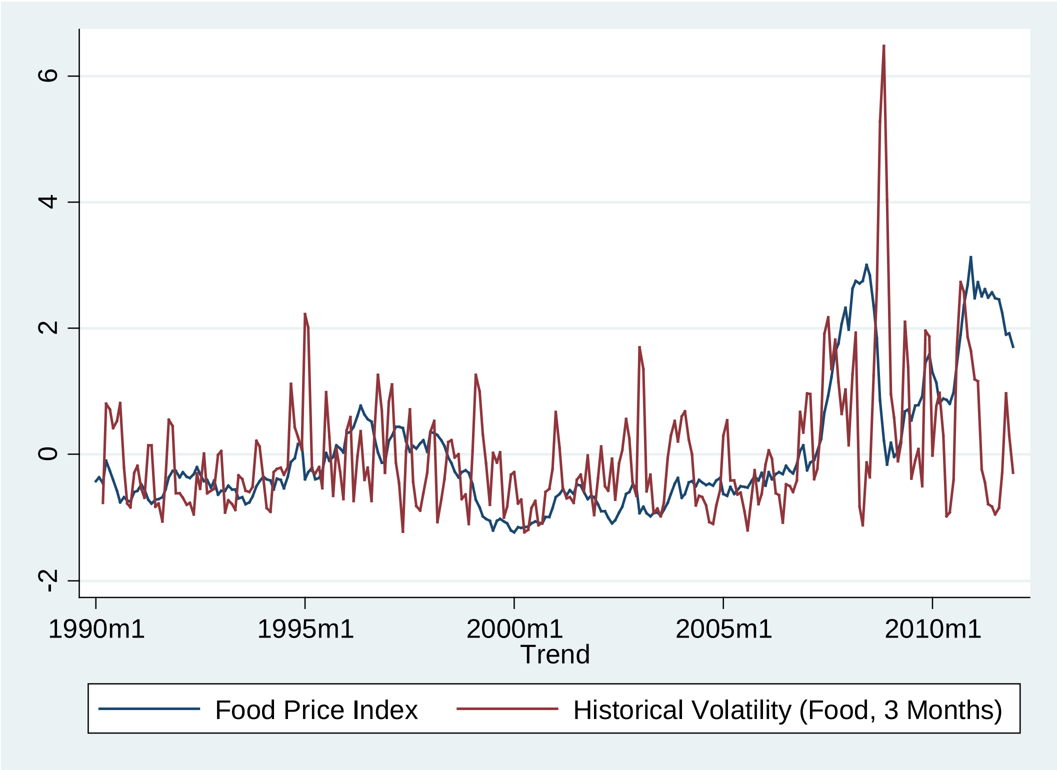

Figure A1. Standardized FAO Food Price Level vs. Volatility, January 1990 to December 2011.

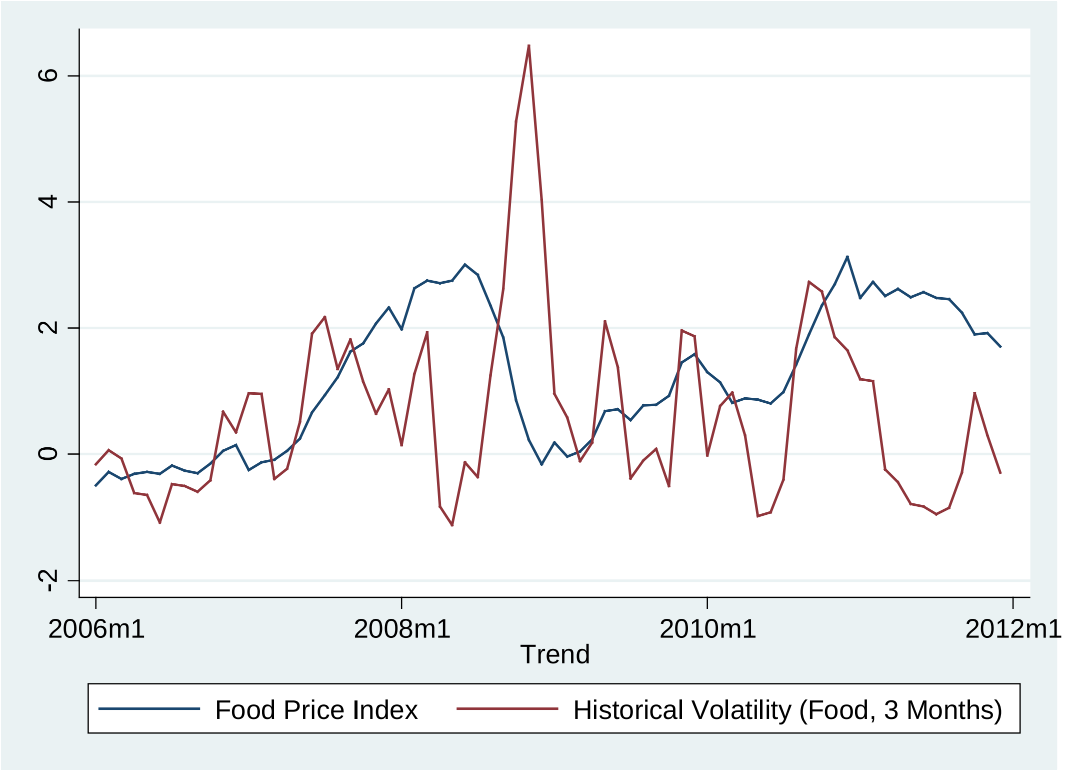

Figure A2. Standardized FAO Food Price Level vs. Volatility, January 2006 to December 2011.

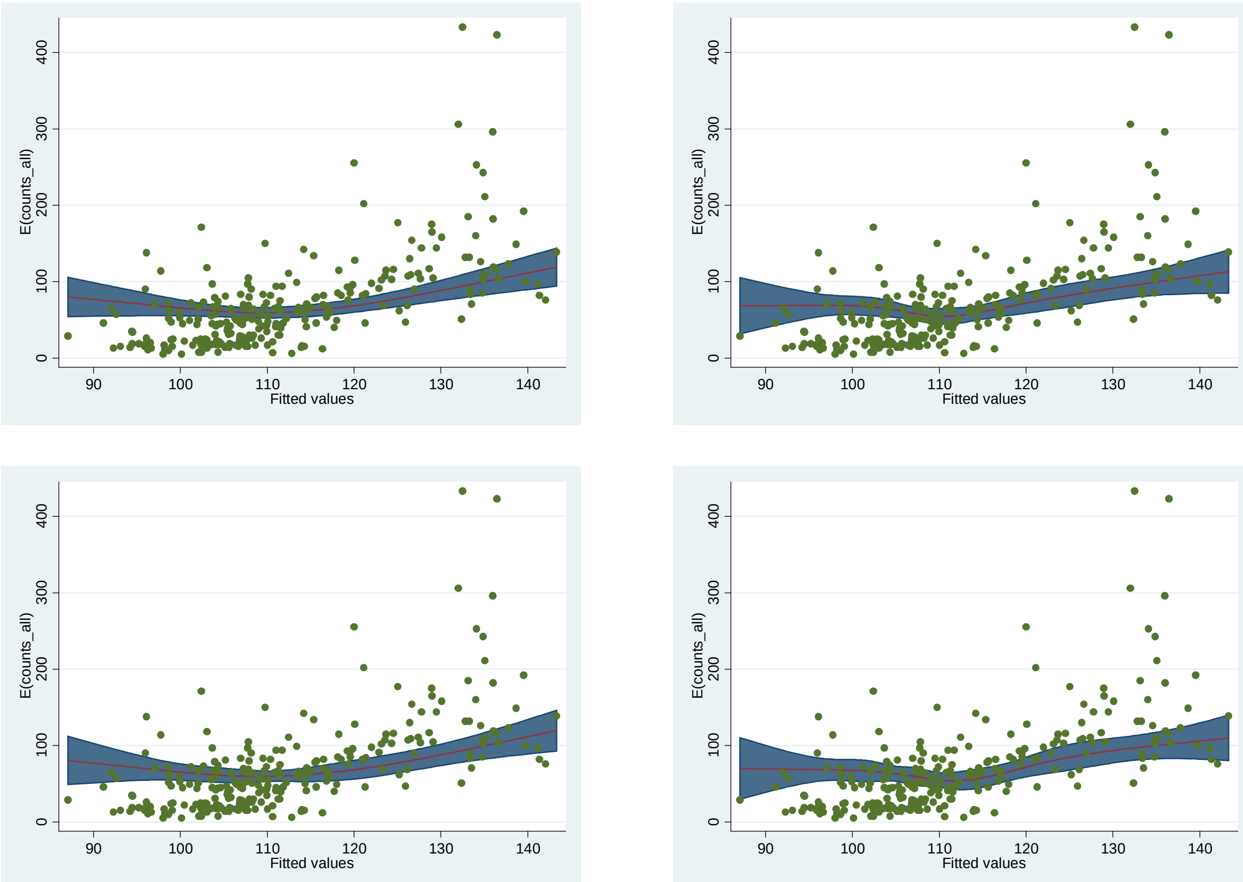

Figure A3. Semiparametric Regressions of Food Riots on Food Prices (Splines with 3 to 6 Knots).

Table A1. OLS Estimation Results for the Reduced Form Relationship between Natural Disasters and Social unrest, 1990-2011.

Variable	**(1)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.	
Count of Natural Disasters	0.787***
	(0.297)
Constant	45.297***
	(9.888)
Observations	264
R-squared	0.026

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2. IV Estimation Results for Robustness Checks on the Determinants of Social unrest Using Alternative Definitions of the Instrumental Variable, 1990-2011.

	IV Includes Drought, Extreme Temperature, Floods, and Insect Infestations		**IV Includes Drought, Extreme Temperature, and Floods**	
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.				
Food Price Index	1.156**		1.116*	
	(0.567)		(0.578)	
Historical Volatility (Food, 3 Months)	-538.209*		-523.827*	
	(283.888)		(286.261)	
Cereal Price Index		0.711**		0.703**
		(0.338)		(0.351)
Historical Volatility (Cereals, 3 Months)		-522.279**		-518.629**
		(208.527)		(213.502)
News Stories about Social Unrest, Previous Month	0.374***	0.402***	0.380***	0.404***
	(0.097)	(0.083)	(0.098)	(0.085)
Trend	0.233***	0.232***	0.234***	0.233***
	(0.047)	(0.046)	(0.047)	(0.046)
Constant	-187.111***	-137.016***	-183.947***	-136.578***
	(49.299)	(27.884)	(50.039)	(28.419)
Observations	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument Test)	22.00	30.36	21.07	27.88
R-squared	0.692	0.704	0.694	0.704

Standard errors in parentheses

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

Table A3. OLS Estimation Results for a Test of Whether Social unrest Granger-Causes Food Prices, 1990-2011.

Variable	**(1)**	**(2)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.		
Food Price Index	-0.837	
	(1.072)	
Historical Volatility (Food, Three Months)	-444.011**	
	(215.478)	
Cereal Price Index		0.014
		(0.672)
Historical Volatility (Cereals, Three Months)		-412.364***
		(142.147)
Food Price Index in t + 1	-0.973	
	(1.083)	
Food Price Index in t + 2	0.897	
	(1.085)	
Food Price Index in t + 3	0.119	
	(0.710)	
Food Price Index in t - 1	0.764	
	(1.063)	
Food Price Index in t - 2	1.849*	
	(1.066)	
Food Price Index in t - 3	-1.040	
	(0.715)	
Cereals Price Index in t + 1		-0.705
		(0.658)
Cereals Price Index in t + 2		0.435
		(0.656)
Cereals Price Index in t + 3		0.227
		(0.424)
Cereals Price Index in t - 1		-0.103
		(0.656)
Cereals Price Index in t - 2		1.559**
		(0.666)
Cereals Price Index in t - 3		-0.877**
		(0.436)
News Stories about Social Unrest, Previous Month	0.437***	0.450***

	(0.060)	(0.058)
Trend	0.245***	0.231***
	(0.044)	(0.043)
Constant	-160.534***	-123.561***
	(25.339)	(21.237)
Observations	258	258
Monthly Dummies	Yes	Yes
R-squared	0.705	0.711

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4. OLS and IV Estimation Results for Robustness Checks on the Determinants of Social unrest Using Six-Month Price Volatility, 1990-2011.

Variable	OLS	OLS	IV	IV
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.				
Food Price Index	0.659***		0.986**	
	(0.164)		(0.415)	
Historical Volatility (Food, Six Months)	-135.503		-214.590	
	(126.454)		(157.372)	
Cereal Price Index		0.486***		0.733**
		(0.124)		(0.317)
Historical Volatility (Cereals, Six Months)		-154.529		-257.844*
		(96.002)		(155.671)
News Stories about Social Unrest, Previous Month	0.449***	0.445***	0.402***	0.395***
	(0.057)	(0.058)	(0.079)	(0.083)
Trend	0.244***	0.238***	0.233***	0.226***
	(0.043)	(0.043)	(0.045)	(0.045)
Constant	-148.063***	-123.287***	-174.337***	-137.573***
	(23.989)	(21.229)	(39.044)	(27.245)
Observations	259	259	259	259
Month Dummies	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument)	-	-	45.56	44.62
R-squared	0.697	0.697	0.692	0.692

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5. **OLS Estimation Results for the Determinants of Social unrest Using IMF Commodity Prices, 1990-2011.**

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.				
Maize Price Index	0.237***			
	(0.057)			
Historical Volatility (Maize, Three Months)	-40.312			
	(94.051)			
Rice Price Index		0.047**		
		(0.021)		
Historical Volatility (Rice, Three Months)		166.919**		
		(73.537)		
Soybeans Price Index			0.130***	
			(0.032)	
Historical Volatility (Soybeans, Three Months)			-23.414	
			(96.453)	
Wheat Price Index				0.127***
				(0.047)
Historical Volatility (Wheat, Three Months)				33.781
				(94.702)
News Stories about Social Unrest, Previous Month	0.435***	0.478***	0.449***	0.494***
	(0.058)	(0.055)	(0.058)	(0.055)
Trend	0.236***	0.255***	0.223***	0.224***
	(0.042)	(0.043)	(0.044)	(0.044)
Constant	-104.326***	-107.250***	-102.383***	-95.465***
	(19.760)	(19.975)	(20.190)	(19.936)
Observations	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes
R-squared	0.701	0.704	0.700	0.692

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6. IV Estimation Results for the Determinants of Social unrest Using IMF Commodity Prices, 1990-2011.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.				
Maize Price Index	0.286**			
	(0.122)			
Historical Volatility (Maize, Three Months)	-59.623			
	(103.448)			
Rice Price Index		0.093*		
		(0.053)		
Historical Volatility (Rice, Three Months)		86.382		
		(112.778)		
Soybeans Price Index			0.155**	
			(0.066)	
Historical Volatility (Soybeans, Three Months)			-34.845	
			(100.032)	
Wheat Price Index				0.270**
				(0.122)
Historical Volatility (Wheat, Three Months)				-74.886
				(128.958)
News Stories about Social Unrest, Previous Month	0.413***	0.442***	0.431***	0.453***
	(0.075)	(0.067)	(0.071)	(0.065)
Trend	0.231***	0.227***	0.216***	0.182***
	(0.043)	(0.052)	(0.047)	(0.056)
Constant	-106.376***	-104.041***	-104.147***	-94.670***
	(20.303)	(20.446)	(20.611)	(20.317)
Observations	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument Test)	68.56	48.44	79.03	44.49
R-squared	0.700	0.698	0.699	0.680

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A7. Poisson Estimation Results for the Determinants of Social unrest, 1990-2011.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.						
Food Price Index	0.002***					
	(0.001)					
Historical Volatility (Food, Three Months)	-3.746***					
	(0.649)					
Cereal Price Index		0.002***				
		(0.000)				
Historical Volatility (Cereals, Three Months)		-4.374***				
		(0.454)				
Maize Price Index			0.001***			
			(0.000)			
Historical Volatility (Maize, Three Months)			-0.377			
			(0.311)			
Rice Price Index				-0.000***		
				(0.000)		
Historical Volatility (Rice, Three Months)				2.456***		
				(0.233)		
Soybeans Price Index					0.001***	
					(0.000)	
Historical Volatility (Soybeans, Three Months)					0.476	
					(0.294)	
Wheat Price Index						0.000**
						(0.000)
Historical Volatility (Wheat, Three Months)						0.060
						(0.285)
News Stories about Social Unrest, Previous Month	0.002***	0.002***	0.008***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trend	0.007***	0.007***	0.008***	0.009***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.317***	0.385***	0.038	-0.393***	0.035	-0.066
	(0.080)	(0.075)	(0.071)	(0.077)	(0.071)	(0.070)
Observations	262	262	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A8. OLS and IV Estimation Results for the Determinants of Food Riots, 1990-2011.

Variable	OLS	OLS	IV	IV
Dependent Variable: LexisNexis Stories about Food Riots.				
Food Price Index	0.232***		0.276**	
	(0.050)		(0.117)	
Historical Volatility (Food, Three Months)	-86.942		-102.242	
	(63.894)		(73.803)	
Cereal Price Index		0.173***		0.189**
		(0.036)		(0.081)
Historical Volatility (Cereals, Three Months)		-74.108*		-81.937
		(43.818)		(56.267)
News Stories about Social Unrest, Previous Month	0.210***	0.201***	0.189**	0.190**
	(0.063)	(0.063)	(0.080)	(0.081)
Trend	0.005	0.002	0.001	-0.000
	(0.011)	(0.011)	(0.015)	(0.015)
Constant	-19.704***	-11.574**	-22.108***	-12.001**
	(5.759)	(5.126)	(8.163)	(5.477)
Observations	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument)	-	-	56.1	60.06
R-squared	0.252	0.257	0.249	0.257

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A9. OLS and IV Estimation Results for the Determinants of Food Riots, 1990-2011

Variable	OLS	OLS	IV	IV
Dependent Variable: Factiva Stories about Food Riots.				
Food Price Index	0.050***		0.072**	
	(0.015)		(0.035)	
Historical Volatility (Food, Three Months)	-11.025		-18.398	
	(19.097)		(22.026)	
Cereal Price Index		0.033***		0.049**
		(0.010)		(0.024)
Historical Volatility (Cereals, Three Months)		-4.645		-12.473
		(13.169)		(17.091)
News Stories about Social Unrest, Previous Month	0.161**	0.167***	0.134*	0.139*
	(0.063)	(0.064)	(0.075)	(0.075)
Trend	-0.004	-0.004	-0.006	-0.007
	(0.003)	(0.003)	(0.005)	(0.005)
Constant	-1.833	0.018	-2.864	-0.234
	(1.641)	(1.501)	(2.237)	(1.548)
Observations	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument Test)	-	-	51.70	54.46
R-squared	0.121	0.118	0.113	0.109

Standard errors in parentheses

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

Table A10. OLS and IV Estimation Results for the Determinants of the Proportion of Riots that Are Food Riots, 1990-2011

Variable	OLS	OLS	IV	IV
Dependent Variable: Proportion of Factiva Riot Stories about Food (0 to 100)				
Food Price Index	0.034***		0.050**	
	(0.009)		(0.021)	
Historical Volatility (Food, Three Months)	-4.383		-9.960	
	(11.511)		(13.341)	
Cereal Price Index		0.026***		0.035**
		(0.006)		(0.015)
Historical Volatility (Cereals, Three Months)		-8.701		-13.157
		(7.894)		(10.250)
Proportion of News Stories, Previous Month	6.131	4.886	2.725	1.969
	(6.417)	(6.444)	(7.618)	(7.744)
Trend	-0.005**	-0.005***	-0.007**	-0.007**
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	-0.458	0.740	-1.157	0.653
	(0.977)	(0.898)	(1.286)	(0.911)
Observations	262	262	262	262
Monthly Dummies	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument Test)	-	-	52.71	55.95
R-squared	0.091	0.099	0.078	0.092

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A11. IV Estimation Results for the Determinants of Social Unrest Using Implied Volatility, 1990-2011.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: LexisNexis Stories about Food-Related Social Unrest.						
Food Price Index	1.039**					
	(0.455)					
Implied Volatility (Food, Three Months)	-553.108**					
	(270.499)					
Cereal Price Index		0.673**				
		(0.301)				
Implied Volatility (Cereals, Three Months)		-355.598*				
		(183.131)				
Maize Price Index			0.298**			
			(0.140)			
Implied Volatility (Maize, Three Months)			-22.877			
			(109.846)			
Rice Price Index				0.119**		
				(0.056)		
Implied Volatility (Rice, Three Months)				-91.112		
				(89.289)		
Soybeans Price Index					0.165**	
					(0.072)	
Implied Volatility (Soybeans, Three Months)					-256.750**	
					(98.995)	
Wheat Price Index						0.302**
						(0.139)
Implied Volatility (Wheat, Three Months)						-244.044*
						(133.427)
News Stories about Social Unrest, Previous Month	0.398***	0.415***	0.410***	0.431***	0.416***	0.436***
	(0.082)	(0.077)	(0.080)	(0.074)	(0.073)	(0.072)
Trend	0.239***	0.226***	0.230***	0.209***	0.242***	0.189***
	(0.044)	(0.046)	(0.043)	(0.049)	(0.047)	(0.056)
Constant	-182.021***	-137.308***	-108.310***	-96.321***	-112.444***	-99.803***
	(42.589)	(27.295)	(20.808)	(20.155)	(20.282)	(20.356)
Observations	261	261	261	261	261	261
Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes

F-statistic (Weak Instrument Test)	36.36	38.81	51.55	35.52	61.47	31.92
R-squared	0.697	0.694	0.699	0.691	0.710	0.681

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A12. OLS Estimation Results for the Determinants of Food Riots in Africa, 1990-2010.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable: SCAD Data Count of Food Riots in Africa						
Food Price Index	0.003**					
	(0.001)					
Historical Volatility (Food, Three Months)	-0.110					
	(1.511)					
Cereal Price Index		0.002**				
		(0.001)				
Historical Volatility (Cereals, Three Months)		-0.722				
		(1.019)				
Maize Price Index			0.001**			
			(0.000)			
Historical Volatility (Maize, Three Months)			-0.174			
			(0.725)			
Rice Price Index				0.000***		
				(0.000)		
Historical Volatility (Rice, Three Months)				0.073		
				(0.539)		
Soybeans Price Index					0.000**	
					(0.000)	
Historical Volatility (Soybeans, Three Months)					0.535	
					(0.739)	
Wheat Price Index						0.000
						(0.000)
Historical Volatility (Wheat, Three Months)						1.095
						(0.691)
Food Riots in Africa, Previous Month	-0.013	-0.015	-0.019	-0.034	-0.020	-0.002
	(0.066)	(0.065)	(0.065)	(0.065)	(0.066)	(0.065)
Trend	-0.000	-0.000	-0.000	-0.001*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.126	-0.029	0.041	0.096	0.091	0.058
	(0.139)	(0.121)	(0.119)	(0.121)	(0.120)	(0.119)
Observations	250	250	250	250	250	250
Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes

R-squared	0.058	0.061	0.062	0.087	0.061	0.055

Standard errors in parentheses

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

Table A13. IV Estimation Results for the Determinants of Food Riots in Africa, 1990-2010.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable: SCAD Data Count of Food Riots in Africa						
Food Price Index	0.006*					
	(0.003)					
Historical Volatility (Food, Three Months)	-1.549					
	(1.999)					
Cereal Price Index		0.004*				
		(0.002)				
Historical Volatility (Cereals, Three Months)		-1.826				
		(1.473)				
Maize Price Index			0.002*			
			(0.001)			
Historical Volatility (Maize, Three Months)			-0.686			
			(0.917)			
Rice Price Index				0.001		
				(0.000)		
Historical Volatility (Rice, Three Months)				-0.255		
				(0.886)		
Soybeans Price Index					0.000*	
					(0.000)	
Historical Volatility (Soybeans, Three Months)					0.335	
					(0.774)	
Wheat Price Index						0.002*
						(0.001)
Historical Volatility (Wheat, Three Months)						-0.170
						(1.068)
Food Riots in Africa, Previous Month	-0.034	-0.038	-0.037	-0.048	-0.040	-0.026
	(0.069)	(0.070)	(0.069)	(0.071)	(0.069)	(0.069)
Trend	-0.001*	-0.001*	-0.001*	-0.001	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.345	-0.098	0.037	0.130	0.120	0.105
	(0.241)	(0.139)	(0.120)	(0.142)	(0.125)	(0.127)
Observations	250	250	250	250	250	250

Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic (Weak Instrument)	34.69	40.32	53.44	40.83	57.76	34.69
R-squared	0.023	0.035	0.047	0.082	0.046	Dropped

Standard errors in parentheses

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