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MARKETS, TRANSPORTATION INFRASTRUCTURE, AND FOOD PRICES IN NEPAL

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We study transportation infrastructure and food markets in Nepal over the period 2002 to 2010, combining monthly price data from thirty-seven local and regional markets, and seven Indian border markets. We use a series of autoregressive models to study price determination, spatial and temporal price transmission, and price variance. We account for district-level agricultural production, correcting for bi-directional causality between output and prices using ground station rainfall data. In addition, to test hypotheses regarding the importance of transportation infrastructure we incorporate information on road and bridge density and fuel costs. For both rice and wheat, we find strong evidence of local price intertemporal carryover and very weak evidence of price transmission from regional, central, and border markets to local markets, suggesting very low degrees of market integration. Fuel costs are positively correlated with food prices, and road and bridge density are negatively correlated with prices. We find evidence of asymmetric effects: positive price shocks are correlated with higher subsequent price volatility compared with negative price shocks of similar magnitude. Roads and bridges are important for moderating price levels and price volatility in Nepal's rice and wheat markets, which explains roughly half of the spatial and temporal variation in price mark-ups between regional and local markets.

Key words: Bridges, food prices, markets, rice, roads, wheat, Nepal.

JEL codes: Q02, Q11, R40.

How important is transportation infrastructure to agricultural markets in a developing country? In this article we provide an answer for Nepal, a country with harsh topography, weak transport linkages, wide differences in food prices across locations, and widespread food insecurity. Over the past several decades, investments in transportation infrastructure have been highly heterogeneous across space and time in Nepal, and have been undermined by weak economic performance, political instability, and a prolonged civil war. The twin earthquakes of 2015, combined with recent politically-driven fuel shortages, have highlighted the fragile nature of the transport and market infrastructure in Nepal, and have renewed interest in the transportation sector as a key driver of overall economic development. Elsewhere, transportation costs have been found to be important contributors to agricultural input use (Qin and Zhang 2016), agricultural productivity (Gollin and Rogerson 2014), and food prices (Minten and Kyle 1999; Goletti 1994). In this article, we add to this relatively small body of literature that seeks to connect the transportation and agricultural sectors of a developing economy.[1]

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[1] Gurung (2010) argues that improved access to roads has lowered food costs in several districts of Nepal, and provided other benefits including greater production of cash crops, improved access to services, and increased employment and incomes.

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By leveraging data on changes in road and bridge density over time, we provide a comprehensive analysis of market connections and price transmission along the marketing chains for two of the most important consumer staples in Nepal—rice and wheat. In Nepal, these marketing chains have multiple nodes, connecting local markets to regional, central, and Indian border markets by a sparse network of footpaths, earthen roads, and all-season roads and bridges of varying qualities and densities. The highly fragmented nature of Nepal's food economy introduces both domestic production and cross-border trade as potential determinants of food prices and price volatility. Although for most countries overall integration into world agricultural markets can affect food security and food price volatility—either negatively, by allowing volatility to enter from the world market, or beneficially, by allowing imports to buffer domestic supply shocks—Nepal is relatively isolated from world markets. Because it is landlocked, with a formidable northern border crossing to Tibet and a controlled and highly politicized southern border with India, local food security is quite sensitive to internal production and trade. If Nepal's local markets are not well-connected to regional and border markets, and if those same local markets are characterized by insufficient production and storage, high price volatility and incomplete price transmission are likely to prevail. Under such conditions, one might hypothesize, as we do here, that isolated markets are not likely to receive either price signals or food shipments in a timely fashion, and that high transportation and storage costs will discourage traders from engaging in the kinds of spatial and temporal arbitrage that improve market integration. For these reasons, Nepal is an excellent case for investigating the importance of transportation in agricultural prices. Below, we empirically test several hypotheses, including a conjecture that higher road and bridge densities at the district level result in lower prices, lower price volatility, and reduced transport costs. We also test whether fuel costs are positively correlated with food prices and food price volatility, and measure their contribution to price differences across locations and time. A key innovation in our approach is to incorporate multiple levels of price-to-price transmission effects simultaneously. That is, contemporaneous and lagged values of regional, border, and central market prices are all included in the model for monthly local prices. Such an approach obviously raises conceptual and statistical concerns regarding multicollinearity among these various prices, an issue that we address by comparing results from models in which regional, border, and central market prices are treated as alternative exogenous prices.

To the best of our knowledge, no previous studies have examined econometrically the connections between road and bridge infrastructure and food prices. Our findings have implications not only for Nepal, but also for other settings where local markets are fairly isolated, either by policy or by structure and geography. Our interest in food prices and food price volatility is motivated by the large catalog of research demonstrating that poor consumers can be adversely affected by increases in food prices (Deaton 1989; Timmer 1989; Bouis 2008; Von Braun 2008; Andreyeva, Long, and Brownell 2010; Alem and Soderbom 2012; Hawkes 2012). Higher food prices undermine expenditures on nutrition-sensitive basic needs such as health care and education (FAO et al. 2011); have been linked to the worsening of child health and nutrition outcomes (Thomas and Strauss 1992; Lavy et al. 1996; Anriquez 2013; Grace, Brown, and McNally 2014); and have been implicated in a range of negative social and nonnutritional outcomes (Swan, Hadley, and Cichon 2009; Hadley et al. 2012), including social unrest (Bellemare 2014).[2] Food price volatility is also of concern. The Food and Agricultural Organization (FAO 2010a) has identified large unexpected price fluctuations as a major threat to food security in developing countries, especially where there is an underlying lack of diet diversity. Price variability has been shown to have a

[2] Higher food prices are potentially beneficial for net-sellers since they result in higher incomes. But in Nepal, a majority of agricultural households are net-buyers of food and a typical household spends 60% of its total budget on food (WFP/NDRI 2008; CBS 2011). As a result of this high food expenditure share, UNOCHA (2008) estimates that about 4.4 million people in Nepal are at nutritional risk from a rise in food prices. In part, nutritional risk in Nepal is driven by geography and isolation. WFP/NDRI (2008) found that communities in Nepal that were located farther away from markets were more likely to face high food prices and to consume lower quality foods.

negative effect on a range of household welfare indicators (Cummings 2012; Dawe and Timmer 2012; Bellemare, Barrett, and Just 2013; Akter and Basher 2014). Further, Kharas (2011) argues that by creating economic and political turbulence, price volatility jeopardizes long-run social stability. Using data from Ghana, Shively (2001) demonstrates that high price volatility raises the cost of stockholding as much as four-fold, thereby reducing incentives for traders and undermining market performance itself.

Given the widespread importance of food prices to nutritional outcomes in developing countries, as well as a specific recognition of the long-standing economic, political, and environmental challenges facing Nepal, it is somewhat surprising that relatively little attention has been devoted to the study of agricultural markets and prices in Nepal. Before the earthquakes of early 2015, problems with food distribution were already widespread and the cost of transportation was high, a situation often attributed to harsh topography and the isolation of food-deficit regions (Nepal Agri-business Promotion and Marketing Development Directorate 2010; Nepalese Ministry of Agricultural Development 2012). The 2015 earthquakes have further complicated the situation and underscored that little is formally known about agricultural price transmission in Nepal. Most studies of Nepal's agricultural markets to date have been highly descriptive in nature (e.g., World Food Programme/FAO 2007; Agostinucci and Loseby 2008; WFP/Nepal Development Research Institute 2008; FAO 2010b). A small number of price studies have employed econometric techniques (see Sanogo 2008; Sanogo and Amadou 2010; Shrestha 2013), but few have focused comprehensively on agricultural price transmission. Moreover, all past studies for Nepal use relatively short price series and an extremely limited set of covariates, making it difficult to draw strong inferences from the findings. We rectify these shortcomings below.

Empirical Strategy

Our empirical approach builds upon price-focused models of commodity trade. Early empirical models testing the law of one price in this way include Blyne (1973), Cummings (1967), and Harriss (1979). Conceptually, whenever the price of a commodity in one market exceeds the price of the same commodity in another market by more than the cost of transportation and marketing, traders have an opportunity to engage in spatial arbitrage until prices converge, thereby restoring spatial equilibrium (Ravallion 1986; Goodwin, Grennes, and Wohlgenant 1990; Sexton, Kling, and Carman 1991; Badiane and Shively 1998). Models in which market segmentation is related to transfer cost thresholds were introduced by Baulch (1997) and Goodwin and Piggott (2001). Myers and Jayne (2012) and Burke and Myers (2014) allow for threshold effects stemming from trade volume. The assumption in all of these models is that suppliers and traders in regional and transit hubs supply grain to various markets, adapting their marketing strategies to target destinations where there is the greatest arbitrage opportunity. Temporary equilibriums and shortages lead traders to shift their short-term focus among different areas and nodes. When markets are well-connected and when price signals are completely transmitted among markets, temporary disequilibria are infrequent and quickly resolved. When information and products do not flow quickly or easily, disequilibria may persist, suggesting potential pathways to improving overall welfare by raising prices for producers, lowering prices for consumers, or both.[3] Our innovation and contribution is to incorporate multiple levels of price-to-price transmission effects simultaneously while explicitly accounting for market-specific factors that affect transfer costs.

Figure 1 illustrates the current market structure in Nepal and highlights the importance of hubs located in the Terai (the plains bordering India) as suppliers and transshipment points to the rest of the country. To provide some sense of the heterogeneity in transportation infrastructure across space and time in Nepal, figure 2 charts changes in transportation density in three representative districts of the country: Jumla, located in the mountains; Kaski, in the middle hills; and Mahottari, in the Terai. Largely because of the low population density and high costs of road construction in the hills and mountains, in past decades the Terai has been given priority for road and bridge construction (time paths of road construction in

[3] Disequilibria also may cause price instability. As Williams and Wright (1991) and Newbery and Stiglitz (1981) point out, exactly who might be harmed by price instability, and by how much, depends on a range of factors including risk-taking behaviors and the slopes of the supply and demand curves.

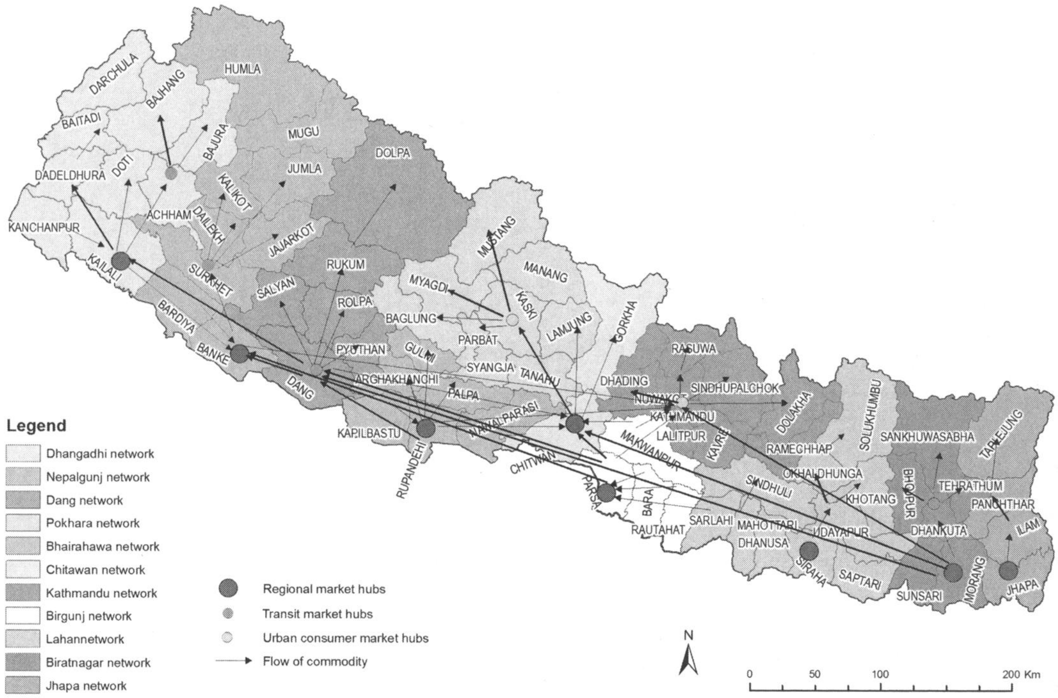

Figure 1. Food grain markets and commodity flows in Nepal

Source: Adapted from WFP/FAO 2007.

these districts is provided in online supplemental appendix figure A.1). More recently, the government has begun to boost investment in road and bridge construction in the hills and mountains, but many remote districts remain inaccessible.[4] As recently as 2010, fifteen of seventy-five districts in the country were not road connected (FAO 2010c), and as of 2015, the Humla and Dolpa districts remained unconnected by roads to other parts of the country. In many locations, several hours or days of road travel are required to reach the district headquarters (Nepal Central Bureau of Statistics 2011). In 2005, it was estimated that more than one-quarter of all households in Nepal had to walk for at least eight hours to reach a road (FAO 2010c). In remote locations, goods are often either airlifted or carried by mules or porters, adding substantially to the price of final goods, especially during some periods of the year.

Roads and bridges, of course, are only one element contributing to transportation costs. Another important component is fuel. Nepal imports all of its required refined oil from India via the Nepal Oil Corporation Limited (NOC), a state-owned trading company that is solely responsible for the importation, transportation, storage, and distribution of petroleum products. Although fuel prices in Nepal are not directly determined by the international market, increases in international fuel prices are usually passed through to domestic consumers by the NOC. Though petroleum products are heavily subsidized, between 1986 and 2013 the nominal diesel price in Nepal increased nearly ten-fold, and spiked several times (appendix figure A.2).

To quantify the transmission of price signals and test the importance of transportation infrastructure to food prices, we begin with Ravallion's (1986) model. We make two fundamental modifications. First, instead of focusing on a single market, we use a panel of local markets. We connect each local market to its (i) Nepal-India border market; (ii) regional market; and (iii) central market. Second, in contrast to studies that treat a

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[4] In 2013–14, the government allocated approximately 8% of its total budget to the transportation sector. In recent years, roughly two-thirds of the total budget allocated for transportation development came from foreign sources (DOR 2012). The World Bank and the Asian Development Bank (ADB) have been the main supporters of road and bridge projects in Nepal.

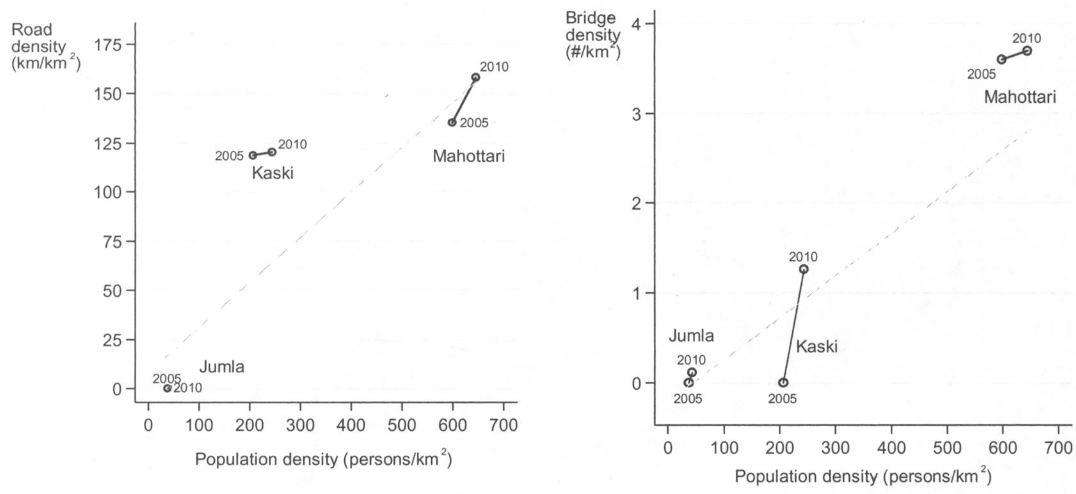

Figure 2. Road and population densities in three districts of Nepal in 2005 and 2010

Note: Jumla is located in the mountain zone, Kaski is located in the hills, and Mahottari is located in the Terai. Road index is weighted by quality. See text for details of construction.
Source: Government of Nepal, Department of Roads.

primary supply location as the central market, we assume that Nepal's central market is Kathmandu. We reason that because approximately 10% of Nepal's population lives in Kathmandu (Nepal Central Bureau of Statistics 2011) and because Kathmandu's demand largely determines the position of the national demand curve (WFP/FAO 2007), demand from the Kathmandu Valley likely plays a key role in setting prices at the margin.

With Nepal's market structure in mind, we define local markets as those small and locally-important trading centers that are located (mainly) in food-deficit districts of the country. These markets receive inflows of foods via border and regional markets. Regional markets are located in districts with high production potential, storage facilities, and comparatively good transportation links to other parts of the country. Border markets connect Nepal with India.[5] The central market for all local markets in Nepal is the capital, Kathmandu. Local food prices are expected to depend on local supply, and to be influenced through trade by prices in regional, central, and border markets.[6] We focus on twenty-eight local markets with fairly complete time series for rice and wheat prices. These markets are typical, but we make no strong claims regarding their overall representativeness for Nepal.

Figures 3–5 display how the border (panel A), regional (B), and central (C) market prices move with local market prices. Time trends for these prices are displayed in panel D of each figure. Prices in Nepal are usually higher than in border markets and are widely assumed to be influenced by Indian market prices. The NRB (2007), in fact, argues that food prices in Nepal are *determined* by India, a conjecture we reject below. Figures 3A–5A show that border market prices are positively correlated with local agricultural prices in the hills and Terai (Kaski and Mahottari) but not the mountains (Jumla).

All of the regional markets are located in the Terai. We expect them to play an important role in stabilizing food prices countrywide by providing storage, spatial and temporal arbitrage, and intermediary activity for imports from India (Action Aid 2006). One might reasonably expect supply shocks affecting regional markets to be transmitted to local markets. For example, figures 3B to 5B illustrate that rice prices in the hills and Terai

[5] Nepal and India share an open and porous 1,185 km border. Of the 30 customs offices in Nepal, 20 are located on the Indian border. All would-be traders must complete a customs transit and summary declaration form through which all imports are officially registered and subjected to customs duty and taxes (Ministry of Finance, Nepal). Although a high volume of Nepal's trade is informal and unregistered inspection, it is reasonable to assume that observed border prices incorporate information regarding total formal and informal trade between India and Nepal.

[6] Recent evidence suggests that trade itself may not be required for price transmission, as long as there is a flow of price information (Burke and Myers 2014; Stephens et al. 2012).

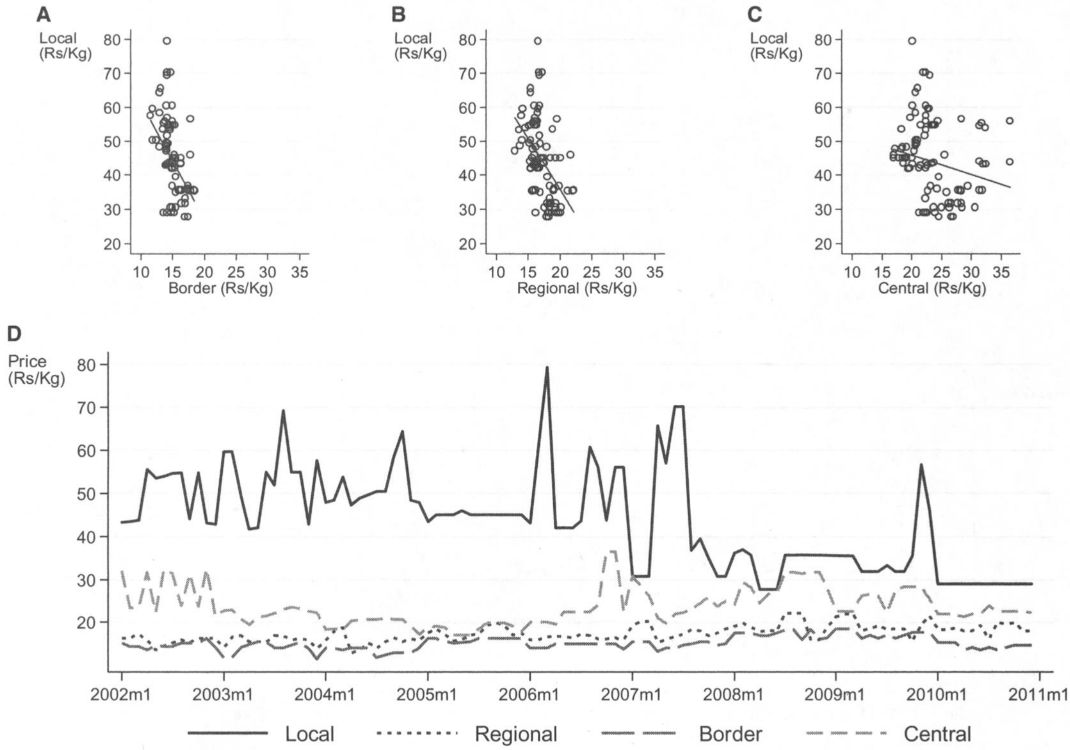

Figure 3. Monthly real rice prices in Jumla (mountains) and companion markets (2002–2010)

Source: Data from the Nepal Agribusiness Promotion and Marketing Development Directorate.

move closely with prices in their corresponding regional markets. Similarly, figures 3C–5C show that the same prices are positively correlated with the central market price.

With the forgoing definitions of markets in mind, we model the local market price as

$$(1)\quad \mathrm{P_{ilt}} = \alpha_{i0} + \alpha_{i1}\mathrm{T} + \alpha_{i2}\mathrm{M} + \alpha_{i3}\mathrm{Y} + \alpha_{i4}\mathrm{L} + \gamma_i \mathrm{P_{ilt-1}} + \sum_{j=0}^{1}\sum_{k=1}^{3}\beta_{ik}\mathrm{P_{ikt-j}} + \theta'\mathbf{D} + \delta'\mathbf{S} + \vartheta_i \mathrm{E_t} + \mu_{ilt}$$

where P_{ilt} represents the retail price for commodity i in market l at time t; T is a unit-step (monthly) time trend; M, Y, and L are month, year, and location (agro-ecology) fixed effects; P_{ikt-j} is the price observed for commodity i in companion market k (either regional, central, or border) at time t, with lag j. Here, α_{is}, γ_i, β_{ik}, θ, ϑ_i, and δ are parameters to be estimated. The error term, μ_{ilt}, is assumed to be independently and identically distributed across the observations. Parameters β_{ik} and γ_i are coefficients for spatial market price transmission and auto-regressive lags, respectively; $\boldsymbol{D}$ and $\boldsymbol{S}$ are column vectors representing demand and supply shifters and E_t is the exchange rate, which we assume can influence both demand and supply. Further, $\boldsymbol{D}$ includes annual district population, $\boldsymbol{S}$ includes infrastructure (roads and bridges), fuel prices, and agricultural production.

Directly incorporating agricultural production as an independent variable in equation (1) is problematic because prices can both influence and be influenced by output. To address the endogeneity issue introduced by this bi-directionality, we predict the quantity harvested (Q_{ilt}) using a time trend (T), rainfall (R_{ilt}), total area planted (A_{ilt}), and a pair of binary ecological zone indicators (Z) for the Terai and the Hills. Here, rainfall serves as an instrumental variable.[7] The maintained

[7] Temperature is also important for production. Temperature is exogenous to price but correlated with rainfall. Including a variable for temperature would likely change the estimated coefficient on rainfall and would probably improve the predictive accuracy of our instrument. Unfortunately, incorporating temperature is a challenge for Nepal because altitude and terrain exert a large influence on solar irradiance and growing conditions, and available temperature datasets provide neither high-

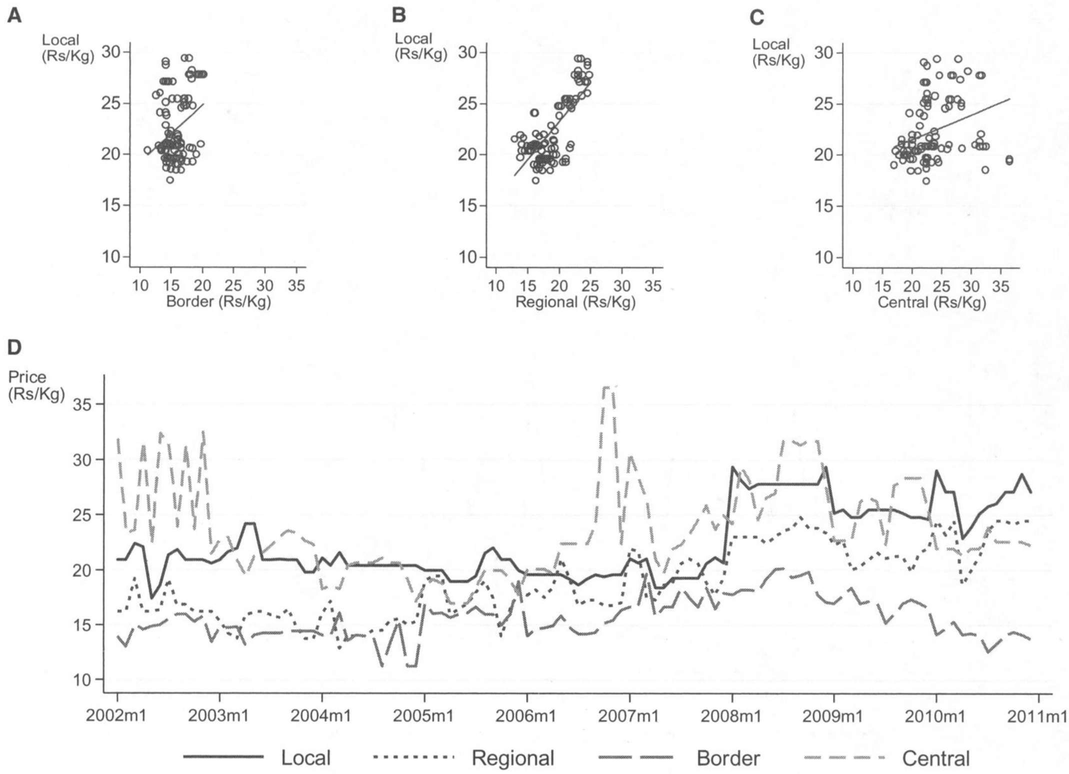

Figure 4. Monthly real rice prices in Kaski (hills) and companion markets (2002–2010)

Source: Data from the Nepal Agribusiness Promotion and Marketing Development Directorate.

assumption is that, at the temporal and spatial scales observed, rainfall influences prices only through production, and can therefore be excluded from the price equation itself. The harvested quantity equation is expressed as

$$(2) \quad \mathrm{Q_{ilt}} = \beta_{i0} + \beta_{i1}\mathrm{T} + \beta_{i2}\mathrm{R_{ilt}} + \beta_{i3}\mathrm{A_{ilt}} + \phi \mathrm{Z} + \epsilon_{\mathrm{ilt}}$$

where β's and ϕ are coefficients to be estimated; ϵ_{ilt} is the error term, which we assume to be independent and identically distributed. Predicted output based on equation (2) is included as a regressor in the estimated version of equation (1).

Using the estimated coefficients from equation (1), a set of specific hypotheses regarding price determinants, market segmentation, and short- and long-run market integration can be tested. In a long-run equilibrium, market prices are assumed to be constant over time and undisturbed by local stochastic effects. If $\beta_{ik} = 0 \ \forall \ k$, then the local market is segmented from other markets. If $\beta_{ik} = 1 \ \forall \ k$ and $\gamma_i = 0$, then local markets are integrated with other markets in the short-run. If markets are integrated in the long-run, then $\gamma_i + \sum \beta_{ik} = 1$, given the number of lags required for the equality to hold.

Our analysis explicitly accounts for specific determinants of prices, including agricultural production, exchange rates, lagged market prices, fuel prices, and roads and bridges. Given the overall negative effects of food price variances on nutrition and food security in Nepal, it seems equally important to investigate the determinants of food price variances. Past studies conducted in Africa have included production measures, exchange rates, and lagged market prices to help explain local market price variances (Shively 1996; Badiane and Shively 1998). Studies from different countries reveal mixed results on the effect of fuel prices on agricultural commodity prices. Abbott, Hurt, and Tyner

resolution ground-level information on temperature, nor geostationary thermal observations at high enough resolution to be useful that have been corrected for solar irradiance and altitude. Excluding temperature is a weakness in our approach, but the fundamental assumptions supporting our choice of instrument still hold.

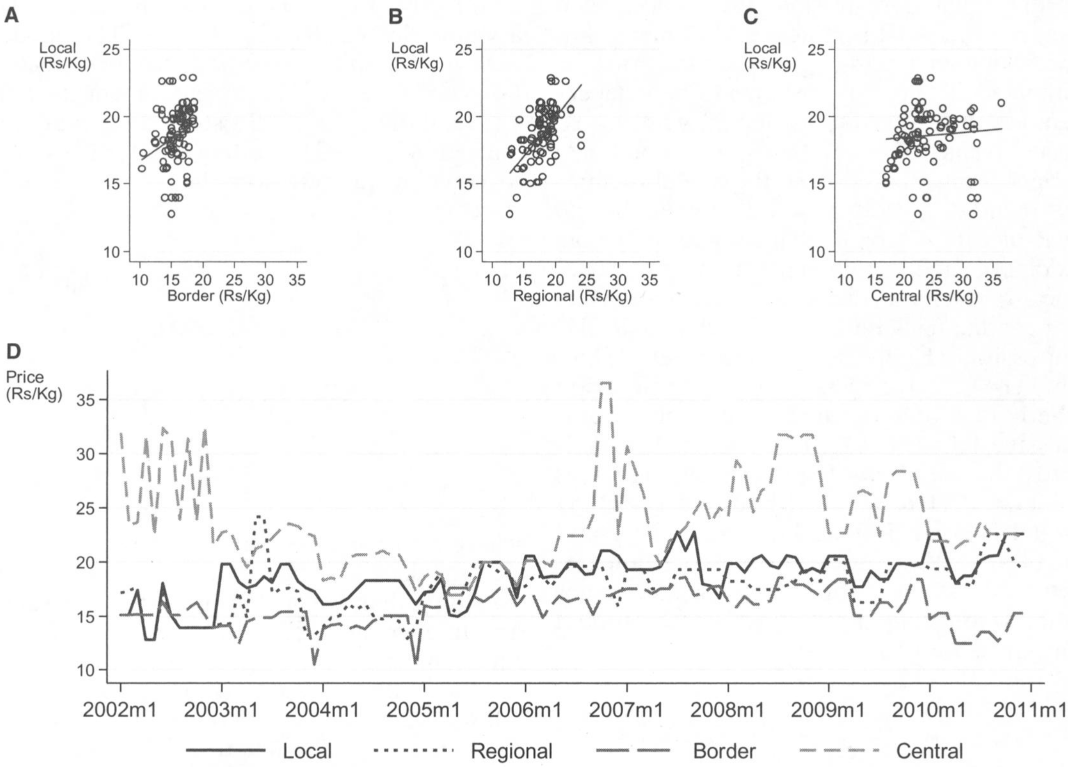

Figure 5. Monthly real rice prices in Mahottari (Terai) and companion markets (2002–2010)

Source: Data from the Nepal Agribusiness Promotion and Marketing Development Directorate.

(2008) and Chang and Su (2010) indicate that oil prices are a main factor driving food prices. In contrast, Zhang et al. (2010) and Gilbert (2010) find no strong linkages between oil prices and agricultural prices. Although fuel prices are directly set by the government in Nepal, and are less volatile than one might find elsewhere, during the last decade the fuel price has fluctuated somewhat, and so it seems possible that fuel prices could have contributed to food price volatility.

When errors exhibit time-varying heteroskedasticity, failing to account for this can distort standard errors and mislead one regarding statistical inference. From a statistical point of view, efficiency gains are possible by using an autoregressive conditionally heteroskedastic (ARCH) estimation strategy instead of OLS (Engle 1982; Bollerslev, Chou, and Kroner 1992). The process involves estimating the parameters of the mean and variance equations simultaneously. The Panel ARCH model can be written as

$$
\begin{aligned}
(3)\quad \mathrm{P_{ilt}} &= \alpha_{i0} + \alpha_{i1}\mathrm{T} + \alpha_{i2}\mathrm{M} + \alpha_{i3}\mathrm{Y} + \alpha_{i4}\mathrm{L} \\
&\quad + \gamma_i \mathrm{P_{ilt-1}} + \sum_{j=0}^{1}\sum_{k=1}^{3} \beta_{ik}\ \mathrm{P_{ikt-j}} \\
&\quad + \theta^{'}\mathbf{D} + \delta^{'}\mathbf{S} + \vartheta_i \mathrm{E_t} + \mu_{ilt}, \\
&\quad i = 1 \text{ to } 2,\ l = 1\ldots 28,\ t = 1.,\mathrm{T}
\end{aligned}
$$

$$
\begin{aligned}
(4)\quad \sigma^2_{ilt} &= \gamma_{i0} + \gamma_{i1}\epsilon^2_{ilt-1} + \gamma_{i2}\mathrm{T} + \gamma_{i3}\mathrm{E_t} + \gamma_{i4}\mathrm{L} \\
&\quad + \sum_{j=0}^{1}\sum_{k=1}^{3}\gamma_{ik}\mathrm{P_{ikt-j}} \\
&\quad + \psi\mathbf{D} + \lambda\mathbf{S} + \vartheta_{ilt}.
\end{aligned}
$$

The ARCH structure adds to the conditional mean equation (3) the conditional variance equation (4). The variances of the regression disturbances (σ^2_{ilt}) are assumed to be conditional on the size of prior unanticipated innovations, that is, ϵ^2_{ilt-1} (lagged values of the squared regression disturbances) and factors expected to influence food price variances. In equation (4), γ_{i1} are parameters to be estimated. The ϑ_{ilt} are assumed to be independently and identically distributed with an expected value of zero. Since the conditional variances must be positive, the model requires $\gamma_{i0}>0$ and $\gamma_{i1} \geq 0$. If $\gamma_{i1} = 0$, then there are no dynamics in the conditional variance equation. Adding lagged conditional variances to equation (4) results in the generalized autoregressive conditionally heteroskedastic (GARCH) regression (Engle 1982; Bollerslev 1986). The GARCH(m,n) is a standard notation where m indicates the number of autoregressive lags (or ARCH terms) and n indicates the number of moving average lags (or GARCH terms). Although a GARCH model is conditionally heteroskedastic and mean reverting, unconditional variance is assumed to be constant. The variance component of the panel GARCH(1,1) model for our needs can be written as

$$(5) \quad \sigma^2_{\mathrm{ilt}} = \gamma_{\mathrm{i0}} + \gamma_{\mathrm{i1}}\epsilon^2_{\mathrm{ilt-1}} + \beta_{\mathrm{i1}}\sigma^2_{\mathrm{ilt-1}} + \gamma_{\mathrm{i2}}\mathrm{T} + \gamma_{\mathrm{i3}}\mathrm{E_t} + \gamma_{\mathrm{i4}}\mathrm{L} + \sum_{\mathrm{j=0}}^{1}\sum_{\mathrm{k=1}}^{3}\gamma_{\mathrm{ik}}\mathrm{P_{ikt-j}} + \psi\mathbf{D} + \lambda\mathbf{S} + \vartheta_{\mathrm{ilt}}.$$

The condition $\gamma_{i1} + \beta_{i1} < 1$ is sufficient to guarantee covariance stationarity for each cross-section in the panel (Bollerslev 1986). Disturbances in the model are assumed to be cross-sectionally independent, a strong assumption that we test below.

Although the linearity property of the GARCH model facilitates parameter estimation and tests for homoscedasticity, GARCH models may suffer from various limitations (Nelson 1991). First, since the conditional variance must be non-negative, the model remains highly constrained. Second, standard GARCH models respond symmetrically to both positive and negative innovations. However, price volatility might behave asymmetrically to positive and negative shocks. Shively (2001), for example, finds price thresholds relating to price volatility in Ghana's maize market, arguing that isolated and thin markets, which tend to be less integrated both spatially and temporally, may be especially prone to non-linear and asymmetric adjustments in price. Agricultural price formation in some markets of Nepal may well be explained by an asymmetric GARCH model. There are many forms of asymmetric GARCH models, including the asymmetric GARCH (AGARCH) model (Engle, Ito, and Lin 1990) and the threshold GARCH (TGARCH) model (Rabemananjara and Zakoian 1993; Glosten, Jagannathan, and Runkle 1993). Adding the term $\gamma_{i2}\epsilon_{ilt-1}$ to equation (5) produces the AGARCH(1,1) structure:

$$(6) \quad \sigma^2_{\mathrm{ilt}} = \gamma_{\mathrm{i0}} + \gamma_{\mathrm{i1}}\epsilon^2_{\mathrm{ilt-1}} + \gamma_{\mathrm{i2}}\epsilon_{\mathrm{ilt-1}} + \beta_{\mathrm{i1}}\sigma^2_{\mathrm{ilt-1}} + \gamma_{\mathrm{i3}}\mathrm{T} + \gamma_{\mathrm{i4}}\mathrm{E_t} + \gamma_{\mathrm{i5}}\mathrm{L} + \sum_{\mathrm{j=0}}^{1}\sum_{\mathrm{k=1}}^{3}\gamma_{\mathrm{ik}}\mathrm{P_{ikt-j}} + \psi\mathbf{D} + \lambda\mathbf{S} + \vartheta_{\mathrm{ilt}}$$

where positive values for γ_{i2} imply that positive shocks result in larger increases in price volatility than negative shocks of the same absolute magnitude. Adding the indicator function term $\gamma_{i2}(I_{\epsilon ilt>0})\epsilon^2_{ilt-1}$ to equation (5) produces the TGARCH(1,1) model, which allows the conditional variance to depend on the sign of lagged innovations,

$$(7) \quad \sigma^2_{\mathrm{ilt}} = \gamma_{\mathrm{i0}} + \gamma_{\mathrm{i1}}\epsilon^2_{\mathrm{ilt-1}} + \left(\gamma_{\mathrm{i2}}\left(\mathrm{I}_{\epsilon_{\mathrm{ilt-1}}>0)}\right)\ \epsilon^2_{\mathrm{ilt-1}}\right) + \beta_{\mathrm{i1}}\sigma^2_{\mathrm{ilt-1}} + \gamma_{\mathrm{i3}}\mathrm{T} + \gamma_{\mathrm{i4}}\mathrm{E_t} + \gamma_{\mathrm{i5}}\mathrm{L} + \sum_{\mathrm{j=0}}^{1}\sum_{\mathrm{k=1}}^{3}\gamma_{\mathrm{ik}}\mathrm{P_{ikt-j}} + \psi\mathbf{D} + \lambda\mathbf{S} + \vartheta_{\mathrm{ilt}}.$$

The indicator function in equation (7) is 1 when the error is positive and 0 when it is negative. If γ_{i2} is positive, negative errors are leveraged and positive shocks have larger effects on volatility than negative shocks. Detailed information on the various forms of ARCH and GARCH models is provided by Bollerslev (2007). We present diagnostic tests and results for five regression models: AR(1), ARCH(1), GARCH(1,1), AGARCH(1,1), and TGARCH(1,1).

Data

Definitions, units of measure, and basic descriptive statistics for all variables used in the regressions are provided in table 1. We estimate our model using the average monthly retail prices of coarse rice and wheat flour from twenty-eight district markets, eight

Table 1. Descriptive Statistics for Variables Used in the Regressions

Variable	Obs.	Mean	St. Dev.	Min.	Max.
Rice harvest (,000 tons)	252	42.3	39.6	2.5	180.6
Wheat harvest (,000 tons)	252	17.0	16.2	1.5	64.5
Rice planted area (,000 ha)	252	16.4	14.6	1.4	65.0
Wheat planted area (,000 ha)	252	8.9	7.2	1.8	32.3
Average monsoon rainfall (May–September, in mm)	252	1,186.2	1,381.1	27.7	8,362.0
Average monsoon rainfall (October–February, in mm)	252	92.7	107.6	0.0	792.5
Local market coarse rice price (real Nepal Rs/kg)	3024	23.3	8.3	9.9	79.4
Regional market coarse rice price (real Nepal Rs/kg)	864	18.2	3.6	12.6	66.2
Central market coarse rice price (real Nepal Rs/kg)	108	23.7	4.4	17.0	36.5
Border market coarse rice price (real Nepal Rs/kg)	756	15.7	2.0	9.4	25.4
Local market wheat flour price (real Nepal Rs/kg)	3,024	25.3	9.9	10.3	134.4
Regional market wheat flour price (real Nepal Rs/kg)	864	18.9	4.4	9.9	138.5
Central market wheat flour price (real Nepal Rs/kg)	108	21.0	2.1	17.4	27.8
Border market wheat flour price (real Nepal Rs/kg)	756	16.7	2.4	9.9	26.2
Total road length in district (km)	252	123.6	66.6	0.0	271.2
Index of road density in district (weighted km/km^2)	252	49.3	44.7	0.0	157.8
Bridge density in district (#/km^2)	252	0.7	1.0	0.0	3.7
Average diesel fuel price in district (real Nepal Rs/liter)	252	40.7	6.8	28.6	56.5
Monthly exchange rate (Nepal Rs/USD)	108	72.7	4.3	63.0	81.8

regional markets, one central market, and seven Indian border markets. These markets are listed in appendix table A.1 and mapped in online supplemental appendix figure A.3. [8] All reported regressions use real prices, expressed in natural logs. Prices cover a period of 108 months between January 2002 and December 2010.[9] Price distributions are displayed in the appendix (see figures A.4 and A.5).

Annual district-level data on total planted area and total harvested amounts for rice and wheat come from the Ministry of Agriculture Development (NMOAD), Nepal (appendix figure A.6). Monthly rainfall data from January 2002 to December 2010 were obtained for 282 rainfall stations from the Department of Hydrology and Meteorology, Nepal. Rainfall stations are always coincident with production locations, and therefore we use these ground station data rather than satellite-derived or interpolated measures. Depending on the size of the district, multiple meteorological stations may be located in or near production areas. Where we have multiple observations for a district, we simply average the available values within a district. The locations of these rainfall stations are indicated on the map included in the online supplemental appendix (figure A.3). We align the rainfall data with the crop calendar. Because rice is produced only once each year in most areas of the country, and depends heavily on the quantity and distribution of monsoon rainfall that arrives between May and September, we aggregate rainfall received during this window for rice. For wheat, production starts in October and ends in March, and so we use this five-month window to build our rainfall measure for wheat.

We obtained district-level data on roads from the Department of Roads (DOR), Ministry of Physical Planning, Works and Transport Management. The DOR publishes *Nepal Road Statistics* (NRS) in alternate years.[10] Annual progress reports prepared by the DOR list all roads completed in a district in that year. The road data published by the DOR, and hence the variables included in the

[8] Nominal prices from the Nepal Agribusiness Promotion and Marketing Development Directorate were deflated using the country-wide consumer price index (CPI) as reported by the IMF (www.indexmundi.com/facts/nepal/consumer-price-index). Out of 24,192 prices in our dataset, 2,364 (9.7%) were linearly interpolated to replace missing values in order to maintain continuity of the series.

[9] We focus on rice and wheat. The main staple food in most parts of Nepal, and for most Nepalese, is rice. Rice is planted in all ecological regions of the country and traded in most markets. Potatoes and barley are important in the hilly and mountainous districts, and wheat flour is considered by many Nepalese to be a close but imperfect substitute for all grades of rice. Prices for these items tend to move together, and have positive and statistically significant pairwise correlations, as shown in online supplemental appendix table A.2.

[10] Missing data for years in which NRS was not published were provided by the DOR's annual, unpublished progress reports, which were obtained directly from government offices in Kathmandu.

regressions, focus on Nepal's "Strategic Road Network," that is, National Highways and Feeder Roads. To account for road quality, we compute an index using weights that account for different road qualities and the travel times these imply. We assume that a blacktopped road is five times faster than a gravel road, and fifty times faster than an earthen road.[11] We then express the index as a density by dividing by district area in $km^2/1{,}000$. The Department of Roads and the Department of Local Infrastructure Development and Agricultural Roads (DoLIDAR) regularly report on bridge construction. Using their data, we calculate the total number of bridges constructed in each district in each year over the period of 2002–2010. We lack the information needed to account for bridge quality. We compute bridge density as the number of bridges existing along the district's strategic roads in each year, divided by district area in $km^2/1{,}000$. Our assumption is that low bridge density indicates low investment, where bridges are needed. We believe this generally holds at the district level in Nepal, but acknowledge that in some districts low density could reflect low demand, where bridges are not needed.

Monthly fuel prices are region-specific; they come from the Nepal Oil Corporation Limited (NOC).[12] The Nepal/India official exchange rate comes from the Nepal Rastra Bank and has been converted to a Nepal/USD index. To account for demand shifts, we include the annual district population as reported by NMOAD. Unfortunately, we cannot incorporate grain storage in the model. Data on private stocks are not available, and data on public storage are incomplete, unreliable, and infrequently reported or updated. We also are unable to incorporate data that shed light on the role of communications infrastructure. Undoubtedly, price patterns across time and geography are influenced by information flows. These flows have been evolving rapidly in conjunction with the build-up of mobile telephone coverage in Nepal. Implicitly, our model assumes either that communication is homogenous across Nepal or perfectly correlated with transportation infrastructure. Failures in this assumption could introduce bias of an unknown form into our regressions. Incorporating information on communications infrastructure for price analysis will likely constitute a fruitful avenue for future research in Nepal and elsewhere.

Results and Discussion

Results are presented in tables 2–5.[13] We begin by discussing our instrumentation approach for district-level agricultural production, and then describe diagnostic tests, regression estimates, and implications for inference regarding market integration. We then discuss robustness of our results and conclude this section with an analysis of transportation costs.

Agricultural Production Function Regressions

Table 2 displays results for the district-level regressions of annual rice and wheat production that we use to generate instrumented values for use in our price models. The time trends for both are positive but insignificant, implying no obvious technical progress in Nepal over the period, at least of a Hicks-neutral form. The coefficients for rice and wheat planted area are positive and statistically significant. These coefficients represent the average productivity (2.64 and 1.71 tons per hectare, respectively) over the period. For both rice and wheat a higher amount of district-level rainfall during the relevant window is associated with a larger subsequent harvest. Rice and wheat yields are higher in the Terai than in the hills and mountains, reflecting the more favorable agro-climatic conditions of the Terai. The predicted values of annual, district-level rice and wheat production derived from these regressions are assumed to be exogenous to prices, and are used as regressors in the price regressions reported below.

Diagnostic Testing

Table 3 reports results from diagnostic tests. Before conducting the time series analysis on prices, we performed panel unit root tests to examine the time series properties of the monthly time series variables. We

[11] Between 2003 and 2013, the length of sealed, gravel, and earthen roads expanded by 129%, 18%, and 47%, respectively (DOR 2013). Our weights are arbitrary, but based on observed transportation time differentials. To assess the importance of our weighting approach, we conduct sensitivity analysis by assuming a range of different weights. These results are reviewed in the *Robustness Checks* subsection.

[12] Diesel is used in large volumes in Nepal, and contributed about 66% of total fuel imports in 2013 (NOC 2013). Petrol constitutes about 20% of fuel imports and is mainly used by light-duty vehicles. We focus on diesel fuel, given its importance in lorry-based food transportation.

[13] All results were generated using the `arch`, `xtcsd`, `xttest2`, `xtunitroot`, `xtserial`, `xtpcc`, and `xtscc` commands and subcommands in Stata version 13.

Table 2. Agricultural production Regression Results

Variables	Rice	Wheat
Time trend (annual unit step)	0.279	0.0237
	(0.186)	(0.683)
Terai (0/1)	0.841	10.122***
	(5.276)	(1.531)
Mountain (0/1)	−2.463**	−1.147***
	(1.114)	(0.295)
Annual planted area: rice (1,000 ha)	2.642***	-
	(0.146)	
Monsoon rainfall (May–September average, in mm)	0.0009***	-
	(0.0003)	
Annual planted area: wheat (1,000 ha)	-	1.713***
		(0.069)
Monsoon rainfall (October–February average, in mm)	-	0.004***
		(0.001)
Constant	−3.36**	−0.332
	(1.603)	(0.554)
Observations	252	252
R-squared	0.97	0.97

Note: Regressions use annual, district-level production (2002–2010) as dependent variables; robust standard errors are reported in parentheses. Asterisks ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

Table 3. Results from Breitung Panel Unit-root Test

Variable	Lambda
Local market coarse rice price (real, log)	−9.04
Regional market coarse rice price (real, log)	−4.07
Central market coarse rice price (real, log)	−3.02
Border market coarse rice price (real, log)	−3.80
Local market wheat flour price (real, log)	−7.13
Regional market wheat flour price (real, log)	−8.60
Central market wheat flour price (real, log)	−3.67
Border market wheat flour price (real, log)	−4.61
Exchange rate (real, log)	−5.96
Fuel price, diesel (real, log)	−2.54

Note: All values are statistically significant at less than the 1% level; the null hypothesis is that the panel contains a unit root. Time trend not included; 28 panels, 108 periods.

implemented a Breitung and Das (2005) test for stationarity for all price series. The test is robust under cross-sectional dependence. Based on results reported in table 3, we rejected the hypothesis that the panels contain unit roots. Consequently, we did not difference our price series.

Given that our model is based on a spatial price transmission process, the assumption of cross-sectional independence of errors is a strong one. To test the validity of the assumption we performed the Pesaran (2004) CD test and the Breusch-Pagan LM test to examine whether the residuals from regression model (1) are spatially independent. Here, the rejection of the null hypothesis implies the presence of spatial dependence. The Pesaran test of cross-sectional independence is -0.69 with a p-value of 0.49. Based on this test, we fail to reject the null hypothesis of spatial dependence at any reasonable level of statistical significance. The Breusch-Pagan χ^2 test statistic for cross-sectional independence is 358 with a p-value of 0, which rejects the null hypothesis of spatial independence. We calculated Driscoll and Kraay (1998) and panel corrected standard errors for our AR(1) model. Although a slight change in the magnitude of standard errors was noticed, overall the pattern of statistical significance of the estimated coefficients is preserved. We assume that similar results hold for the Panel ARCH/GARCH models. Unfortunately, we are not aware of any method to correct the standard errors for the Panel ARCH/GARCH models. Despite finding evidence of spatial cross-sectional error, the extent of bias in our results, if any, depends on the degree of spatial correlation across the panels. Given the poor infrastructure and high market frictions in Nepal, we are confident in assuming that spatial correlation is likely to be small, and therefore not likely to exert significant influence over our results.

The test for ARCH effects is a Lagrange multiplier (LM) test that relies on the F-statistic for the regression of the squared residuals on their own lagged values. Equation (1) was estimated for each crop using ordinary least squares and residuals were retained and used for the tests. For rice and wheat, the LM test statistics have values of 136.5 and 541.9, respectively. These are statistically significant when judged against the χ^2 1% critical value of 6.63. The null hypothesis of homoscedasticity is rejected in favor of first-order autoregressive conditional heteroskedasticity.

We also conducted Wooldridge tests of the null hypothesis of no first-order autocorrelation in panel data (Wooldridge 2002; Drukker 2003). The null hypothesis is rejected in favor of the alternative hypothesis of first-order autocorrelation for both the rice and wheat flour price equations at less than a 1% level of statistical significance. This suggests a first-order process for both commodities.[14]

We estimated AR(1), ARCH(1), and three versions of GARCH and tested for the best-fitting model. As indicated by Akaike information criterion (AIC) values, the AGARCH model of Engle (1990) best fits rice prices, and the TGARCH model of Glosten, Jagannathan, and Runkle (1993) best fits wheat prices. For most variables, only a slight change in the magnitude of coefficients is observed across models. Our discussion focuses on results from our preferred, best-fitting models. Tables 4 and 5 report results for the rice and wheat regressions. The upper panels of each table report results for the mean equations and the lower panels report results for the variance equations.[15]

Mean Equation Regression Results

In the mean price components of the regressions we find mixed evidence for a statistically significant upward trend in real wheat prices, and no change in the real price of rice over the period examined. Coefficients for lagged local prices are positive, less than one, and statistically significant. These indicate strong local persistence in prices. A 1% increase in the real price of rice or wheat is associated with price increases of 0.90% and 0.87% in the subsequent month. From a statistical point of view, regional prices appear to be more important for price formation in the rice market than in the wheat market, and to exhibit positive contemporaneous correlation and negative lagged correlation. Conversely, wheat prices appear to be more strongly associated with border market prices. Results regarding the strength of central market influence are mixed, with positive contemporaneous correlation in the case of rice and negative lagged correlation in the case of wheat. The current price transmission elasticity between the regional market and local market is about 0.06. This means that a 1% increase in the regional market price is correlated with the increase of 0.06% increase of local market price. In case of the central market, the current price transmission elasticity between the central market and the local market is about 0.03. For wheat, the current price transmission elasticity between the border market and the local market is 0.09. Overall, these patterns suggest markets in which there is a relatively weak transmission of price information from aggregator markets to local markets.[16]

[14] For the coarse rice price equation, the Wooldridge test for autocorrelation in panel data (H_0: No first-order autocorrelation) yields the results F(1, 27) = 164.78 (Prob>F = 0.00). For the wheat flour price equation, the test yields F (1,27) = 36.43 (Prob>F = 0.00).

[15] The standard errors reported in tables 4 and 5 are uncorrected. The literature provides little guidance regarding alternative procedures for correcting standard errors in panel ARCH and GARCH models incorporating instrumented variables. Our preferred approach would be to bootstrap over the entire set of covariates included in each regression, but when we do this our full models do not iterate to convergence with the given data. Bootstrapping more parsimonious versions of the reported models generally leads to statistical inferences that differ little from those drawn from the non-bootstrapped results reported in the tables. However, in the specific case of the standard errors for predicted values of output (rice and wheat), when we use a partial bootstrapping technique (drawing 50 times from the distribution of the instrumented production variables only), to generate the standard errors for the production variable point estimates reported in the mean and variance equations of tables 4 and 5, the resulting standard errors are larger, and the significance of these variables is substantially lower. In the order presented, by column, the adjusted standard errors are 0.0135, 0.0104, 0.1726, 0.0095, 0.1796, 0.0111, and 0.1880 for the rice models, and 0.0257, 0.0199, 0.3881, 0.0180, 0.9130, 0.0188, and 0.6964 for the wheat models, none of which support a hypothesis that the coefficient on the production variable is significantly different from zero at standard test levels. Given that we are unable to produce fully corrected standard errors for these models in a definitive fashion, one should exercise caution when interpreting results for the annual production variables.

[16] These patterns do not necessarily preclude market integration between adjacent district markets or between district markets and adjacent border markets. For example, Sanogo and Amadou (2010) studied market integration between a regional market (Morang) and its neighboring border market (Jogbani) using monthly wholesale coarse rice prices. For these markets, border market price transmission to the regional market was very high. A one-unit increase in the border market price increased the regional market rice price by 0.88 units. However, these results were derived using a regression that included just the border market price as a regressor, raising the strong possibility of omitted variable bias in their estimate and potential model misspecification.

Table 4. Regression Results for Real Rice Prices in Nepal, 2002–2010

	AR	ARCH	GARCH	AGARCH
Mean Equation				
Time trend (monthly unit-step)	−0.00006	0.00008	0.00007	0.000004
	(0.00016)	(0.00014)	(0.00015)	(0.00014)
Local price (t-1)	0.89358***	0.89848***	0.90817***	0.89708***
	(0.00822)	(0.00770)	(0.00809)	(0.00846)
Regional market price (current)	0.04457**	0.05130***	0.05659***	0.06164***
	(0.01827)	(0.01545)	(0.01501)	(0.01464)
Regional market price (t-1)	−0.05396***	−0.05912***	−0.05722***	−0.05415***
	(0.01850)	(0.01296)	(0.01446)	(0.01395)
Central market price (current)	0.01727	0.03075*	0.02870*	0.02744*
	(0.01865)	(0.01667)	(0.01596)	(0.01517)
Central market price (t-1)	0.01534	0.00338	0.00562	0.01172
	(0.01770)	(0.01583)	(0.01507)	(0.01465)
Border market price (current)	−0.03083	−0.01012	−0.01036	−0.01460
	(0.02356)	(0.01995)	(0.01972)	(0.01911)
Border market price (t-1)	0.01812	0.01484	0.00557	−0.00130
	(0.02234)	(0.01751)	(0.01660)	(0.01657)
Road density (weighted km/km^2)	−0.00033***	−0.00021***	−0.00020***	−0.00018***
	(0.00009)	(0.00008)	(0.00007)	(0.00007)
Bridge density (#/km^2)	−0.00319	−0.00403	−0.00456*	−0.00412**
	(0.00351)	(0.00250)	(0.00245)	(0.00206)
Mountain × Road density (interaction)	−0.00056***	−0.00049*	−0.00039*	−0.00059***
	(0.00021)	(0.00026)	(0.00023)	(0.00022)
Mountain × Bridge density (interaction)	−0.03137	−0.00962	−0.02477	0.06495
	(0.13566)	(0.21744)	(0.17294)	(0.17181)
Terai × Road density (interaction)	−0.00013	−0.00001	−0.00007	−0.00013
	(0.00028)	(0.00026)	(0.00023)	(0.00020)
Terai × Bridge density (interaction)	0.00906	0.00803	0.01021*	0.01076**
	(0.00710)	(0.00571)	(0.00523)	(0.00469)
Monthly fuel price (Rs/liter)	0.07788**	0.04450	0.04096	0.05568*
	(0.03890)	(0.03432)	(0.03628)	(0.03347)
District population (#/km^2)	0.00011**	0.00006	0.00007	0.00007
	(0.00005)	(0.00005)	(0.00005)	(0.00004)
Rice production (1000 MT)[a]	−0.00458***	−0.00333	−0.00365	−0.00416*
	(0.00175)	(0.00313)	(0.00262)	(0.00250)
Monthly exchange rate (Nepal Rs/USD)	−0.13413***	−0.12487***	−0.12164***	−0.12635***
	(0.05124)	(0.04121)	(0.04250)	(0.03832)
Terai (0/1)	−0.03093**	−0.03353**	−0.02778**	−0.02468**
	(0.01378)	(0.01379)	(0.01218)	(0.01207)
Mountain (0/1)	0.02512***	0.02392**	0.01997**	0.02624***
	(0.00868)	(0.01091)	(0.00978)	(0.00949)
Constant	0.61776***	0.62004***	0.59370***	0.59170***
	(0.22943)	(0.18076)	(0.18058)	(0.17097)
Variance Equation				
Time trend (monthly unit-step)		0.00483***	0.00729***	0.00778***
		(0.00076)	(0.00110)	(0.00115)
Regional market price (t-1)		−0.86301***	−2.40035***	−2.58417***
		(0.14516)	(0.29140)	(0.30193)
Central market price (t-1)		0.60384***	1.23128***	1.55865***
		(0.10990)	(0.15432)	(0.17907)
Border market price (t-1)		0.44107**	1.09205***	0.68651**
		(0.18111)	(0.27366)	(0.28588)
Road density (weighted km/km2)		−0.01068***	−0.00987***	−0.01100***
		(0.00076)	(0.00089)	(0.00110)
Bridge density (#/km2)		−0.00088	0.01901	0.02329
		(0.03116)	(0.03984)	(0.04543)
Monthly fuel price (Rs/liter)		−2.01761***	−1.88669***	−1.87075***

Continued

Table 4. continued

	AR	ARCH	GARCH	AGARCH
		(0.16199)	(0.21345)	(0.23513)
District population (#/km2)		0.00191***	0.00192***	0.00186***
		(0.00033)	(0.00038)	(0.00041)
Rice production (1000 MT)[a]		−0.06817**	−0.07126**	−0.06180**
		(0.02769)	(0.02896)	(0.02858)
Monthly exchange rate (Nepal Rs/USD)		−3.11732***	−2.41057***	−2.56508***
		(0.31058)	(0.39955)	(0.49125)
Terai (0/1)		0.08380	−0.01993	0.13433
		(0.10714)	(0.12923)	(0.13049)
Mountain (0/1)		0.66053***	0.54614***	0.50983***
		(0.06250)	(0.07243)	(0.07076)
Constant		15.21905***	11.12585***	12.24641***
		(1.78097)	(2.15816)	(2.64345)
L.ARCH		0.08820***	0.11664***	0.12002***
		(0.01189)	(0.01300)	(0.01261)
L.GARCH			0.57512***	0.60096***
			(0.02926)	(0.02782)
L.AGARCH				0.01669***
				(0.00203)
Districts	28	28	28	28
Observations	2,996	2,996	2,996	2,996
AIC	−5547.54	−6010.79	−6093.93	−6133.51

Note: Standard errors appear in parentheses; superscript [a] denotes an instrumented value (see footnote 14); Asterisks ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Agricultural prices, fuel prices, exchange rate, and harvest variables have been converted to natural logarithms. Agroecological zone ($k = 3$), year, and monthly fixed effects are included in the mean equations.

Turning to our main hypotheses of interest, regarding transportation, we find that the estimated coefficients for the road density index are negative and statistically significant at less than 1% test levels in all estimated models. The estimated coefficients for bridge density and road density are negative and, in all cases except bridge density in the wheat model, statistically significant at the 1% test level. To account for potential differences in infrastructure effects across AEZs, we include interaction terms between Agroecological Zone (AEZ) and our transportation variables. The estimated interaction coefficients between mountain and road density index are negative and statistically significant for both the rice and wheat flour price models, suggesting the especially crucial influence of roads on food prices in the mountains. The estimated coefficient on the interaction term is negative and statistically significant in the case of the mountain zone. This indicates greater than average price-moderating effects of roads in the mountains. Not surprisingly, the estimated coefficient for the monthly fuel price is positive in both cases, and statistically significant in the rice model. The fuel price transmission elasticities are low: roughly 0.06 for rice and 0.03 (and not significantly different from zero) for wheat. We return to this evidence of a weak correlation between fuel and food prices below.

Annual district population, a demand shifter, has a positive correlation with price, although only at statistically significant levels in the case of wheat. The estimated coefficients for rice and wheat production are negative and, in the case of wheat, statistically significant at the 1% test level. In aggregate terms, each 10% increase in annual wheat production is associated with a 0.6% decrease in the annual price. The coefficients on the monthly exchange rate are negative in both models, but significant only for rice. Higher-valued Rupees facilitate imports, driving down local prices. Agroecological zones (AEZs) enter the regressions as binary indicators (for mountains and the Terai; the omitted category is hills). As expected, we find rice and wheat prices to be higher, on average, in the mountains and lower in the Terai than in the hills.

Variance Equation Regression Results

Results from the variance equations are presented in the lower panels of tables 4 and 5. In both cases, asymmetric GARCH effects

Table 5. Regression Results for Real Wheat Prices in Nepal, 2002–2010

	AR	ARCH	GARCH	TGARCH
Mean equation				
Time trend (monthly unit-step)	0.00024	0.00029*	0.00031**	0.00020
	(0.00021)	(0.00017)	(0.00015)	(0.00015)
Local price (t-1)	0.79054***	0.81685***	0.86825***	0.88336***
	(0.01123)	(0.00992)	(0.00807)	(0.00849)
Regional market price (current)	0.00788	0.03407	0.01809	0.01561
	(0.02238)	(0.02150)	(0.01882)	(0.01897)
Regional market price (t-1)	−0.02033	−0.02793	−0.03185*	−0.02566
	(0.02222)	(0.02358)	(0.01832)	(0.01900)
Central market price (current)	0.05017	0.03913	0.01649	0.02647
	(0.03597)	(0.02884)	(0.02608)	(0.02778)
Central market price (t-1)	−0.10670***	−0.11712***	−0.11211***	−0.09958***
	(0.03294)	(0.02512)	(0.02062)	(0.02054)
Border market price (current)	0.00120	0.05980**	0.06959***	0.08353***
	(0.03171)	(0.02519)	(0.02138)	(0.02093)
Border market price (t-1)	−0.05933*	−0.09804***	−0.10522***	−0.10184***
	(0.03033)	(0.02461)	(0.01940)	(0.01960)
Road density (weighted km/km^2)	−0.00060***	−0.00035***	−0.00029***	−0.00030***
	(0.00012)	(0.00009)	(0.00007)	(0.00008)
Bridge density (#/km^2)	−0.00170	−0.00416	−0.00120	0.00039
	(0.00444)	(0.00279)	(0.00222)	(0.00233)
Mountain × Road density (interaction)	−0.00168***	−0.00140***	−0.00071***	−0.00070***
	(0.00030)	(0.00031)	(0.00020)	(0.00025)
Mountain × Bridge density (interaction)	−0.09603	−0.09837	−0.25420	−0.16598
	(0.17095)	(0.17630)	(0.16110)	(0.16078)
Terai × Road density (interaction)	0.00065*	0.00059*	0.00043*	0.00015
	(0.00037)	(0.00032)	(0.00023)	(0.00025)
Terai × Bridge density (interaction)	0.00358	0.00363	0.00362	0.00407
	(0.00904)	(0.00664)	(0.00508)	(0.00561)
Monthly fuel price (Rs/liter)	0.03495	0.05804	0.02729	0.03496
	(0.05015)	(0.03909)	(0.03678)	(0.03669)
District population (#/km2)	0.00006	−0.00001	0.00003	0.00006
	(0.00007)	(0.00006)	(0.00005)	(0.00005)
Wheat production (1000 MT)[a]	−0.01839***	−0.00909**	−0.00454	−0.00680*
	(0.00519)	(0.00435)	(0.00318)	(0.00361)
Monthly exchange rate (Nepal Rs/USD)	−0.00247	−0.03878	−0.03046	−0.02942
	(0.06339)	(0.04635)	(0.04496)	(0.04517)
Terai (0/1)	−0.07731***	−0.06738***	−0.06270***	−0.03799***
	(0.01785)	(0.01500)	(0.01242)	(0.01287)
Mountain (0/1)	0.08362***	0.07568***	0.05976***	0.05531***
	(0.01266)	(0.01196)	(0.00907)	(0.00958)
Constant	0.93708***	0.85502***	0.85015***	0.66032***
	(0.30636)	(0.23704)	(0.20911)	(0.20998)
Variance equation				
Time trend (monthly unit-step)		0.00110	−0.00622***	−0.00478***
		(0.00089)	(0.00199)	(0.00174)
Regional market price (t-1)		0.04317	−0.47785	−0.74719
		(0.20005)	(0.56856)	(0.53708)
Central market price (t-1)		1.39358***	2.87326***	3.40730***
		(0.18690)	(0.61448)	(0.53416)
Border market price (t-1)		0.40386***	2.45252***	2.18289***
		(0.14429)	(0.39280)	(0.37957)
Road density (weighted km/km2)		−0.01839***	−0.01085***	−0.00968***
		(0.00086)	(0.00195)	(0.00166)
Bridge density (#/km2)		−0.07268***	−0.04810	0.02304
		(0.02731)	(0.06351)	(0.04815)
Monthly fuel price (Rs/liter)		−1.82765***	−0.66597	−0.93467***
		(0.19184)	(0.42652)	(0.35195)

Continued

Table 5. continued

	AR	ARCH	GARCH	TGARCH
District population (#/km2)		0.00312***	0.00085	0.00096
		(0.00037)	(0.00066)	(0.00059)
Monthly exchange rate (Nepal Rs/USD)		−1.14529***	3.20059***	0.33904***
		(0.35907)	(0.77033)	(0.05739)
Wheat production (1000 MT)[a]		0.09084***	0.27129***	2.96762***
		(0.03096)	(0.06546)	(0.7205)
Terai (0/1)		−0.37612***	−0.14566	−0.40826***
		(0.11007)	(0.18010)	(0.15676)
Mountain (0/1)		0.26411***	0.61174***	0.83793***
		(0.04541)	(0.10319)	(0.08501)
Constant		1.5877	−32.24587***	−30.60131***
		(1.892)	(4.01647)	(3.69811)
L.ARCH		0.20467***	0.29731***	0.14089***
		(0.02053)	(0.01793)	(0.01751)
L.GARCH			0.66565***	0.67152***
			(0.01430)	(0.01372)
L.TGARCH				0.26551***
				(0.02828)
Districts	28	28	28	28
Observations	2,996	2,996	2,996	2,996
AIC	−4144.75	−4960.55	−5224.51	−5254.30

Note: Standard errors appear in parentheses; superscript [a] denotes an instrumented value (see footnote 14); Asterisks ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. Agricultural prices, fuel prices, exchange rate, and harvest variables have been converted to natural logarithms. Agroecological zone ($k = 3$), year, and monthly fixed effects are included in the mean equations.

are observed. This suggests that both the magnitude and direction of price shocks matter to price volatility. For rice, the positive and statistically significant value of the asymmetric term implies that a positive price shock is correlated with a larger increase in future price volatility than a negative price shock of the same absolute magnitude. The conditional variance is positive for the rice equation. In the case of wheat, the threshold effect is positive, which implies that positive shocks are amplified.

In the variance equations the lagged values of the squared regression disturbances are statistically significant at a 1% test level, implying dynamics in the conditional variance equation. In both the rice and wheat models, higher lagged monthly border and central market prices are associated with greater local market price variance. However, a higher regional market price is correlated with subsequently lower local price variance for rice. An increase in district-level rice production is significantly correlated with a lower local price variance of rice. Importantly, we find consistent evidence across all estimated models in support of our hypothesis that road density is negatively correlated with price variance. Contrary to expectations, higher fuel prices are negatively correlated with price variances.[17] Population density is positively correlated with price variance. Results for the monthly exchange rate are mixed.

Tests of Market Segmentation and Market Integration

Tests for local market segmentation and market integration between local and regional, central, and border markets reject the null hypothesis of local market integration at a level of statistical significance below 1%. First, we find strong local carryover in prices, with between-period coefficients on local prices in the 0.80-0.90 range. Second, for both rice and wheat the coefficients on the regional, central, and border market prices are all either insignificant or significant and very small (on the order of 0.01-0.10). Since price increases in regional, central, and border markets are not immediately passed through to local markets, we easily reject the hypothesis of short-run market integration. We also tested the null hypothesis of long-run market

[17] The fuel price only varies across ecological zones, so perhaps it is only an imprecise measure of local transport costs. A more precise measurement of transport cost would account for actual miles traveled and effort required, perhaps by accounting for changes in elevation.

integration, namely $\gamma_i + \beta_{ik}=1$. This hypothesis is rejected in every model at less than a 1% level of significance for both rice and wheat.[18] With the observed low price transmission elasticity (typically less than 5%) between local and companion markets, and the rejection of the short- and long-run market integration hypothesis, results indicate poor price transmission/pass-through of price changes from regional (and central and border) markets to local markets. Conditions hinder the flow of price signals to economic agents and prohibit spatial and temporal arbitrage, which suggests the persistence of a rather wide price band in local markets. We suspect these results are driven by the high transaction costs and marketing margins that characterize trade in Nepal, and are relatively more important for wheat than for rice since imports from India constitute a larger proportion of overall trade for wheat than rice. We address this conjecture in greater detail below.

Robustness Checks

As a check of the robustness of these results, in online supplemental appendix tables A.3 and A.4 we provide results from a set of similar regressions estimated using the same sample but various subsets of our independent variables. Although point estimates are broadly similar in sign, magnitude, and significance to those of the fully-specified models reported in tables 4 and 5, there are occasional differences that are noteworthy. Of particular importance to our investigation of the role of transportation infrastructure in price determination, it seems clear that regressions using price data alone overestimates the magnitude of "pure" price transmission between regional and local markets (by something on the order of between 2–20%). This is likely because a proportion of the explanatory power of companion market prices is more appropriately attributed directly to infrastructure (and local production). Moreover, there seems to be some misspecification bias associated with omitting transportation variables from the price regressions, in particular in the rice model (where the under-specified model assigns no significant influence to the central market). To the extent that price transmission occurs in Nepal, it occurs because roads and bridges facilitate it. And to the extent that markets are segmented, local prices are closely tied to local production. This is both confirmatory evidence of the importance of infrastructure and agricultural production in Nepal's agricultural markets, and cautionary evidence against inference based on parsimonious regressions employing price data alone.

Results reported in appendix table A.5 address the potential for imprecise estimates and type II errors. If, for example, local prices are influenced by central market prices and central market prices are influenced by regional prices, then both regional and central market prices have some effect on local prices. Econometrically, this is a problem of multicollinearity, but conceptually it could lead one to falsely conclude that one market or the other (or both) has no influence on local prices. We estimate a series of separate regressions parallel to those reported in tables 4 and 5 in which regional, border, and central market prices are treated as alternative exogenous prices. Point estimates are highly consistent across these models, leading us to conclude that multicollinearity is unlikely to be a problem in our main regressions. As further confirmation, we tested for multicollinearity among our price series using a variance inflation factor (VIF) test; VIFs are consistently below 10, the threshold value of concern (see online supplemental appendix table A.6).

As a final check on the robustness of our results to assumptions regarding the weights used to construct our quality-adjusted road index, we re-estimated our regressions using road index values that are weighted under the alternative assumptions that sealed roads are 10x or 20x faster than earthen roads. These results are reported in appendix table A.7. We find point estimates in the mean equations to be largely invariant in sign and significance across a plausible range of weighting schemes. The primary effect of changing weights appears to be one of scaling in the estimated values of the constant and index parameters in the variance component of the model. Inference regarding our main investigation remains unchanged.

Transaction Costs

To further explore the nature of the transaction costs implied by our regressions, and

[18] The coefficients on the first lag of the local market price and the current and first lag of the regional, central, and border market prices were used to test the long-run market integration hypothesis. The relevant test results are F(1, 2957)=7.27, Prob> F = 0.01 (for rice), and F(1, 2957)=24.94, Prob> F = 0.00 (for wheat).

the role of transportation infrastructure and fuel prices as drivers of price differentials, we re-estimated the regressions reported in the final columns of tables 4 and 5 after making three modifications. First, we incorporated annual time steps as fixed effects, in combination with the district fixed effects. Second, we focused our attention on price transmission between the regional and local markets only. And third, we estimated the price regressions in levels. These auxiliary regressions provide for each commodity a set of time- and market-specific intercepts corresponding to the regression equation $p_{it}^{local} = a_{it} + bp_{it}^{regional} + \mathbf{c}'\mathbf{Z} + e$, where $\mathbf{Z}$ includes the set of all other regressors used in our reported regressions. This structure allows us to directly interpret the point estimates of $\hat{a}_{it}$ as the estimated costs (in Rupees) of transporting one unit of rice or wheat from the respective regional market to local market i at time t. This covers nine years and twenty-eight markets for each commodity. Stacking these 252 cost estimates as data, we then estimate a set of parsimonious regressions in which our road density, bridge density, and fuel price variables appear as explanatory variables. Overall, we find strong and consistent patterns of negative correlations between the estimated transport cost and road and bridge density, and a consistent positive correlation between cost and fuel price. Using analysis of variance (ANOVA) decomposition for these models, we find that bridge density explains less than 2% of the observed variance in the estimated transport cost for both rice and wheat. Road density accounts for 54% of the variance in cost for wheat and 41% of the variance for rice. Fuel costs account for 12% of the variance for wheat, but only 2% for rice. The latter patterns are not surprising, and are consistent with two observations: Nepal's relatively larger reliance on imports of wheat than rice; and the relatively small differences observed in our fuel price data across locations.

Conclusion

We measured movements in the means and variances of monthly rice and wheat prices in Nepal, and tested the importance of transportation infrastructure in price formation. Data came from twenty-eight district markets, eight regional markets, and seven Indian border markets, and covered the period 2002 to 2010. Panel ARCH effects were found to be significant in both price series. AIC tests confirmed that an asymmetric GARCH model was the best fit to rice prices and a threshold GARCH model was the best fit to wheat prices.

For rice, regional and central market prices were found to matter for both local price levels and price variances. A price increase in the regional market is associated with an increase in the local price but a decrease in price variance. Lagged central market prices were found to be correlated with local price variance for rice. Although an increase in the border rice price was found to be associated with an increase in local price variance, no statistically significant evidence was found for the effect of border prices on the local rice price level. For wheat, an increase in the border price was correlated with both the mean and variance of local price.

We tested several hypotheses regarding the importance of transportation infrastructure for prices and transport costs. Improved market infrastructure, measured here by an increase in a quality-adjusted road density index, was found to be associated with statistically significant decreases in the means and variances of rice and wheat prices. The association between roads and food prices was found to be stronger and statistically significant in mountain districts. Increased bridge density was found to be significantly and negatively correlated with rice prices. District-level rice production is negatively correlated with rice price variance, while district-level wheat production is negatively correlated with local wheat price levels. Exchange rate movements are negatively correlated with price levels and variances for both rice. We found relatively weak price transmission between local and regional markets, and strong evidence of between-period price persistence at the local level, which supports a conjecture that markets in Nepal are segmented. Results from an analysis of estimated transport margins suggest that differences in road densities across time and space explain a much larger share of the variance in transport costs (on the order of between 40–50%) than do differences in bridge density or fuel costs.

Five policy recommendations emanate from our findings. First, district-level rice and wheat harvests are negatively correlated with food prices and food price variance. From a policy perspective, this underscores the importance of continuing to emphasize policies at all levels that help to strengthen Nepal's agricultural capacity. Second, improving connections between local and regional markets through the construction or improvement of roads and bridges will undoubtedly strengthen price transmission in Nepal, reducing price levels in remote locations and dampening price volatility in local markets. This means that policies aimed at infrastructure improvement can be supported on food security grounds, and highlights that food security advocates should also become strong advocates for investments in roads and bridges. Third, and closely related to the previous point, we note (without direct evidence) that segmented local markets and low price transmission can be caused not only by weak transportation and physical infrastructure, but also by deficient commercial and institutional infrastructure (such as a weak or corrupt commercial legal system that fails to protect property and enforce contracts).[19] These institutional shortcomings, which are difficult for the econometrician to measure but nonetheless amenable to change, can create high market risk and transaction costs that also segment markets and impede price transmission. Fourth, although the elasticities of price transmission from regional and border markets to local markets are relatively small, some pass-through occurs, suggesting that policies directed at companion markets will have spillovers in local markets. For rice, regional markets in Nepal seem to be the appropriate point of entry for market interventions and market improvements, while for wheat, border markets matter more. Lastly, higher fuel prices are associated with higher food prices, but the overall importance of fuel costs to the final price of food in Nepal's markets seems to be modest, and perhaps less important than commonly asserted. Our findings and policy implications are likely applicable in other settings where local food markets are isolated from the world market. The results also reinforce the need for analysts to incorporate data on transportation infrastructure in studies of prices, price volatility, and market integration in order to improve statistical inference and strengthen economic insights. Collecting such data currently requires time-consuming "old school" approaches, including visiting government offices and combing through written records. In time, however, more streamlined methods based on remote sensing and mapping may prove to be fruitful avenues for exploration, as will the incorporation of information on communication infrastructure, perhaps using mobile telephone data.

[19] For this insight, we thank an attentive and engaged referee.

Supplementary Material

Supplementary material is available online at http://oxfordjournals.org/our_journals/ajae/online.

References

Abbott, P.C., C. Hurt, and W.E. Tyner. 2008. What's Driving Food Prices? Farm Foundation Issue Report, July 2008. Oak Brook, IL: Farm Foundation.

Action Aid. 2006. *Import Surge in Nepal, a Case Study of Rice*. Katmandu: Action Aid Nepal.

Agostinucci, G., and M. Loseby. 2008. Soaring Food Prices and Food Security in LIFDCs: The Case of Nepal. *Rivista de Economia Agraria* 63 (4): 573–96.

Akter, S., and S.A. Basher. 2014. The Impacts of Food Price and Income Shocks on Household Food Security and Economic Well-Being: Evidence from Rural Bangladesh. *Global Environmental Change* 25 (1): 150–62.

Alem, Y., and M. Soderbom. 2012. Household-Level Consumption in Urban Ethiopia: The Effects of a Large Food Price Shock. *World Development* 40 (1): 146–62.

Andreyeva, T., M.W. Long, and K.D. Brownell. 2010. The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food. *American Journal of Public Health* 100 (2): 216–22.

Anriquez, G., S. Daidone, and E. Mane. 2013. Rising Food Prices and Undernourishment: A Cross-Country Inquiry. *Food Policy* 38: 190–202.

Badiane, O., and G.E. Shively. 1998. Spatial Integration, Transport Costs, and the Response of Local Prices to Policy Changes in Ghana. *Journal of Development Economics* 56 (2): 411–31.

Baulch, B. 1997. Transfer Costs, Spatial Arbitrage, and Testing for Food Market

Integration. *American Journal of Agricultural Economics* 79(2): 477–87.

Bellemare, M.F. 2014. Rising Food Prices, Food Price Volatility, and Social Unrest. *American Journal of Agricultural Economics* 96 (1): 1–21.

Bellemare, M.F., C.B. Barrett, and D.R. Just. 2013. The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia. *American Journal of Agricultural Economics* 95 (4): 877–99.

Blyne, G. 1973. Price Series Correlation as a Measure of Market Integration. *Indian Journal of Agricultural Economics* 28 (1): 56–9.

Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 31 (3): 307–27.

Bollerslev, T., R.Y. Chou, and K.F. Kroner. 1992. ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence. Journal of Econometrics 52 (1–2): 5–59.

Bollerslev, T. 2007. Glossary to ARCH (GARCH). Duke University and NBER. Available at: http://public.econ.duke.edu/~boller/Papers/glossary_arch.pdf on 12/26/2014.

Bouis, H. 2008. *Rising Food Prices will Result in Severe Declines in Mineral and Vitamin Intakes of the Poor*. Washington DC: HarvestPlus.

Breitung, J., and S. Das. 2005. Panel Unit Root Tests under Cross-Sectional Dependence. *Statistica Neerlandica* 59: 414–33.

Burke, W.J., and R.J. Myers. 2014. Spatial Equilibrium and Price Transmission between Southern African Maize Markets Connected by Informal Trade. *Food Policy* 49 (1): 59–70.

Central Bureau of Statistics Nepal. 2011. Nepal Living Standard Survey. Kathmandu: Nepal Central Bureau of Statistics.

Chang, T., and H. Su. 2010. The Substitutive Effect of Biofuels on Fossil Fuels in the Lower and Higher Crude Oil Price Periods. *Energy* 35 (7): 2807–13.

Cummings, R.W., Jr., 2012. Experience with Managing Food Grains Price Volatility in Asia. *Global Food Security* 1 (2): 150–6.

Dawe, D., and C.P. Timmer. 2012. Why Stable Food Prices are a Good Thing: Lessons from Stabilizing Rice Prices in Asia. *Global Food Security* 1 (2): 127–33.

Deaton, A. 1989. Household Survey Data and Pricing Policies in Developing Countries. *World Bank Economic Review* 3 (2): 183–210.

Department of Road. 2012. Annual Progress Report. Kathmandu: Department of Road.

———. 2013. Annual Progress Report. Kathmandu: Department of Road.

Driscoll, J., and A.C. Kraay. 1998. Consistent Covariance Matrix Estimation with Spatially Dependent Data. *Review of Economics and Statistics* 80: 549–60.

Drukker, D.M. 2003. Testing for Serial Correlation in Linear Panel-Data Models. *Stata Journal* 3: 168–77.

Engle, R. 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflations. *Econometrica* 50 (4): 987–1008.

Engle, R., T. Ito, and W.L. Lin. 1990. Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market. *Econometrica* 58 (3): 525- 42.

FAO, IFAD, IMF, OECD, UNCTAD, WFP, WB, WTO, IFPRI, and UNHLTF. 2011. *Interagency Report to the G20 on Food Price Volatility*. Rome: FAO.

Food and Agriculture Organization of the United Nations. 2010a. Price Volatility in Agricultural Markets (Economic and Social Perspectives Policy Brief 12). Rome: Food and Agriculture Organization of the United Nations.

———. 2010b. Pricing Policies for Agricultural Inputs and Outputs in Nepal. Rome: Food and Agriculture Organization of the United Nations.

———. 2010c. Assessment of Food Security and Nutrition Situation in Nepal. Pulchowk, Nepal: Food and Agriculture Organization of the United Nations.

Gilbert, C.L. 2010. How to Understand High Food Prices. *Journal of Agricultural Economics* 61 (2): 398–425.

Glosten, L.R., R. Jagannathan, and D. E. Runkle. 1993. On the Relation between the Expected Value and the Volatility of the Nominal Excess Returns on Stocks. *Journal of Finance* 48 (5): 1779–801.

Goletti, F. 1994. The Changing Public Role in a Rice Economy Approaching Self-Sufficiency: The Case of Bangladesh. IFPRI Research Report 98. Washington DC: IFPRI.

Gollin, D., and R. Rogerson. 2014. Productivity, Transport Costs, and Subsistence Agriculture. *Journal of Development Economics* 107: 38–48.

Goodwin, B.K., T.J. Grennes, and M.K. Wohlgenant. 1990. A Revised Test of the Law Of One Price Using Rational Price Expectations. *American Journal of Agricultural Economics* 72 (3): 682–93.

Goodwin, B.K., and N.E. Piggott. 2001. Spatial Market Integration in the Presence of Threshold Effects. *American Journal of Agricultural Economics* 83(2): 302–17.

Grace, K., M. Brown, and A. McNally. 2014. Examining the Link between Food Prices and Food Insecurity: A Multi-Level Analysis of Maize Price and Birth-Weight in Kenya. *Food Policy* 46: 56–65.

Gurung, N.S. 2010. Community-Led Rural Road Construction in Nepal. Occasional Paper. Future Generations, Graduate School. Applied Community Change and Conservation. Available at: http://future.edu/wp-content/uploads/2016/02/Rural-Road-Construction-in-Nepal-.pdf on 11/1/2014.

Hadley, C., E.G.J. Stevenson, Y. Tadesse, and T. Belachew. 2012. Rapidly Rising Food Prices and the Experience of Food Insecurity in Urban Ethiopia: Impacts on Health and Well-Being. *Social Science & Medicine* 75 (12): 2412–9.

Harriss, B. 1979. There Is Method in My Madness: Or Is It Vice Versa? Measuring Agricultural Market Performance. *Food Research Institute Studies* 17: 197–218.

Hawkes, C. 2012. Food Taxes: What Type of Evidence Is Available to Inform Policy Development? *Nutrition Bulletin* 37 (1): 51–6.

Kharas, H. 2011. *Making Sense of Food Price Volatility*. Washington DC: Brookings Institution. Available at: http://www.brookings.edu/research/opinions/2011/03/03-food-prices-kharas.

Lavy, V., J. Strauss, D. Thomas, and P.D. Vreyer. 1996. Quality of Health Care, Survival and Health Outcomes in Ghana. *Journal of Health Economics* 15 (3): 333–57.

Minten, B., and S. Kyle. 1999. The Effect of Distance and Road Quality on Food Collection, Marketing Margins, and Traders' Wages: Evidence from the Former Zaire. *Journal of Development Economics* 60 (2): 467–95.

Myers, R.J., and T.S. Jayne. 2012. Multiple-Regime Spatial Price Transmission with an Application to Maize Markets in Southern Africa. *American Journal of Agricultural Economics* 94(1): 174–88.

Nepal Ministry of Agricultural Development. 2012. Statistical Information on Nepalese Agriculture. Kathmandu: Ministry of Agricultural Development.

Nepal Agri-business Promotion and Marketing Development Directorate. 2010. Agricultural Marketing Information Bulletin. Kathmandu: Nepal Agri-business Promotion and Marketing Development Directorate.

Nelson, D.B. 1991. Conditional Heteroscedasticity in Asset Returns: A New Approach. *Econometrica* 59: 347–70.

Nepal Oil Corporation. 2013. Import and Sales. Available at: http://www.nepaloil.com.np/Import-and-Sales/22/. Kathmandu: Nepal Oil Corporation.

Nepal Central Bureau of Statistics. 2011. National Population and Housing Census 2011. National Report. Volume 01. Government of Nepal. National Planning Commission Secretariat. Central Bureau of Statistics. Kathmandu, Nepal.

Nepal Rastra Bank. 2007. Inflation in Nepal. Research Department. Nepal Rastra Bank. Kathmandu.

Newbery, D.M.G., and J.E. Stiglitz. 1981. *The Theory of Commodity Price Stabilization: A Study in the Economics of Risk*. Oxford, UK: Clarendon Press.

Pesaran, M.H. 2004. General Diagnostic Tests for Cross Section Dependence in Panels. Cambridge Working Papers in Economics No. 0435. Cambridge University, Faculty of Economics.

Qin, Y., and X. Zhang. 2016. The Road to Specialization in Agricultural Production: Evidence from Rural China. *World Development* 77: 1–16.

Rabemananjara, R., and J.M. Zakoian. 1993. Threshold ARCH Models and Asymmetries in Volatility. *Journal of Applied Econometrics* 8 (1): 31–49.

Ravallion, M. 1986. Testing Market Integration. *American Journal of Agricultural Economics* 68 (1): 102–9.

Sanogo, I. 2008. Spatial Integration of the Rice Markets: Empirical Evidence from the Mid-West and Far-West Nepal and the Nepalese–Indian Border. *Asian Journal of Agriculture and Development* 4 (1): 139–56.

Sanogo, I., and M.M. Amadou. 2010. Rice Market Integration and Food Security in Nepal: The Role of Cross-Border Trade with India. *Food Policy* 35 (4): 312–22.

Sexton, R.J., C.L. Kling, and H.F. Carman. 1991. Market Integration, Efficiency of Arbitrage, and Imperfect Competition: Methodology and Application to U.S. Celery. *American Journal of Agricultural Economics* 73 (3): 568–80.

Shively, G. 1996. Food Price Variability and Economic Reform: An ARCH Approach for Ghana. *American Journal of Agricultural Economics* 78 (1): 126–36.

Shively, G.E. 2001. Price Thresholds, Price Volatility, and the Private Costs of Investment in a Developing Country Grain Market. *Economic Modelling* 18 (3): 399–414.

Shrestha, R.B. 2013. Factors Affecting Price Spread of Rice in Nepal. *Journal of Agriculture and Environment* 13: 47–52.

Stephens, E.C., E. Mabaya, S. von Camon-Taubadel, and C.B. Barrett. 2012. Spatial Price Adjustment with and without Trade. *Oxford Bulletin of Economics and Statistics* 74 (3): 453–69.

Swan, S.H., S. Hadley, and B. Cichon. 2009. Feeding Hunger and Insecurity: The Global Food Price Crisis. Hunger Watch Briefing Paper. New York: Action Against Hunger.

Thomas, D., and J. Strauss. 1992. Prices, Infrastructure, Household Characteristics, and Child Height. *Journal of Development Economics* 39 (2): 301–331.

Timmer, C.P. 1989. *Food Price Stabilization: Rationale, Design, and Implementation*. Cambridge, MA: Harvard Institute for International Development.

United Nations Office for the Coordination of Humanitarian Affairs. 2008. Nepal Needs Analysis Framework. Key Findings. September 2008. Kathmandu: United Nations Office for the Coordination of Humanitarian Affairs.

Von Braun, J. 2008. Food and Financial Crises: Implications for Agriculture and the Poor. Washington DC: International Food Policy Research Institute.

Williams, C.J., and D.B. Wright. 1991. *Storage and Commodity Markets*. Cambridge: Cambridge University Press.

Wooldridge, J.M. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

World Food Programme and Food and Agricultural Organization of the United Nations. 2007. Food and Agricultural Markets in Nepal. Final Report of the World Food Program. Kathmandu: United Nations Food and Agricultural Organization.

World Food Programme and Nepal Development Research Institute. 2008. Market and Price Impact Assessment – Nepal. Kathmandu: United Nations World Food Programme and Nepal Development Research Institute.

Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein. 2010. Food versus Fuel: What Do Prices Tell Us? *Energy Policy* 38 (1): 445–51.