ABSTRACT

Title of Document: ANALYZING MILLET PRICE REGIMES AND MARKET PERFORMANCE IN NIGER WITH REMOTE SENSING DATA

Timothy Michael Essam, Doctor of Philosophy, 2013

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This dissertation concerns the analysis of staple food prices and market performance in Niger using remotely sensed vegetation indices in the form of normalized differenced vegetation index (NDVI). By exploiting the link between weather-related vegetation production conditions, which serve as a proxy for spatially explicit millet yields and thus millet availability, this study analyzes the potential causal links between NDVI outcomes and millet market performance and presents an empirical approach for predicting changes in market performance based on NDVI outcomes. Overall, the thesis finds that inter-market price spreads and levels of market integration can be reasonably explained by deviations in vegetation index outcomes from the growing season. Negative (positive) NDVI shocks are associated with better (worse) than expected market performance as measured by converging inter-market price spreads. As the number of markets affected by negatively abnormal vegetation production conditions in the same month of the growing season

increases, inter-market price dispersion declines. Positive NDVI shocks, however, do not mirror this pattern in terms of the magnitude of inter-market price divergence. Market integration is also found to be linked to vegetation index outcomes as below (above) average NDVI outcomes result in more integrated (segmented) markets. Climate change and food security policies and interventions should be guided by these findings and account for dynamic relationships among market structures and remotely sensed vegetation indices outcomes.

ANALYZING MILLET PRICE REGIMES AND MARKET PERFORMANCE IN NIGER WITH REMOTE SENSING DATA

By

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Dedication

I dedicate this to my wife Rashmi, my daughter Malina, and my entire family. Without your incredible support and encouragement, I could not have finished this endeavor.

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Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

Cereal Markets in Niger and Normalized Difference Vegetation Index (NDVI)

This dissertation concerns the analysis of staple food prices in Sub-Saharan Africa using National Aeronautics Space Administration's (NASA) remote sensing data, in the form of Normalized Difference Vegetation Index (NDVI). In this study, we[1] propose a novel method for linking NDVI to changes in millet prices for the purpose of understanding cereal market behavior in Niger. By exploiting the link between weather-related vegetation production conditions, which serve as a proxy for spatially explicit millet yields (Rasmussen, 1997, 1998) and thus likely production, and are highly correlated with millet prices (Brown, Pinzon and Prince, 2006), we propose a series of models to 1) understand better the explicit links between NDVI and millet market outcomes, 2) examine potential causal relationships between extreme NDVI outcomes (shocks) and cereal market performance for the most food insecure areas of Niger, and 3) predict changes in market performance based on observed NDVI outcomes for food security related outcomes.

The sheer size of Niger, nearly three times the size California, combined with general state of development in the country, where average GDP is around $900 per capita[2], means that high quality and timely data on specific market-level factors such as household demographics and income aggregates, trade volumes and transactions costs, and other time-varying market heterogeneities simply do not exist or are

[1] The term "we" and "our" is used throughout this dissertation instead of of "I" or "my". All work presented has been done solely by the author and all errors are my responsibility.
[2] https://www.cia.gov/library/publications/the-world-factbook/geos/ng.html

measured with significant error. Thus, the construction of a comprehensive cereal price forecasting model is not the purpose of this study. Instead, we seek to exploit and understand the links between NDVI outcomes and millet prices using the myriad tools of economic and statistical analysis in order to inform food security analysts and policy makers of the analytical usefulness of NDVI as it relates to millet market performance in Niger.

This study demonstrates that NDVI can help food security analysts and policy makers develop a more complete understanding of market conditions than may be afforded by production data and millet prices alone, particularly when markets are inefficient and the appropriate price signal is not being fully transmitted down the marketing chain (Baulch, 1997a). NDVI data are reported in near real-time and can provide a rich time series about the state of vegetation production conditions when data are objectively and consistently measured and processed, and appropriate corrections are made to account for factors that can lead to erroneous NDVI values (Goward et al., 1991). Production estimates, on the other hand, are normally not available until many months after the growing season, contain a great deal of measurement error, and may face upward revisions later in the year due to political pressures (Araujo, Bonjean and Burnelin, 2010). Prices are available in a timelier manner, but may not contain the appropriate signal when market inefficiencies exist. Moreover, prices are subject to measurement error, limited to a spatial range of markets, and not collected or published in a timely or consistent manner over space and time. By complementing prices and production data (and other data when available) with NDVI data, we can bridge many of these informational gaps and achieve a better understanding of what the appropriate price signal should look like and how markets are expected to function before, during and after production shocks.

This research is among the few studies (Brown, Hintermann and Higgins, 2009) to link explicitly remotely-sensed agricultural production monitoring indicators with millet prices at the market-level to provide market-wide predictions regarding the nature of market connectedness and to assess market performance. The ability to predict accurately staple food price movements and market responses in the presence of market inefficiencies is crucial for combating food security and ensuring the timely delivery of food aid. Knowing how markets will function and move staple food supplies in times of production shortfalls has direct policy implications for food aid interventions. Moreover, by incorporating lessons on the relationship between NDVI outcomes and market performance, this research provides insights into flexible methods of specifying and estimating regime switching, price forecasting models in sub-Saharan Africa.

Overview of Findings

Our approach relies on a blend of methods to provide an objective assessment of the analytical usefulness of NDVI and to extract maximum information from the NDVI data. We start by analyzing the relationship between cumulative, monthly NDVI anomalies, defined as observed NDVI values subtracted from their long-term mean, and potential millet price bubbles. Analysis of NDVI data reveals many consecutive months of below average outcomes leading up to the 2004-05 food security crises, suggesting that vegetation production conditions were far below what one would expect on average. To investigate further this finding, we estimate the relationship between NDVI outcomes and millet production statistics over a 14-year period for Niger. We show that aggregate NDVI anomalies have a strong, positive correlation with official millet production statistics. We also find that NDVI anomalies, aggregated pixel-by-pixel at the regional level, from as early as June are positively correlated with production outcomes. However, our full analysis demonstrates that the phenological events of the millet growing season complicate the creation of an optimal NDVI metric for analyzing and predicting market performance.

In order to understand better the temporal and geospatial economic relationships in our millet price data, we turn to the tools of spatial price analysis. We first consider if marketing years can be divided into different regime types by looking at how prices deviate from fundamentals across marketing years. Our price correlation analysis shows that in years following production shocks, market prices appear to move more closely in tandem than years of abundant production. Paying close attention to the evolving nature of millet market relationships, we test for both static and dynamic Granger-causing relationships. The results suggest that markets in major food production zones, as indicated by the spatial intensity of millet production, tend to generate leading price signals to periphery markets located in less connected and less intensive production zones. The temporal nature of these relationships appears to be varied but recent trends point towards improvements in overall market integration.

To investigate how millet market performance varies with NDVI outcomes, we estimate a price dispersion model that analyzes the impact of exogenous NDVI shocks, defined as NDVI outcomes based on a 50 kilometer buffer that depart +/- two standard deviations from their 11-year smoothed, moving average,, on absolute price spreads between markets using a difference-in-difference estimation approach. Our analysis reveals an uneven temporal distribution of NDVI shocks, with the majority of positive shocks occurring prior to the year 2000, and negative shocks clustering in the years 2000-2010. Our empirical estimates indicate that negative (positive) NDVI shocks are associated with better (worse) than expected market performance as measured by converging inter-market price spreads. As the number of markets affected by negatively abnormal vegetation production conditions in the same month of the growing season increases, measured by the percent of markets with NDVI shocks (as defined above), price dispersion declines between nearly 6 to 10 CFA. Positive NDVI shocks, however, do not mirror this pattern in terms of the magnitude of inter-market price divergence. The results are robust across standard fixed-effects models and specifications that include a dynamic adjustment factor. We also correct standard errors to account for general forms of cross-sectional and temporal dependence (Hoechle, 2007; Driscoll and Kraay, 1998).

Building off our price dispersion results, we investigate how market connectedness varies across millet marketing years by analyzing the relationship between NDVI outcomes, which we use as a proxy for millet supply (and implied trade flows), and the influence of neighboring prices on a central market. Specifically, we assess if millet markets are characterized by different types of price regimes in years of excessively good or bad millet production, as predicted by NDVI anomalies. Econometric analysis of historical price data suggests that markets are more segmented in years with above average vegetation production condition, when compared to years with average and far below average vegetation production conditions. Using model fit criteria (Akaike Information criterion and Bayesian Information criterion), our analysis shows that including binary or tertiary regime variables interacted with lagged price bands from neighboring markets improves the overall fit of a base millet price model. This insight suggests that millet price prediction models for Niger should explore the inclusion of multiple switches to account for different types of marketing year price regimes. Building off our conclusions about market performance and connectedness, we finish our analysis by analyzing how well NDVI anomalies can predict marketing year price regimes. Our results suggest that NDVI anomalies from May, June and July have a limited ability to predict future price regimes. However, as we include additional monthly NDVI anomalies, our prediction accuracy improves.

As a final exercise, we test how our NDVI-based regime estimates perform in our base model. Our predictions suggest that in bad years, on average, markets appear to be better connected when compared with average or good years. Thus, in bad years, on average, food aid policies should focus on making food available to the market and letting spatial arbitrage opportunities drive food deliveries, while at the same time monitoring the financial capacity of households to purchase food. In aggregate good years, spatial arbitrage incentives are less pronounced and weak spatial market integration means that surplus food cannot be fully absorbed by distant markets, so food security policies should prioritize local food availability and storage systems for improved consumption smoothing opportunities. Localized production shortfalls in isolated markets should be monitored closely to ensure that food reaches these markets, households have adequate access to food supplies, and household purchasing power remains adequate to afford food. Overall, improving the quality and quantity of local granaries and establishing micro-credit systems so that farmers are not forced into selling their harvest when prices are low and later repurchasing millet during the hungry season when prices are high would help rural households regardless of the type of market regime encountered.

This study reinforces the point that outcomes of using models forced by NDVI are closely linked to millet price realizations, market performance, and ultimately household well-being throughout Niger. With an evolving climate, extreme weather outcomes that drive variation in vegetation production are likely to grow in magnitude and frequency resulting in potentially new geospatial production patterns and changes in food trading patterns, thus necessitating food security policies that address short-term food insecurities, long-term food availability, and overall market performance. Because Nigeriens already face the realities of an extreme climate and have developed coping strategies for surviving on marginal lands, we can learn much from studying how this population has currently adapted to extreme weather and production variability. Understanding the structure and reaction of market systems to extreme climate and production outcomes today may provide insight into the impacts of climate change in other places and the role of markets in adaptation planning. Focusing on crop resilience and/or new crop varieties may be beneficial for exploiting new climatic patterns and improving yield potentials. And even if seed varieties and production patterns are appropriately modified (adapted) to exploit fully a changing climate, rural households may still not fully reap the rewards if markets fail to function well. Based on historical assessment, major crop failures will occur and markets will be the primary mechanism by which food and resources are delivered to vulnerable households throughout the region. A better understanding of the current relationship between market structures and environmental shocks in one of the harshest climates of today can help inform researchers, policy makers, and planners of the potential of markets in mitigating the deleterious effects climate change in the future.

In addition to the understanding the potential benefits of NDVI, we also highlight some of its limitations and offer practical tips for its use in food security analysis. One of the main empirical difficulties with NDVI is that the phenological events of the millet growing seasons fluctuate widely from year to year, so no two growing seasons look exactly the same. While the study finds that August NDVI is positively correlated with millet production outcomes, it does not necessarily imply a fixed and linear relationship between the two variables.

It is also important to remember that NDVI is a processed metric, which may be measured with error or perturbed by varying factors, used to detect variations in vegetation production conditions over a pixel of land measured remotely from a satellite orbiting above the earth. NDVI data cannot tell us if an area is actually being cultivated or in which crop – only vegetation conditions of a swath of land, which we use as a surrogate for millet availability and indirect trade flows. NDVI tells us nothing about the expectations of traders, the income, asset, and demographic profiles of consumers, the current volume of food in storage, the trade networks of a town or village, the political situation of country, or other characteristics of a location that can influence how prices are determined, how markets behave and whether or not these outcomes are a threat to household well-being.

For food security analyst, who are overwhelmed by data from the Early Warning System (EWS) monitoring pillars and are often asked to make policy recommendations based on imperfect information, knowing where and when to focus their analytical efforts is critical for delivering actionable information to food security policymakers. Brown and Brickley (2012) point out that Famine Early Warning System Network (FEWSNET) analysts rely on rainfall data 84 percent of the time, remote sensing data 28% of the time, and gridded crop models 10% of the time for assessment of food security problems. We advocate for intensifying the use of NDVI data in food security analysis along at least three lines.

First, NDVI data should be exploited to develop local and regional vegetation production condition balance sheets for the short and long-term. A ranking system would enable analysts to quickly contextualize outcomes and draw initial conclusions regarding the spatial nature of NDVI, likely millet availability, and expected trading patterns. This could be referenced against historical NDVI and economic data to understand how markets may function given historical outcomes.

Second, NDVI data should be analyzed regularly to detect and monitor extreme vegetation production conditions at the market-level and to track their potential impact on market performance. Developing a metric to reflect the geospatial extent and potential production impact of NDVI shocks would help in distinguishing among local, national, and regional shocks. National and regional shocks will likely result in different market regimes and levels of market integration.

Finally, incorporating current and recent NDVI data into food security assessments when price signals are abnormal due to bubble-like conditions, herding behavior, and/or inadequate information flows will enable analysts to develop a better understanding of what the appropriate price signal should look like, how it is likely to move up or down, and what impact this may have on scheduled or current food aid deliveries. Collectively, we feel that these three actions can add value, at little cost, to existing food security assessment methods. A full set of suggestions is discussed in Chapter 9.

Outline of Dissertation

This dissertation is organized as follows. The second chapter reviews early warning systems (EWS) and the role of NDVI, production data and commodity prices in food security analysis. The final part of chapter two introduces the reader to the myriad factors that affect millet production, consumption, and trade in Niger. Chapter three demonstrates the usefulness of NDVI in food security analysis and assessment when traditional price signals are of poor quality, missing or questionable due to speculative behavior or informational inefficiencies. While NDVI is not a substitute for price or production data, it can be viewed as a complement that can provide an objective measure of vegetation production conditions prevailing in agricultural production zones. Chapter four presents a brief literature review of NDVI studies, spatial price analysis methods, and cereal market performance in Niger. Chapter five describes the millet price data used in the analysis, the various manipulations and statistical tests conducted on the data in preparing them for analysis, and the results from our spatial price analysis summary. We then turn to a discussion of the NDVI data in Chapter six, providing a similar statistical analysis. Chapter seven reviews historical NDVI shocks and presents a price dispersion model to test the impact of these shocks on cereal market performance. Chapter eight considers the relationship between NDVI outcomes and price regimes. The final chapter presents conclusions, recommendations, study limitations, and a research agenda extending some of the initial analysis and proposing new lines of investigation.

Chapter 2: Early Warning Systems, Food Security Monitoring and Millet in Niger

This chapter provides a review of the primary tools used by food monitoring systems as well as an overview of millet production, consumption and trading in Niger. The second half focuses on the determinants of millet prices.

Review of Early Warning Systems

As a result of the horrific famines of the 1970s and 1980s, the international development community has increasingly turned to early warning systems (EWS) for monitoring food security situations around the world. Emphasis has been placed on monitoring food production systems and markets in Sub-Saharan Africa and the horn of Africa, which historically have faced some of the worst food shortages. Typically, an EWS is composed of three to five monitoring pillars (FAO, 2000):

i) Agricultural production monitoring (agro-climatic) and harvest forecasts;
ii) Market information monitoring (prices, storage, transportation costs, etc.)
iii) Livelihoods assessments or vulnerability profiles;
iv) Food and nutrition surveillance; and
v) Direct food aid monitoring

In practice, many of the pillars are difficult to put into operation due to local and international infrastructural, institutional, and capacity constraints. For example, detailed market information such as transaction costs and trade flows are difficult to track, even in the most developed markets. Because most production systems monitored are highly dependent on local weather and environmental conditions, and limited data are available on regional area planted or yields, many EWS rely heavily on remotely-sensed data such as Normalized Difference Vegetation Index (NDVI) (see Hutchinson, 1991) or rainfall data to make timely harvest forecasts. These projections are analyzed through vulnerability profiles to make food security assessments and predictions.

Less emphasis has been placed on analyzing and understanding remote sensing outcomes and how they relate to market performance and exceptional price movements, which is somewhat surprising as prices alone may be one of the best indicators of famine-like conditions. This trend appears to be changing as USAID's Famine Early Warning System Network (FEWSNET) Markets and Trade Strategy for 2005-2010 explicitly calls for methods and models analyzing the behavior of market systems (FEWSNET, 2008). While this change is welcomed, the process faces considerable challenges. Economic models available to study and diagnose market behavior are greatly limited by the data availability and quality. For generating forecasts at the micro-level, there are few panel-based forecasting models (Baltagi, 2007), particularly for developing countries of the Sahel. Traditional spatial price analysis itself may only provide confirmation or rejection of whether or not data exhibit certain statistical properties (Barrett, 1996; McNew and Fackler, 1997; Fackler and Goodwin, 2000; Rashid and Minot 2010). Moreover, because West African millet markets are weakly integrated with world cereal markets, popular food price indices such as the FAO food index are not appropriate for monitoring and forecasting the impacts of local and global production shocks (Brown et al., 2012).

In Niger (see Figure 1 below), one of the poorest countries in the world, millet prices exhibit tremendous inter and intra annual variation, which may well be an indicator of poorly functioning or inefficient markets. Spatial price analysis tools, such as correlation analysis, Granger-causality tests, and co-integration models, may help confirm or reject the presence, in a statistical sense, of market integration. But test results alone may be of limited use to policy makers and EWS analysts (Rashid and Minot, 2010). EWS analysts and policymakers are likely more interested in models that can link remote sensing data to economic outcomes, help forecast exceptional price movements, and explain how markets respond to localized and regional production shocks. Aker (2010b) echoes this latter point suggesting that disaggregated crop monitoring at the market-level will help analysts better understand the extent of droughts and the subsequent effects on market performance.

Figure 1. Continental and country-level map of Niger

Source: Central Intelligence Agency: The World Factbook

This explicit link between the agro-climatic monitoring pillar and the market information systems pillar, at both the macro and micro-level, appears to be a vital missing link in the EWS toolkit. FAO (2000) notes this shortcoming attesting that one of the constraints of EWS is that data from different pillars are often monitored independently and not appropriately linked. Previous work has shown that NDVI data can be used to detect deviations in vegetation conditions and has been shown to be correlated with net primary production and crop yields (Tucker et al., 1981; Prince, 1991; Fuller, 1998). But there remains a gap in understanding the relationship between NDVI outcomes and millet price movements (market behavior) and whether the relationship can be exploited to generate accurate price and market performance forecasts, particularly in isolated markets located in or near weather-driven production zones. Because prices are one of the best indicators of famine-like conditions, research is needed to document this link and to propose models that can ingest real-time remote sensing data and accurately convey how price signals are linked to market performance based on relationships among past NDVI outcomes. We now turn a discussion of millet in Niger.

Millet Consumption and Production in Niger

In rural areas of Niger, millet is the primary crop of consumption and production for households. It is widely grown by rural households because of its ability to withstand harsh climatic conditions and thrive in the sandy soils of sub-Saharan Africa. Specifically, pearl millet has the highest yield potential of all millet varieties under extreme heat and irregular moisture conditions, largely due to its deep rooting system and short life cycle (Léder, 2004). In fact, the cereal alone provides 75 percent of the total calories consumed by Niger's population (ibid, 2004). On a per capita basis, millet consumption in Niger is the highest in all of Western Africa (Obliana, 2003). Anecdotal evidence from rural households also suggests that millet may be preferred over wheat or rice because its rich nutritional content allows individuals to sustain hard physical labor for long periods of time. Because cereal production conditions are less than ideal throughout Niger, the country imports millet from neighboring countries such as Nigeria.

Generally, millet is grown in areas with rainfall of about 125-900 millimeters and grows better than sorghum in dry conditions (Rachie and Majmudar, 1980). Its growing cycle can range from 80-120 days in West Africa (Maiti and Bidinger, 1981). Under ideal conditions, millet planting occurs after the first major rain (occurring in May-July), which flushes the topsoil and activates organic matter near the surface. Because rains are sporadic in the Sahel, farmers rush to their fields to plant at the first signs of precipitation during the months of May, June and July. Across of many parts of Niger, the best conditions for planting and growing millet occur in May when the days are long and the sun is intense (Hash, C.T. 2011).

Households likely have two motivations for early planting. First, in terms of optimizing plant health, early planting decreases millet's susceptibility to harmful weeds (striga) and molds that commonly affect crops planted later in the growing season. A farmer who can plant in late April or early May can sharply reduce the risk of striga and mold outbreaks, while also improving potential millet grain quality and quantity. Second, in terms of optimizing economic returns, early planting means a farmer may harvest his/her crop ahead of the harvest cycle and thus fetch a higher farm gate price by delivering before other farmers. Early planting is not without risk. If a farmer does choose to sow early and the crop does not withstand the occasional dry spells of May and June (false rainy starts)[3], they may be forced to replant in July, given they have adequate financial and agricultural resources. Because millet can reach full height in 60 days, one could technically plant as late as August and still have an October harvest. However, the plant biomass is likely to be small and the yield low (Hash, C.T. 2011).

In reality, most rural Nigerien households do not have the luxury of early planting because they lack access to high quality millet seeds, face considerable credit constraints, possess only rudimentary agricultural inputs and limited land holdings, and may not have the necessary assets to recover from a rainy season false start. Even under some of the best conditions, many households must rely on loans to purchase agricultural inputs (seeds) at the beginning of the growing season when prices are high. The consequences of these actions are pernicious over time as households who borrow at the start of the growing season (near the peak of the lean season) are often forced to repay loans at the end of the growing season when millet prices are remarkably low. Because many of the loans are repaid by selling millet, households face unfavorable terms-of-trade at the time of repayment.

Further compounding the problem is the fact that most rural areas lack proper storage facilities and have less than ideal infrastructure through which they can purchase food and market their own production. Collectively, these issues force households to buy millet for consumption later in the year when prices are higher. Unfortunately, millet is the most frequently purchased grain when a household's own stocks are depleted (Brown, 2008). Because of the uncertainty of crop production and

[3] In neighboring Burkina Faso researchers have documented multiple false starts in the rainy season and suggest that plant growth is strongly correlated with the number and frequency of dry days (Prouda & Rasmussena, 2011).

the extreme price volatility of millet, many households supplement their income with livestock production, seasonal migration (the Exode[4]) and low paying, rural income generating activities.

The millet harvest typically occurs in October and November depending on the rain cycle. In some years, the process may start earlier or later depending on planting dates, the variety of millet (mainly pearl millet), and the prevailing weather conditions. Threats to fully grown millet include birds, insects, and molds. Rachie and Majmudar (1980) note that unless bristles (Figure 2, below) are present on the millet heads, birds will feast on millet seeds. In fact, birds can be a major problem if the millet grain ripens at the wrong time. Agrarian laborers harvest the plant by cutting the millet stalk in half and keeping the upper half where the grains are contained. Post-harvest, bundled millet may be stored on its head in granaries or moved to a threshing area for debranning. Traditional millet processing involves debranning the millet head in a wooden mortar with a wooden pestle. After breaking the seed from the stalk, the seed is gently tossed until it separates from the chaff. The debranned grain can then be stored or continually processed for consumption.

Figure 2. Millet bristles, processing, and storage

Millet bristles | Millet storage | Millet processing

Source: Author's photos

[4] The Exode (French for exodus) is a pattern of seasonal migration which generally involves rural populations travelling to neighboring countries for work during the dry season (January – April).

All parts of the millet plant are used throughout Niger. After harvest, some millet may be dried (stover) and left in the fields for livestock grazing. Near urban centers, millet stalks are sold or used for a variety of building materials, such as mats, fences, granaries materials, or burned as fuel (Lamers & Feil, 1993). Because the majority of the population depends on millet products throughout the year, poor agricultural outcomes can influence household consumption, production and income through multiple on and off-farm channels.

At a macroeconomic level, millet production constitutes nearly 80 percent of all cereal output in Niger (Cornea and Deotti, 2008). Despite the historical growth in area planted and overall millet production (as show in below in Table 1) yields have remained flat and far below that of neighboring countries. Part of this can be attributed to poor long-term agricultural policies of the last 20 years (Cornia, Deotti, and Sassi, 2012) and part may be due to the fact that input use is extremely limited. Thus, millet yields are highly correlated with weather conditions prevailing during the growing season. What is troubling about these practices is that if yields remain flat, millet availability will only keep pace with population growth (3 percent per year) by expanding the base area planted or increasing imports. Given that many marginal lands have already been introduced into the production process, the marginal gains from additional lands planted are likely to be decreasing (and likely at an increasing rate). This troubling trend may only exacerbate the effects of production shocks, especially when coupled with Niger's fertility rate of over 7 children per woman.[5] From a broad international trade perspective, millet is unique in that it is not traded globally and thus there are few trans-oceanic trade channels through which domestic

[5] https://www.cia.gov/library/publications/the-world-factbook/rankorder/2127rank.html

prices are affected (Brown et al, 2012). In fact, nearly all of the millet that is consumed in West Africa is produced and traded within the area.

The major millet producing regions of Niger are shown below. Figure 3 depicts the regions of Niger overlaid with agro-ecological zones from FEWSNET and spatial production maps from Harvest Choice's Spatial Production Allocation Model (SPAM) model. The red circles indicate a market that is in the study sample. A review of the figure shows that markets are reasonably well-distributed spatially and by production zones. The major millet producing regions of Zinder and Maradi are represented by eight markets, a few of which are major cereal collection points, such as the market of Maradi. The red lines represent major transportation routes. Most markets are connected to infrastructure points, though the quality of the infrastructure may be less than ideal. The distribution of markets by agro-ecological zone is also balanced with 10 markets falling in the rainfed agricultural zone.[6]

[6]For the most recent information on the livelihood zones see: http://www.fews.net/docs/Publications/Niger%20Livelihoods%20zoning%20report%20Final.pdf

Figure 3. Map of markets analyzed and major production zones

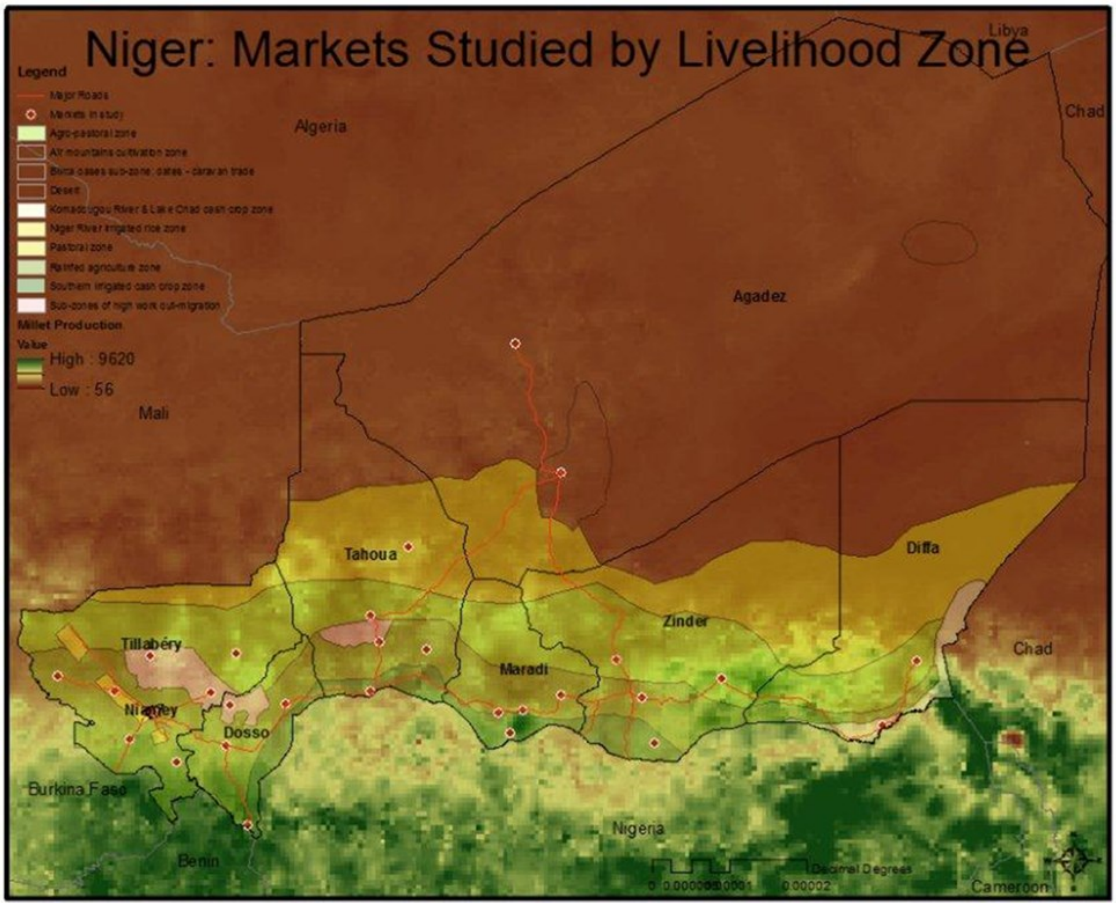


Table 1. Official millet production statistics 1996-2009

Yield = production/area planted*100		1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
		Millet	Millet	Millet	Millet	Millet	Millet	Millet	Millet	Millet	Millet	Millet	Millet	Millet	Millet
DIFFA	Area	76,537	62,253	76,156	93,515	77,785	90,675	110,368	106,324	53,166	140,718	139,520	140,885	156,977	152,583
	yield	417	59	560	518	55	488	434	367	169	319	451	545	470	196
	Production	31,896	3,670	42,665	43,394	4,251	44,263	47,895	3,921	9,010	44,895	62,974	76,749	67,882	29,968
DOSSO	Area	639,029	737,069	838,732	826,085	833,554	809,839	910,558	945,264	1,003,051	941,953	1,051,581	1,053,928	1,183,105	1,136,316
	yield	508	339	419	501	370	583	559	513	484	496	581	485	606	552
	Production	324,396	249,776	351,650	413,531	308,597	471,974	508,864	484,804	485,913	466,775	610,725	511,667	716,567	627,520
MARADI	Area	1,209,583	1,086,510	1,254,567	1,224,150	994,286	1,050,626	1,200,072	1,128,302	1,094,049	1,181,100	1,345,041	1,351,371	1,515,601	1,476,109
	yield	319	339	462	347	384	404	457	564	395	444	495	467	512	417
	Production	386,175	368,689	579,954	424,254	381,764	424,270	548,409	635,987	432,693	524,407	665,836	630,981	776,289	615,704
TAHOUA	Area	920,372	758,737	878,450	883,527	921,975	899,726	989,682	1,067,147	1,050,723	1,094,329	1,152,375	1,165,885	1,254,941	1,242,518
	yield	446	370	501	478	351	472	426	464	317	447	538	501	578	370
	Production	410,726	280,504	439,751	422,335	323,925	424,573	421,757	495,100	333,604	489,226	620,233	584,606	725,914	460,066
TILLABERY	Area	857,441	911,144	1,104,230	1,071,799	1,074,134	1,110,093	1,237,152	1,400,000	1,342,557	1,321,563	1,372,653	1,341,970	1,512,073	1,278,550
	yield	348	174	507	443	274	472	452	424	290	473	431	390	447	382
	Production	298,331	158,675	559,423	474,442	294,500	524,045	559,784	592,986	389,763	625,552	591,476	523,215	676,113	488,084
ZINDER	Area	1,079,086	927,951	1,195,052	1,236,122	1,232,093	1,251,657	1,111,685	1,104,586	1,040,080	1,197,883	1,149,352	1,098,923	1,181,570	1,199,950
	yield	281	307	343	410	293	368	425	441	363	412	389	405	430	365
	Production	302,911	284,707	410,443	506,533	360,597	460,797	472,074	487,482	377,130	493,140	446,525	445,433	508,272	437,481
Agadez/Niam	Area	7,763	19,971	18,868	16,005	17,568	19,320	16,606	19,670	20,729	16,383	19,426	17,217	24,617	27,118
	Yield	460	295	392	268	284	457	508	484	463	513	557	539	746	702
	Production	3,570	5,897	7,396	4,297	4,997	8,820	8,436	9,528	9,601	8,397	10,815	9,276	18,354	19,032
Niger	Area	4,789,811	4,503,635	5,366,055	5,351,203	5,151,395	5,231,936	5,576,123	5,771,293	5,604,355	5,893,929	6,229,948	6,170,179	6,828,884	6,513,144
	yield	367	300	446	428	326	451	460	476	364	450	483	451	511	411
	Production	1,758,005	1,351,918	2,391,282	2,288,786	1,678,631	2,358,742	2,567,219	2,744,908	2,037,714	2,652,392	3,008,584	2,781,927	3,489,391	2,677,855

Source: FEWSNET Niger/Government of Niger; Area planted measured in hectares and production measured in metric tonnes.

In a typical production year, cereal harvests from the surplus zones of Maradi, Zinder are gathered and transported across the country to cereal deficit zones in the north and west.[7] Millet imports from Nigeria also make their way into Niger through Gaya and other border towns. Mali and Burkina Faso typically supply cereal to Western Niger, whereas cereal supplies from central and southern Niger are augmented by imports from Nigeria. The markets of Zinder and Maradi are central reference markets for the surplus regions and points of major agribusiness activities.

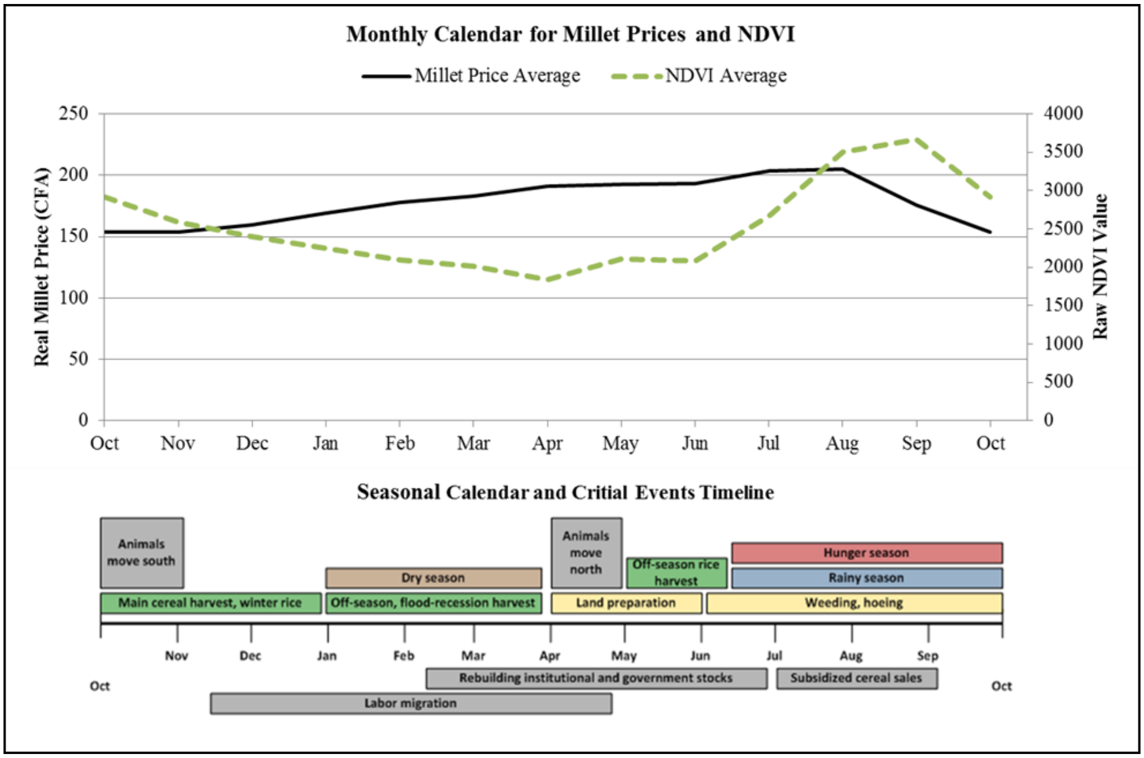
Determinants of Millet Price Outcomes

Figure 4, below, summarizes major food supply and demand events that occur throughout the year and their relative relationship to long-term average millet prices and NDVI outcomes. The graphic is presented on a month-by-month basis to demonstrate the myriad fixed factors that influence cereal supply, cereal demand, and overall market performance. For most of our analysis we use NDVI and price anomalies so that predictable seasonal events (or market fundamentals) are already accounted for. That is, we focus on whether observed NDVI and price outcomes are above or below what we normally expect at that time of the year, for any given year after controlling for expected market fundamentals. As is depicted in the graphic, average (raw) NDVI values rise continuously throughout the growing season, reflecting the growth of vegetative cover, until reaching a normal peak in September. While this behavior is normal and reflects average NDVI, the extreme weather variability of Niger means that NDVI values in some years deviate far from average, and early or late growing seasons may occur depending on the rainfall patterns.

[7] See http://www.fews.net/docs/Publications/ne_fullmap_millet_norm.pdf for an full example of typical millet flows.

Outside of the growing season, NDVI declines steadily until the following growing season starts.

Figure 4. Events calendar for Niger



Source: FEWSNET & Author's calculations.

In reviewing the figure above it is easy to gain a sense of the pattern millet prices follow throughout the agricultural marketing season. The actors in the cereal marketing chain consist of smallholders, primary and secondary cereal collectors, wholesalers, transporters, retailers and a cadre of large traders who are responsible for many exports and imports (World Food Program, 2005). The typical marketing season commences with harvest in October through December and runs through September of the following year. In terms of millet price fluctuations, the largest percentage decline normally occurs between August and September and between September and October as central markets aggregate cereal supplies, traders begin to restock their storage facilities, and information on remaining harvest volumes comes to light. Collectively, these factors put downward pressure on local and national millet prices.

However, because storage facilities are limited, particularly at the micro level, and other market inefficiencies emerge throughout the year, prices tend to fluctuate both intra and inter-annually. From October-December, millet prices typically fall to some of their lowest levels and exhibit the least amount of volatility (standard deviation) due to sufficient cereal supplies and less uncertainty across markets. This is also the time during which traders begin to rebuild their stocks for the coming year. In rural areas, farmers may start restocking millet in local granaries, and at the wholesale level stocks are rebuilt after harvest, but usually held for short periods. In fact, Aker (2010b) suggests these periods generally do not exceed two months. At the national level, government stocks are replenished at the end of harvest. However, official figures may not be published until the first trimester of the following year, and are thought to suffer a serious upward bias (Araujo-Bonjean and Simonet, 2011).

Depending on the quality and quantity of the harvest, the volume of existing millet stocks, the flow of millet from surrounding countries, the supply of millet substitutes, and the degree of market inefficiencies, millet prices typically start to increase at the beginning of the dry season. In marketing years with below average production (1997-98 and 2004-05), prices may increase as early as February or March. On the other hand, in marketing years with abundant production, prices tend to remain flat throughout the winter months. Typically, the largest, pre-hungry season percentage change in millet prices occurs between March and April. Towards the end of the dry season, imports from surrounding markets start to make their way into the

Nigerien markets. By April and May, millet prices are elevated as land preparation starts, the hungry season approaches, and rural households continue to draw down their local supplies of millet.

At the peak of the hungry season, June to August, millet prices climb to their highest levels and exhibit the greatest amount of volatility. This is partially due to the lack of proper storage facilities, the uncertainty of future crop production, the changing expectations of traders about available cereal supplies, and increased demand from households who have exhausted their own millet supplies. Collectively, these events put tremendous pressure on households that are down to their final grains of millet. For example, during the poor marketing years of 1997-98 and 2004-05 millet prices reached historical high points in these months. In July of 2005 prices were nearly 100 CFA above average. To ease the pressure caused by rising prices on households, the Government of Niger may introduce subsidized sales of millet during the peak of the hungry season. As the growing season reaches its final months, millet prices start on a downward path as more and more information regarding the quality and quantity of harvest is revealed to the markets. Depending on the timing of the growing season and the nature of the harvest, the decline may start as early as July (such as in 2002-03 marketing season) or as late as September.

As documented in our review, millet production, consumption, and trade are affected by numerous factors that take many forms (fixed, stochastic, observed, and unobserved) and are difficult to collect data on in a timely manner. Moreover, market inefficiencies and imprecise measurement of data mean that price and production statistics alone may not convey the appropriate message for making food security assessments and ultimately decisions. What is needed is an objective, apolitical, metric that is measured in real-time and can be used to detect vegetation production conditions, and thus likely millet production outcomes and inferred trade flows. This is the primary advantage of NDVI. In the following section we demonstrate its usefulness for contextualizing millet price and production outcomes in a period of great food insecurity, the 2004-05 food security crises which affected an estimated 2.4 million Nigeriens, of which 800,000 were classified as critically food insecure (FEWSNET 2005)

Chapter 3: Using NDVI to Improve Spatial Price Analysis

This chapter demonstrates the usefulness of NDVI in analyzing and contextualizing price outcomes in Niger during the 2004-05 food security crises. We start by briefly discussing why market imperfections that are likely present in Niger can distort price signals. We then turn to a discussion of how NDVI can be used to add value to price analysis for the purpose of food security assessments. The final part of the chapter focuses on the benefits and limitations of remote sensing data for food security assessment.

Using NDVI to Analyze the 2004-2005 Food Security Crises

In developing countries, Niger in particular, markets are often not well integrated due to inadequate provision of public goods, such as infrastructure and telecommunication systems, inefficient flows of information, and missing institutions (Rashid and Minot, 2010). Markets may also be inefficient in that prices at a given point in time may not reflect the current state of knowledge of food availability and expectations regarding future food scarcity. When these types of market failures and/or inefficiencies are present, the appropriate price signal may not be fully transmitted down the marketing chain (Baulch, 1997a). Storage facilities, where they exist, may be of poor quality and actual data on storage volumes may be missing, incomplete, or even manipulated for political purposes (Araujo, Bonjean and Burnelin, 2010). Expectations about future price movements may be more dependent on rumors (informational failures) than on stylized facts and underlying data. Under these conditions, satellite-based remote-sensing data that reflect actual vegetation production conditions on the ground (given there is adequate remote sensing resolution) are available in a timely basis, are objective and consistent when appropriate processing corrections are made, and are not subject to the influence of rumors or political manipulation, can be powerful tools for informing an analyst of impending price movements and even food aid starting or stopping points. This issue is particularly relevant in Niger where millet prices exhibit extreme variation often associated with pricing bubbles, production shocks are common, and cereal market performance fluctuates widely and appears to fall into different types of pricing regimes.

The theoretical conditions associated with competitive spatial market equilibrium and spatial price integration allow for multiple types of price regime outcomes (Barrett and Li, 2002). The first concept, which is concerned with long-run competitive equilibrium, is typically defined by conditions from Enke-Samuelson-Takayama-Judge spatial equilibrium model. The model states that two markets are in long-run equilibrium either when trade occurs, and rents to spatial arbitrage are exhausted, or when no trade occurs and rents to spatial arbitrage are less than or equal to zero. Thus, even if markets are in equilibrium, no trade may occur and millet prices may not be highly correlated across space. One could plausibly see this scenario unfolding when millet production is abundant throughout the Sahel and spatial arbitrage incentives are greatly diminished, so that local prices follow different patterns.

Spatial price integration differs in that it is usually concerned with the physical flow of commodities and/or the degree by which a shock is transmitted between two markets. Even if trade does not occur, two markets may be integrated as long as arbitrageurs face zero marginal returns (Barrett and Li, 2002). Because both concepts typically rely on three variables for analysis: prices, transactions costs and trade volumes, the overlap of conditions generated by the two concepts can be used to define different types of market conditions. As presented by Barrett and Li (2002), six types of regimes, all shown in the table below, may be observed in spatial price data.

Table 2. Types of price regimes

	Arbitrage conditions bind	Positive profits to spatial arbitrage	Negative profits to spatial arbitrage
Trade occurs	Perfect integration (1)	Imperfect integration (3)	Imperfect integration (5)
No trade occurs	Equilibrium / Unexercised tradability (2)	Segmented disequilibrium (4)	Segmented equilibrium (6)

Adopted from Barret and Li (2002).

Under each scenario, trade may or may not occur which leads to different conclusions regarding the characterization of spatial market equilibrium and integration. When arbitrage conditions bind and trade occurs (1), markets would be classified as being perfectly integrated and in equilibrium, or if no trade occurs (2), markets may still be in equilibrium and integrated, but not exercising tradability. Moving to the middle of the table, we observe what happens when positive profits remain from spatial arbitrage opportunities. When trade occurs (3) markets are said to be imperfectly integrated, because through trade arbitrageurs can earn positive profits. On the other hand, if no trade occurs (4) markets are characterized as being in a segmented disequilibrium because arbitrage opportunities that are profitable are not fully exploited. The last column describes a scenario (5) under which traders actually earn negative profits from trade and markets are characterized as being imperfectly integrated. On the other hand, no trade may occur (6) and markets are in a categorized as being in a segmented equilibrium.

To determine accurately the nature of the price regime which characterizes millet markets in Niger at a given point in time requires millet prices, inter-market millet trade volumes, and inter-market transactions costs of spatial arbitrage. While we do not observe trade flows or transportation costs, we do observed spatially explicit NDVI outcomes which may serve as a proxy for local millet availability (millet supply), which in itself can reveal information about potential trade flows between markets. When vegetation production conditions are above normal during the growing season, we assume this indicates greater local availability of millet and thus less trade flow from normal food surplus markets to normal food deficit markets. Moreover, NDVI also correlates well with rainfall in semi-arid regions (Nicholson, 2011), which means it potentially can serve as a crude indicator for transactions costs under the assumption that below (above) average precipitation outcomes decrease (increase) normal transportation costs. While there is error in these correlations and NDVI data are by no means are a substitute for prices, NDVI does have the advantage over prices of not being affected by market inefficiencies and failures. When the appropriate price signal is not being transmitted down the marketing chain, the objectiveness of NDVI may reveal information not contained in the price signal. This point is illustrated through an analysis of the 2004-05 food security crises in Niger.

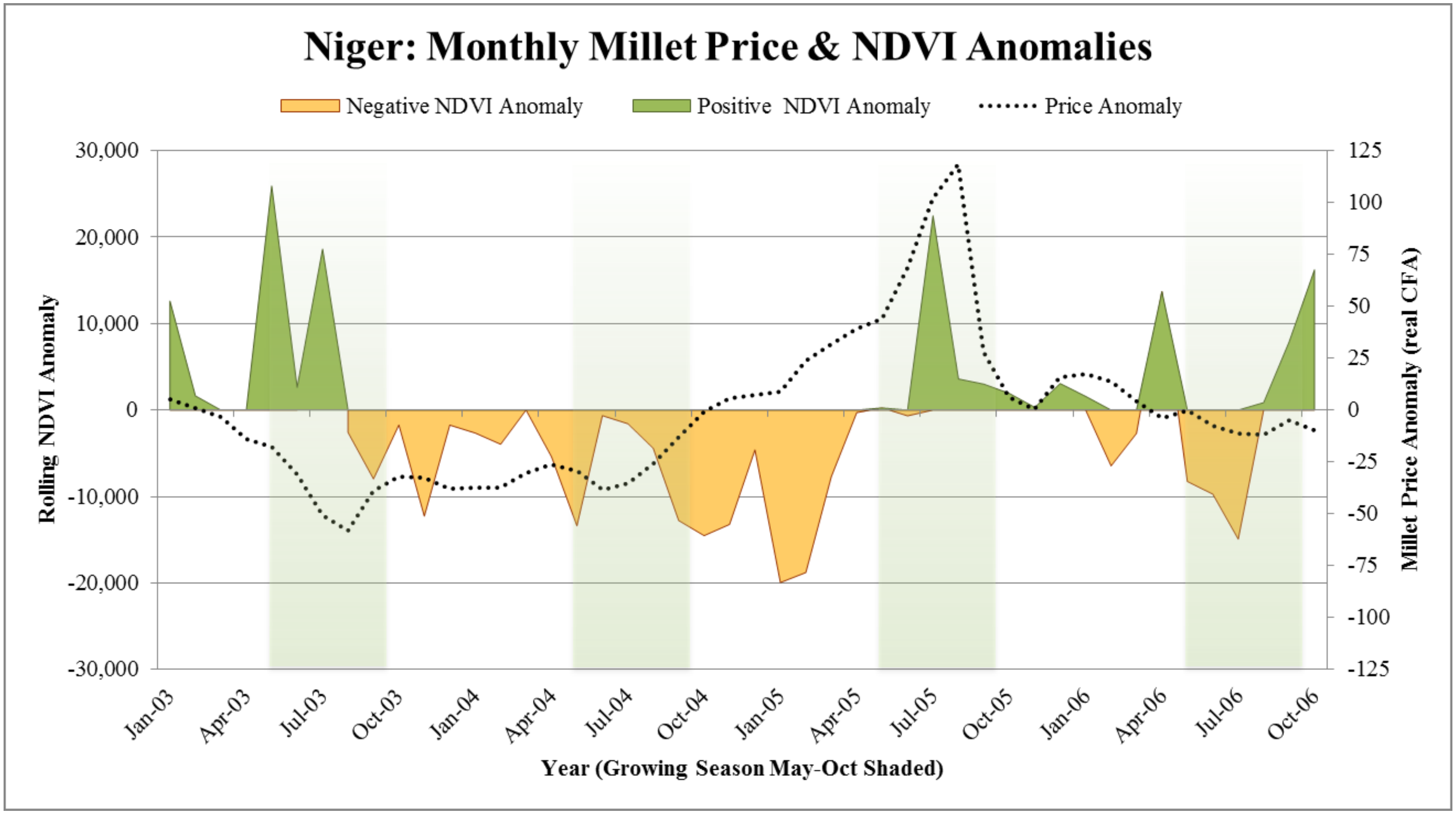
Figure 5, below, depicts real millet price anomalies (in black) and a rolling, twelve-year, monthly deviation of cumulative NDVI for millet production zones (in green and brown) in Niger. Major production zones are derived by intersecting pixels from the NDVI database with Harvest Choice's Spatial Production Allocation Model (SPAM). NDVI pixels falling within areas where SPAM crop production is greater than zero hectares are considered to be active production zones. While only data from 2003 through 2006 are shown, the cumulative anomalies are calculated over the entire period of study. To create the price anomalies we remove all seasonal and market fixed-effects (pricing fundamentals) that normally influence millet prices. That is, for each market we regress the observed prices on a vector of monthly dummy variables, a continuous set of temporal variables (period and period squared), and a market fixed-effect. We then calculate a monthly residual for each market. This residual represents the price anomaly, or how far prices have deviated from predictable fundamentals for a given market, in a given month. To generate a national-level anomaly, we calculate the mean of the estimated price residuals across all markets.

For NDVI anomalies, we follow a similar procedure, but at the pixel-level using a rolling window with monthly and pixel-level fixed effects removed. The NDVI monthly anomaly is smoothed (or updated every month) in order to incorporate only the last twelve years of monthly NDVI data. Twelve year NDVI windows are used because NDVI data start in July of 1981 and millet price data are most consistent starting in 1993. We aggregate all anomalies across space to construct a single cumulative NDVI metric for Niger. When reading Figure 5, prices and NDVI values can be interpreted as follows: millet prices or NDVI outcomes that are close to the vertical axis at zero represent normal conditions, or that the values are close to what one would expect on average. When millet prices are above the vertical axis at zero, this indicates that prices, on average, have deviated from expected market fundamentals. On the other hand, NDVI values above (below) the vertical axis at zero indicate an above (below) average period of aggregated vegetation production conditions. The shaded green bars in Figure 5 represent the annual growing season, which runs from May to October.

We start by focusing our attention on May 2003, during which we notice a strong correlation between the NDVI and price signals. First, average, aggregated NDVI anomalies were far above what we would have expected for a normal millet growing season. Aggregated NDVI anomalies for May suggest not only an early start to the growing season but also above average vegetation production conditions and thus more millet availability earlier in the year. Millet price deviations reflect this early start and promising millet harvest as they remained well below average throughout the growing season. In fact, the deviations actually grew in magnitude from May through September which may reflect the early offloading of millet stocks by traders and/or the early harvest of millet. Only in October of 2004 did prices reach their expected value, indicating a likely abundance of millet throughout Niger.

As markets continued to incorporate information from the 2004 harvest, price deviations increased in magnitude throughout the beginning of 2005. Price anomalies steadily increase in value throughout the spring months and then exploded in the summer of 2005. In fact, by July 2005, price anomalies were more than 100 CFA above their long-run, expected value. At this point in time, no purely price-driven econometric model could provide an adequate picture as to how prices would move in the future, given how far off the expected path prices already were. Moreover, from a food security standpoint, it would have been tremendously difficult to know whether the extreme price levels accurately represented the availability of millet in the markets, or were associated with a pricing bubble that may have been due to rumors or expectations of millet traders in Niger.

Figure 5. Long-term millet price and cumulative NDVI anomalies in Niger (2003-2006)



Source: Author's calculations

Media outlets, institutional researchers, and EWS personnel have proposed many competing hypothesis to explain why millet prices reached such extreme values. At one end of the spectrum, some international media outlets hypothesize that the rapid rise in millet prices was a figment of the international community, perpetuated to raise humanitarian funds (Sultbløffen "The Famine Scam", March 2008, TV2). Other media outlets and think tanks posit that the price hikes were due to the locust invasion, excessive trader hoarding (the Oakland Institute), and lower national food reserves (Aker 2010b). USAID FEWSNET characterizes the rapid rise in prices as a localized food security crisis caused by impoverishment among landholders in the southern districts (Eilerts, 2006). Aker (2008), and to some extent Rubin (2008), suggest that unfavorable terms of trade with Nigeria reduced incentives to import millet into Niger and that a majority of Nigerien regions were actually affected by production shocks. What appears to be missing from the debate is an objective assessment of the variation in vegetation production conditions across Niger during the same period.

Shifting focus to the green and yellow shaded areas, which represent NDVI anomalies, we can see three clear messages emerge: i) an early growing season occurred in 2003 that put substantial downward pressure on millet prices during the hungry season, and increased the amount of time between normal food production periods; ii) cumulative NDVI anomalies for late 2003, all of 2004, and half of 2005 that were far below normal levels and likely contributed to the deterioration in food prices during the spring and summer of 2005; and iii) NDVI anomalies were far above their expected values in July of 2005, and foreshadowed the bumper harvest experienced later that year.

Regarding the first point, the positive NDVI anomalies in May and July of 2003 suggest an early start to the growing season, an early harvest, and an atypical amount of time between production periods. Because household and community level storage facilities are less than ideal and government and wholesale storage actors tend not to store millet for long periods of time due to high storage costs, credit constrained households are not able to adequately smooth consumption across growing seasons. An early growing season followed by a poor growing season and very bad non-growing season, may have exacerbated this problem. Moreover, reviewing NDVI anomalies for August through November 2003, we see that cumulative NDVI anomalies are far below where one would expect. This may be interpreted as evidence of an early harvest, given the above average NDVI outcomes from early in the growing season.

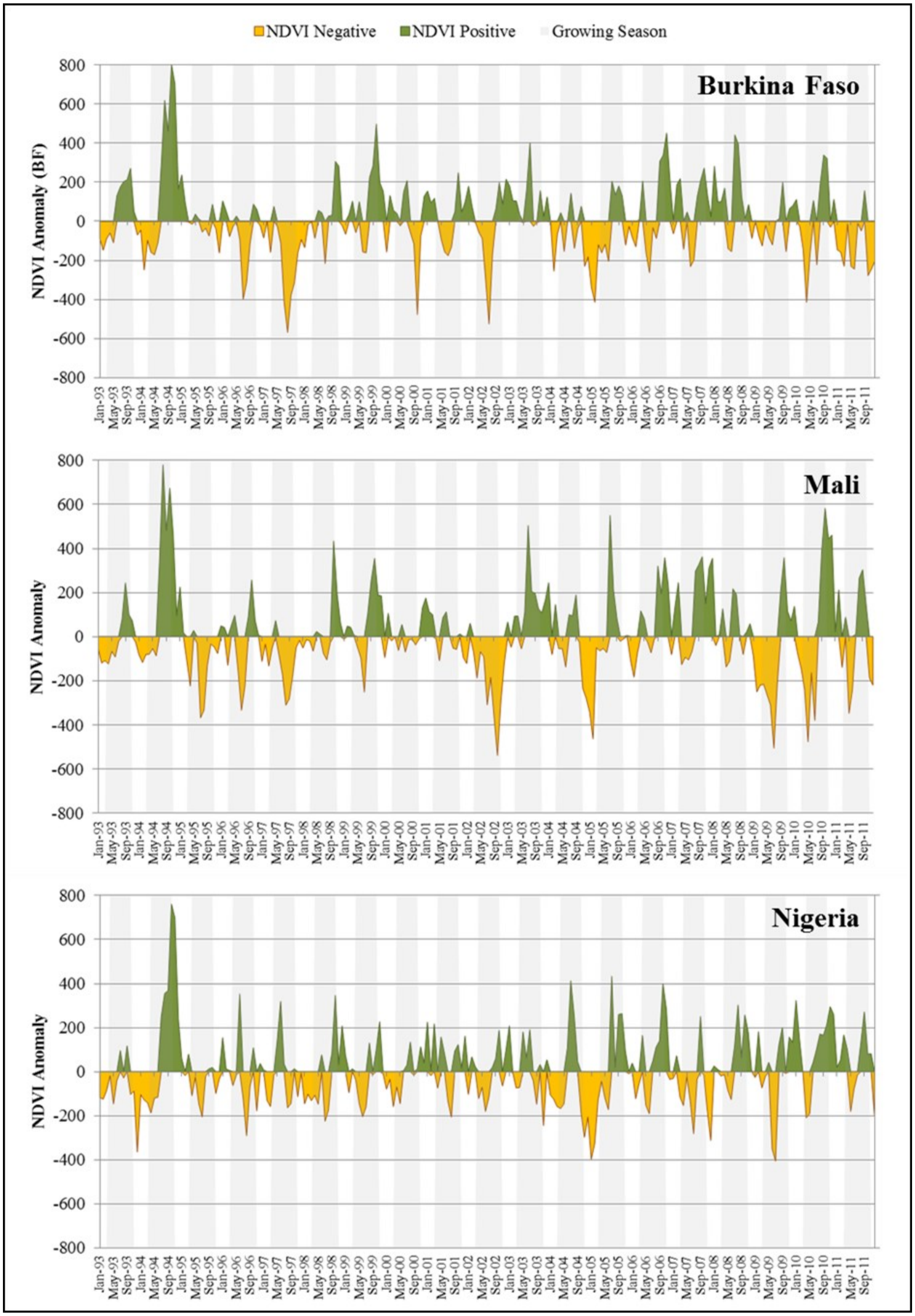
At the start of the 2004 growing season (May/June/July), NDVI remained far below average, suggesting a poor or delayed start to the growing season. The remaining months of 2004 growing season did not fare better as each month, staring with June, was progressively worse through November of 2004. This sharp downward trend continued into the first part of 2005 with a substantial number of negative NDVI shocks recorded in January and February of 2005.[8] However, it is unclear how to interpret these shocks as they occurred in the dry season during which NDVI should have limited analytical value. Analyzing the same period with

[8] The study recommends additional research regarding the NDVI outcomes from January and February of 2005 in order to determine the values can be explained by other sources of error found in the NDVI data. The extent of shock is observed across a wide geographic space in our NDVI database.

alternative NDVI anomalies (long-term and short-term anomalies), we reach largely the same conclusion. Using a long-term cumulative NDVI anomaly, we calculate that Niger experienced 15 consecutive months (April 2004 – June 2005) of below average NDVI outcomes. The number would have been 20 consecutive months were it not for the normal levels recorded in March of 2004. In terms of short-term NDVI anomalies, the results are comparable as the 13 out of 15 months were far below average for the entire region. Also, particularly relevant is the fact that in neighboring Burkina Faso, Mali and Nigeria, NDVI levels were far below normal for seven consecutive months suggesting a regional-wide phenomenon. Average NDVI levels from the breadbaskets of these countries are depicted below in Figure 6.

Finally, regarding our third point, returning to Figure 1 and focusing on the 2005 growing season, particularly July and August, we see that the aggregated NDVI anomaly variable was far above its expected value. In fact, when we rank average NDVI anomalies from that point in time against values from the past 12 years, anomalies from July of 2005 rank second overall. At the same time, in the Malian and Nigerian zones of intensive millet production NDVI readings were at their highest levels in the past 12 years. These above average NDVI outcomes, which we interpret to be an indicator of above average yield potential (millet production) and declining millet prices, occurred well before millet prices actually fell in the fall of 2005.

Figure 6. NDVI anomalies for production zones of Burkina Faso, Mali, and Nigeria



Source: Author's calculations

Advantages of NDVI Data

In this situation, incorporating NDVI into a food security assessment and millet price forecasting model appears to deliver benefits in a couple of ways. [9] First, in terms of providing additional information on millet price levels, NDVI data could have informed analysts of three important points: i) that there was a substantial time-lag between production periods from 2003 to 2004, ii) that the vegetation production conditions from late in the 2003 growing season through early 2005 were far below normal both during and outside of the growing season (and particularly bad in January and February of 2005), and iii) that cumulative, monthly NDVI anomalies for the 2005 growing season were far above average and this was known as early as July of 2005. NDVI appears to help predict in a timely manner the precipitous decline in millet prices following the 2005 harvest. While analysts would have known the vegetation production conditions of given pixels from the satellite data, conducting analysis only with the prices coming across their desks in July and August of 2005 may have resulted in vastly different conclusions.

Additionally, because official millet price data typically take weeks to collect and process and are often only available on government websites with a considerable lag, the actual prices available for analysis at the height of the crises may have been dated or inaccurate. As for official production estimates, Araujo, Bonjean and Burnelin (2010) point out that these are not available until late fall, or even early winter. These authors also note that official statistics are often biased and may face

[9] Currently, the primary use of NDVI within FEWSNET is to compare the current state of vegetation with previous time periods. This may be done by looking at a reference year and comparing current conditions to the same seasonal progression in all previous years (http://www.fews.net/pages/imageryhome.aspx?pageID=1&l=en). It is unclear how this is integrated with analysis of millet prices or market performance metrics.

upward revisions if millet prices start to rise too early in the year. NDVI data, on the other hand, can be processed in near real-time, in front of an analyst's eyes in a matter of hours, and are less subject to revision post-delivery. But these are not the only advantages of NDVI data.

In terms of food aid logistics, knowing that NDVI data had been abnormal, across the entire region, throughout 2004 and into 2005 may have provided better insight into the urgency of food aid needed during the early part of 2005. The NDVI anomalies from the winter of 2005 potentially suggest that the 2004 locust invasion was quite severe and may have adversely affected a household's ability to derive income from secondary channels. Conversely, knowing that farmers across the entire Sahel were experiencing above average vegetation production conditions in July and August of 2005 would have been tremendously useful in informing donor agencies of the need for additional food aid shipments to the region, particularly if pending shipments only arrive with a substantial lag. If a subsistence farmer were to experience a bumper harvest at the same time that international food aid saturated a local market, then that farmer may be even worse off, depending on the magnitude of the endowment income effect.[10] Instead of being rewarded for a bumper crop, a farmer may face lower millet prices because of the oversupply in local cereals caused by the untimely delivery of food aid. Thus, NDVI may not only be useful in predicting impending prices movements and when and where to start food aid deliveries, but it can also be valuable in determining when and where to stop planned

[10] Recall from the Slutsky equation that a price shock to a seller will have three effects, the substitution effect, the ordinary income effect, and the income endowment effect. Depending on the magnitude of the endowment income effect, farmers may be worse or better off after a change in prices during the harvest months.

food aid deliveries to prevent market distortions and preserve the livelihoods of rural households.

From a data perspective, using NDVI alongside prices delivers other benefits. Price data alone are fraught with missing observations and measurement error, and are confined to a fixed geographic space, all features which can limit the conclusions drawn from their analysis. For example, price data from two markets that are separated by geographical features (mountains or a lake) and have no trade history may appear to co-move because of similar weather (drought). In reality, the markets may not be at all integrated, but because vegetation production conditions are not immediately available, we may draw incorrect conclusions by looking only at co-movements of prices. NDVI, on the other hand, can allow us to control for the vegetation production conditions surrounding markets and can help in detecting the influence of varying conditions on price changes and market performance when measured with adequate spatial, temporal, radiometric and spectral resolution. NDVI can provide a rich time series when it is objectively and consistently processed and appropriate corrections are made to account potential sources of error such as atmospheric effects (aerosols and dust), cloud cover, soil effects, orbital effects (anisotropic), and sensor degradation (Goward et al., 1991). Thus, when corrections are made in a consistent and objective manner NDVI data are available over a long time horizon, cannot be manipulated politically to establish a desired trend or mask bad news, and are not influenced by the presence of geo-political borders or the availability of environmental observations of growing conditions. The latter point means that a food security analyst can readily assess other productive zones of the

Sahel and rapidly develop a sense of the state of regional vegetation production conditions. This is particularly relevant, given that during 2000-2004, 75-85 percent of millet and sorghum imports into Niger originated from northern Nigeria (Cornea & Deotti, 2008).

Disadvantages of NDVI Data

While NDVI has many analytical benefits, it also has numerous limitations. NDVI is simply a metric used to detect vegetation production conditions over a pixel of land remotely sensed from a satellite orbiting above the earth. Studies (Rasmussen 1997, 1998) have shown that it is highly correlated with millet yields. However, many potential sources of error (as mentioned above) can affect the spectral signal used to calculate NDVI. Moreover, because in semi-arid areas NDVI correlates well with many parameters, such as percentage of surface cover, biomass and leaf area index, as well as rainfall, there may be temptation to over-use NDVI for analysis, some of which NDVI was never designed (Nicholson, 2011). NDVI cannot tell us if an area is actually being cultivated or in which crop – only the spectral signature of live vegetation which is related to the vegetation production conditions and by implication the moisture conditions of plants. NDVI tells us nothing about the expectations of traders, the income and asset profiles of consumers, the current volume of food in storage, the trade networks of a town or village, the political situation of country, or other characteristics of a location that can influence how prices are determined, how markets behave and whether or not these outcomes are threats to household well-being. Satellite remote sensing is not embedded in economic theory through any formal framework. We know that prices will generally be the best food availability indicator because when markets are efficient prices will reflect all information available to the market as well as expectations regarding future food scarcity. If given the choice between NDVI or price data, price data are generally better as an indicator of food availability when available in a timely and consistent manner. Thus, NDVI data are not a substitute for prices.

But, NDVI data do serve as a complement to price data in that when the quality of price data is poor, unavailable, or questionable due to bubble-like conditions and herding mentality, NDVI data can greatly aid in understanding and forecasting how prices are likely to change, and as we show in the following chapters, what future market performance may look like. While we may not be able to disentangle or control for all the factors that influence prices, we can start to disentangle what we observe in the NDVI data. Knowing in advance whether NDVI outcomes have substantially departed from historical averages can help in interpreting price signals, forecasting market conditions, and providing policy makers an objective view of the production and environmental conditions on the ground.

Chapter 4: Literature Review

In this chapter we review the literature on NDVI studies, spatial price analysis, and market performance in Niger. While numerous studies have examined the linkages among NDVI and vegetative outcomes or crop yields, there have been few attempts to explicitly link NDVI anomalies to millet price outcomes for the purposes of analyzing cereal market performance. With that said, this literature review is by no means comprehensive, but instead illustrative and focuses on highlighting the major bodies of work related to topics in this dissertation.

A Review NDVI Studies

The use of satellite data in forming vegetation indices dates back to the 1970s when researchers demonstrated that combinations of red and photographic infrared radiances could be employed to monitor photosynthetically active biomass (Rouse et al. 1974; Tucker 1979). In the 1980s, Tucker et al. (1981) demonstrated that NDVI was directly related to wheat yields. Many studies, focusing on the remote sensing of biomass production in the Sahel, followed (Tucker et al., 1983; Tucker et al., 1985; Prince & Tucker, 1986). Prince (1991), focusing on three Sahelian countries, concludes that satellite observations of vegetative indices and seasonal primary production are strongly linked. Using a longer time series of NDVI and rangeland and agricultural data, Fuller (1998) asserts that correlations between trends in maximum NDVI and field measures of rangeland and crop production are positive and statistically significant. Others (Nicholson, 1994; Tucker and Nicholson, 1999) suggest that NDVI is correlated with precipitation.[11]

Within the food security community, NDVI has long been part of monitoring programs (see Hutchinson, 1991). In particular, when FEWSNET was launched in 1985 it included the United States Geological Survey (USGS) USGS and NASA as implementing partners due to the importance of remote sensing to the monitoring task in Sub-Sahara Africa (USGS, 2010). Despite the popularity of NDVI in the EWS community, few attempts have been made to link explicitly NDVI anomalies to commodity price movements and/or market performance. Brown, Pinzon and Prince (2006) appear to be the first to document a negative linear relationship between NDVI anomalies and millet prices in Burkina Faso, Mali and Niger using price data from the 1980s and 1990s. Later work (Brown, Pinzon and Prince, 2008) highlights the importance of rainfall variations, as captured by NDVI, on the evolution of millet prices. However, the study stops short of providing an econometric-based forecasting model and does not explore the time-series properties or spatial dynamics among NDVI and millet prices. We now turn to a discussion of spatial price analysis.

Spatial Price Analysis

Spatial price analysis is concerned with examining how markets perform over time and space. At the heart of the analysis is the law of one price (LOP), which posits that if regional markets are linked by trade and arbitrage, they will have a common, unique price (Fackler and Goodwin, 2001). In developing countries, price analysis is often concerned with investigating two other concepts, market integration

[11] This literature review is not meant to be exhaustive, rather illustrative, as numerous studies on NDVI and crop production exist.

and market efficiency, linked to the LOP. Following Fackler and Goodwin (2001), this study considers market integration as the degree to which a shock in one market is transmitted to another market. For example, if two markets are highly integrated, we would expect that a supply shock in one market would have a strong effect on prices in another market. In mathematical notation, we can think of this as a transmission ratio (TR) denoted:

$$TR_{AB} = \frac{\partial P_B / \partial \varepsilon_A}{\partial P_A / \partial \varepsilon_A} \tag{1}$$

Where P_A and P_B are the prices in each region and ε_A is the supply shock that has occurred. If markets are perfectly integrated, the transmission ratio will be one. The concept of market efficiency is different in that it normally considers the allocation of resources and aggregate welfare. If a market is efficient, then the "allocation of resources is such that aggregate welfare cannot be further improved upon through a reallocation of resources" (Fackler and Goodwin, 2001). In a spatial sense, one can think of this as implying that no further arbitrage opportunities exist for spatial traders.

Researchers have proposed many empirical tools to test market performance. Early studies relied on correlation analysis to determine the degree of co-movement between prices. It was posited that if spatial markets were integrated, then their prices would tend to move together. However, this approach was criticized as many common components (inflation, climate patterns and population growth) can exert similar influence over of prices, even if markets are not linked. At the opposite end of the spectrum, a monopolistic market structure may yield correlation coefficients of 1.0, regardless of the degree of interaction between markets (Harriss, 1979). The technique also cannot distinguish between markets in which delivery lags produce a lag in the price response between markets (Barrett, 1996). In the 1980s, analysts turned to more advanced techniques such as Granger-causality, dynamic regression tests (such as Ravallion's 1986 model), vector autoregressive (VAR) models, co-integration analysis, and switching regression models. An advantage of these approaches is that they better capture the dynamics of agricultural commodity prices. We briefly review some of the commonly used techniques: Granger-causality, cointegration methods, and switching regime models.

One technique that has been used to study Nigerien grain market integration is Granger-causality. If lagged prices from a market (j here) are useful in forecasting prices in another market (i here), even after controlling for own-lagged prices in the market i, then market j is said to Granger-cause price movements in market i. The procedure is usually carried out within the framework of a bivariate regression, a vector autoregressive or error-correction model and confirmed or rejected with an F-test on estimated coefficients. Some analysts have taken the presence of Granger-causality to mean that shocks to prices in one market may induce a significant response in another, with a lag. Others have considered it as an indicator of the flow direction of information between markets. Baulch (1997) adds that if two-way Granger-causality exists, then prices are simultaneously determined. However, Fackler and Goodwin (2001) point out the test only allows inferences about lead/lag relationships and little can be said about the causal framework that underlies the dynamic adjustments.

In her 2010 study on the impact of drought on grain market performance, Aker uses an error correction model and pairwise Granger-causality tests between 42 millet markets in Niger. She finds that markets in millet deficit regions are Granger-caused more often than they Granger-cause and that markets in surplus regions tend to Granger-cause more than they are Granger-caused. This leads her to conclude that price movements in Niger respond to supply shocks and that food security programs should carefully monitor price movement in key Granger-causing markets. Using a VAR framework, Araujo, Bonjean, and Brunelin (2010) conduct a series of Granger-causality tests on millet prices from Burkina Faso, Mali and Niger and assert that the markets of Maradi and Gaya are the main Granger-causing markets in Niger.

Cointegration analysis is another commonly used empirical tool. The concept is built on the idea that prices, on their own, may trend or wander extensively over time and thus may be nonstationary.[12] If a data series is found to be nonstationary and the spatial analyst does not account for this data property, statistical inference may be wrong, as standard regression tests will results in inconsistent standard errors. To overcome these limitations, cointegration tests have been developed over the years (see Fackler and Goodwin for a summary listing, 2001). Cointegration tests consider if two or more nonstationary data have a stable long-run (equilibrium) relationship. For prices, the test is conducted by the estimating the following co-integrating regression:

$$P_{it} = a + \beta P_{jt} + \varepsilon_t \qquad (2)$$

[12] Formally, a data series is considered to be covariance-stationary if its first and second moments are time invariant.

$$\begin{aligned} E(Y_t) = E(Y_{t+1}) &= \mu \quad && \forall\, t \\ Var(Y_t) = \gamma_t &< \infty && \forall\, t \\ Cov(Y_t, Y_{t-k}) &= \gamma_k && \forall\, t, \forall\, k \end{aligned}$$

where the Ps are the prices for market i and j, and ε_t is the error term. The estimated residual is checked for stationarity using the augmented Dickey-Fuller test (Dickey and Fuller, 1979).[13] If the residual is found to be stationary then the markets are said to be cointegrated. Moreover, if two time series are cointegrated, then one of the series must Granger-cause the other according to the Granger representation theorem (Engel and Granger 1987 cited in Baulch, 1997). One of the drawbacks of the technique is that it only answers whether or not two markets are cointegrated, it does not reveal anything about the nature of market interconnection. Moreover, the fact that both Granger-causality and cointegration methods assume a linear relationship between prices is inconsistent with the "discontinuities in trade implied by the spatial arbitrage conditions" (Baulch, 1997). Many other critiques have also been leveled about the conclusions that can be drawn from cointegration analysis (Barrett, 1996; McNew and Fackler, 1997; Rashid and Minot 2010, for example).

In many developing countries trade flows themselves are dynamic as transportation costs fluctuate, exogenous shocks (bridge outages, extreme weather) deter trade, and seasonality influences arbitrage opportunities. For instance, in 2005 in Niger, some observed that millet was being exported to Nigeria, which is a reversal of normal trade flows. To account for these market characteristics, researchers developed varying types of switching regime models (Spiller and Wood, 1988; Baulch 1997; Obsfeld and Taylor, 1997, Barrett and Li, 2002). The basic idea behind these models is that movement between different regimes is based on either observable characteristics or thresholds found within the data. The main criticism of these methods is that results are often sensitive to the underlying distributional

[13] Cointegration can also be tested for in a VAR framework.

assumption (Fackler, 1996). Preliminary analysis of the Niger price data suggests that prices may behave rather differently in growing seasons with below average NDVI than in growing seasons with above average NDVI. Thus, the idea of multiple regimes is investigated in detail in the study.

Spatial price analysis is a framework for testing hypotheses about market integration and efficiency. Using different empirical models, an analyst can uncover important insights into how markets are linked and perform. If prices are found to be non-stationary, cointegration analysis can be investigated to examine long-run relationships. As it pertains to this study, the goal of spatial analysis is to provide guidance on which markets are important for price discovery, how price shocks are transmitted across time and space, and to understand how these details can be incorporated into food security assessment.

Determinants of Market Performance

To examine spatial market equilibrium through a theoretical lens, we consider the Enke-Samuelson-Takayama-Judge (ETSJ) spatial equilibrium model (Enke, 1951, Samuelson 1952, Stigler 1966, and Takayama and Judge 1981) as reviewed by Fackler and Goodwin (2001), Barrett (2005) and presented by Aker (2010b). Applied to millet in Niger, a basic trade model for millet (a homogenous good) can be summarized as:

$$P_{it} - P_{jt} + TC_{ij,t} = 0, \qquad Q_{ij,t} > 0 \quad Trade\ Occurs \tag{3}$$

$$P_{it} - P_{jt} + TC_{ij,t} \leq 0, \qquad Q_{ij,t} = 0 \ \ No\ Trade\ Occurs \tag{4}$$

where P_{it}, P_{jt} are the autarky prices in two spatially distinct markets at time t, i and j, respectively, and $TC_{ij,t}$ are the transactions costs associated with moving millet from market i to market j. Equations three and four represent the no spatial arbitrage conditions, at which point two markets are in long-run competitive equilibrium. Equation three states that if trade occurs freely between the markets, then each additional trader who enters the market will earn zero marginal profits. Equation four reflects the conditions under which marginal profits are less than or equal to zero, and no trade occurs. This basic model can be manipulated to derive basic comparative static predictions for the impact of environmental conditions on market performance. As Aker (2010b) points out, if transportation costs remain constant and a negative production shock induces a supply shock that affects a market pair simultaneously, but increasing the prices in each market at different rates, then equilibrium price dispersion could decrease. However, if a production shock only occurs in a single market, the comparative static predictions are ambiguous. There may be a decrease in price dispersion if the other market is not affected. If an observed shock affects transportation costs, such as an oil shock, we would expect price dispersion to increase in equilibrium. As our NDVI anomalies capture extreme deviations from expected vegetation production conditions, we discuss different possible scenarios that we observe in the data at different times of the marketing year.

A Review of Market Performance and Millet Price Forecasting

In terms of relevant empirical studies that have analyzed market performance, Aker (2010a) considers the impact of mobile phones on millet price dispersion in Niger. She finds that the introduction of mobile phone services reduces millet price dispersion across markets by about 10 percent. In a related paper, also discussed above, Aker (2010b) considers how extreme rainfall affects grain markets during

1996-2006. The study finds that drought reduces grain price dispersion. However, the construction of the rainfall variable only incorporates rainfall data from July through September. This may misrepresent the changing dynamics of the rainy season (particularly if it starts earlier or later than expected such as was the case in May 2003) and only allows the study to consider how price dispersion changes during the rainy season (3 months of the year). What appears to be missing is analysis on if and how anomalous vegetation production condition outcomes, both positive and negative in nature, affect price dispersion throughout the entire growing season.

On a related note, Araujo, Araujo-Bonjean, and Brunelin (2011) reach an opposing conclusion, using a KPSS unit root test, regarding the time series nature of Nigerien millet price data. They find that the data are integrated of order 0, I(0), or do not contain a unit root, which may have an effect on the inference that is drawn from related time-series analysis (i.e. Granger-Causality, cointegration tests). The authors continue and develop a model for identifying crises periods showing that it is possible to identify crises using only observation of past price movements. However, out-of-sample simulations derived from the model are satisfactory. Araujo-Bonjen and Simonet (2011) consider the volatility of millet prices in Niger and ask if they are due to rational or partially collapsing speculative bubbles. Their econometric results are suggestive of the existence of speculative bubbles, but are sensitive to their econometric specifications.

Turning to NDVI and price forecasting models, Brown, Hintermann and Higgins (2009) propose an autoregressive millet price forecasting model that incorporates NDVI to control for local production conditions across Burkina Faso, Mali and Niger. The authors allow for market dynamics by including lagged prices and for market interaction by using lagged prices from surrounding markets. Millet prices are estimated using a fixed-effect, panel model which allows them to make predictions at the market-level after controlling for unobserved, time-invariant heterogeneity. While the model's overall fit is impressive, it is plagued by many problems. It is highly driven by lagged prices, the impact of NDVI is small, and the model does a poor job of forecasting peaks and valleys. Furthermore, the NDVI anomaly used in the study is based on a long-term anomaly rather than a rolling-anomaly. This essentially allows the model to "cheat" by incorporating NDVI data from the future.[14] Finally, the proposed model produces only a single forecast whereas the forecasting literature advocates combining forecasts (Timmerman 2006; Armstrong 2001). The model predictions also are not tested against a simple benchmark auto-regressive model, which should be done to determine the value added by NDVI.

Literature Review Conclusions and Our Contribution to the Literature

Based on the assessment of the literature, we envision our research contributing to the literature linking NDVI anomalies to commodity price movements in many ways. First, at a high level, we anticipate this research contributing to the debate on the 2004-05 food security crises by discussing the economic implications of below average NDVI outcomes associated with the event. To our knowledge, no prior studies have documented how deteriorating vegetation production conditions may

[14] For example, if the model were to generate a prediction for 2005 prices the NDVI anomalies used in the predictions are based on a deviation from a long-term deviation that incorporates future NDVI readings. A more appropriate method may be to construct a rolling NDVI anomaly that only incorporates past and current information.

have affected millet production and household incomes. At lower level, we seek to establish an updated statistical link between rolling, filtered NDVI anomalies and economic outcomes for the most productive areas of Niger through the use of explicit spatial production maps that are used to filter NDVI data in order to isolate productive and non-productive pixels. We also extend traditional spatial analysis beyond a static window of time and analyze the dynamics of price correlations and Granger-causality results. This exercise demonstrates the effects of potential trade discontinuities, shows which markets exhibit stable trade patterns over time, and provides a methodology for rolling analysis for food security assessment.

We also propose a method for understanding the effect of NDVI shocks on market performance by looking at the effects of both positive and negative NDVI shocks and we demonstrate the temporal clustering of shocks. Econometrically, our model tests and accounts for cross-sectional dependence in the standard errors, showing that clustered standard errors may be downwardly biased leading to potentially incorrect inference.

In terms of forecasting models, we demonstrate that explicitly modeling price regimes can lead to improved model fit. We also introduce a two-step method for using NDVI to predict price regimes and degrees of market connectedness. Regarding the price data, we rely on a longer time series (1993-2012) of millet prices than previously analyzed. This enables us to capture better the changing nature of millet markets across Niger. Finally, the research produces an operational, probability forecasting model that can ingest real-time data to make projections on future market performance for early warning systems. We now turn to a discussion of data used in the analysis, starting with a discussion of the millet price database.

Chapter 5: Millet Prices, Millet Production and Consumption, and Price Dynamics

This chapter reviews the millet price data used in the analysis. The first part of the chapter focuses on the methods applied to create the price database used in the study. The second half of the chapter discusses the empirical properties of millet prices in detail, proposes a methodology for classifying historical millet price regimes as determined by price anomalies, and presents a spatial price analysis summary.

Overview of the Millet Price Database

A series of steps were undertaken to create the price database used in the study. Figure 7 below, summarizes the process. All millet prices are from USAID's FEWSNET and the Systéme d'Information sur les Marchés Agricoles Niger (SIMA-Niger). We assembled price data initially from FEWSNET and augmented the database through a site visit conducted in the May and June of 2011 and subsequent internet downloads from the SIMA website. The latest update to the price database was from the April 2012 (Bulletin mensuel cereals) bulletin.[15] To match the historic prices from FEWSNET with the current prices available from SIMA, each market name is assigned a unique identity. Prices are matched to markets using the market name, the unique identifier, and a time variable. After merging all price data together, an outlier check is performed on each market price series. Each market is also assigned a latitude and longitude point using Google Earth and past datasets from SIMA.[16]

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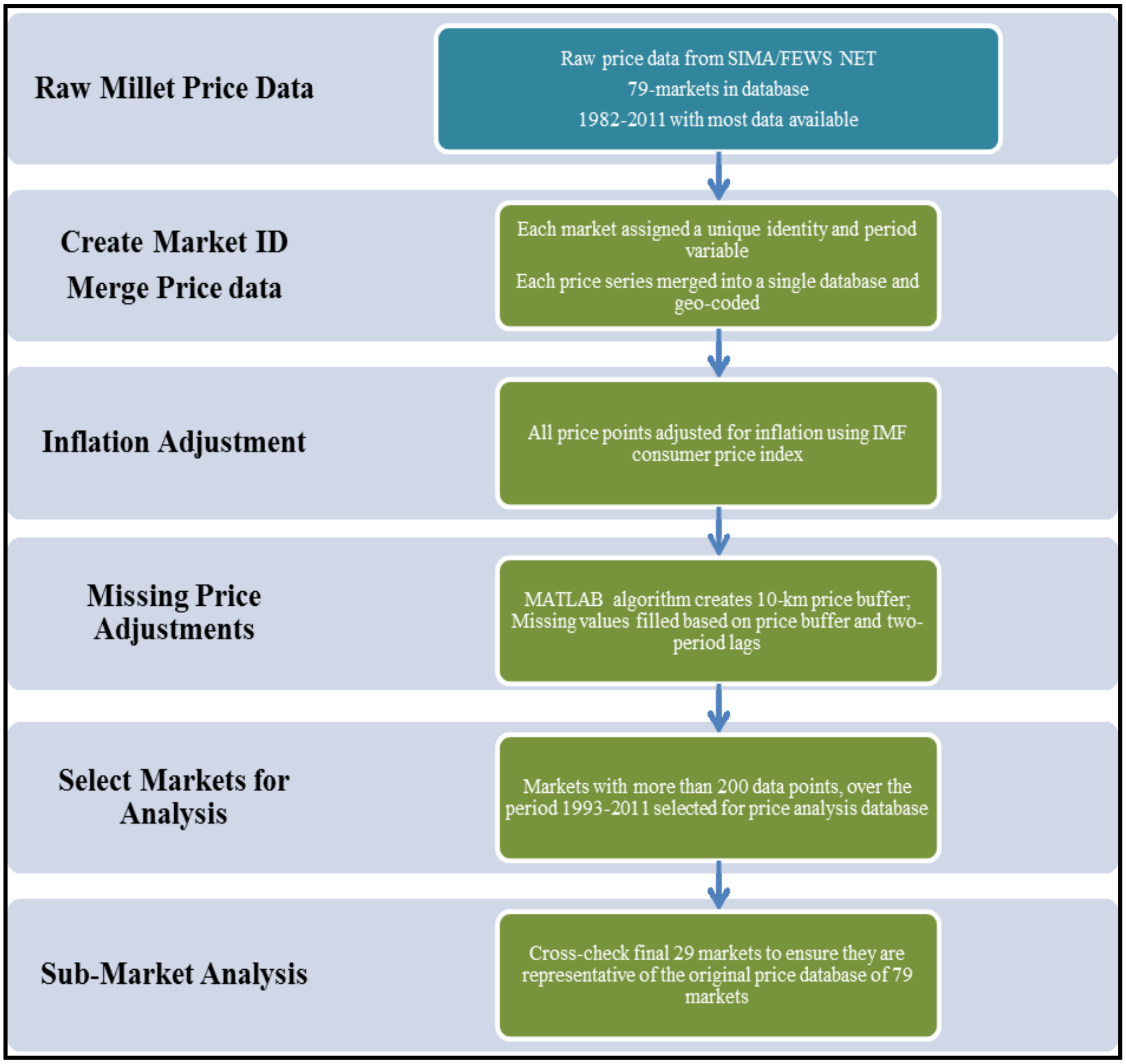
[15] http://www.sima-niger.net/publications-mois.php
[16] Markets with irregular spellings and/or coordinates were verified using http://www.nationsonline.org/oneworld/map/google_map_niger.htm

Figure 7. Millet price database construction process



All raw price data are recorded in nominal West African CFA franc. To adjust for the influence of inflation and other macro-level factors, a number of modifications are made. We use the consumer price index for Niger, available from the International Monetary Fund's International Financial Statistics database, to convert all prices to 2008 terms. Because of the irregularity of price data prior to 1993 and the liberalization of markets near that time, this study focuses on prices from 1993-2012.

In total, price data are available for 79 markets. However, at the market-level many of the price series are irregular, missing for consecutive periods, or take on constant values for many consecutive periods. A series of tasks are undertaken to find reasonable substitutes for the missing price points. First, all price series are exported into MATLAB along with the corresponding market latitude and longitude. We calculate the Euclidean distance between each market and store the results in a matrix, from which we construct concentric price bands at the market level, with a buffer size running from 10 to 100 kilometers. Each price band consists of the average of all price points falling within a buffer surrounding a market. Price buffers are created for each market, over all time periods. The resulting data are exported into Stata and matched to the corresponding market as a new variable. Missing price points at the market-level are replaced with the average price of all markets falling within a 10 kilometer price buffer. That is, period-by-period, the average price of all markets within a 10 kilometer band of the market with missing prices is substituted for the missing price point. This modification affects about 1,200 prices points, or about 7 percent of the universe of price points. A final round of data modifications are carried out using two-period lags and leads to smooth out missing periods across each market.

After completing these steps the data are tabulated and sorted by the number of price points per market. All markets (29 in total) with more than 200 price points are reserved for analysis. All markets with fewer than 200 price points are excluded from the price analysis, but used in portions of the NDVI analysis to ensure adequate geospatial coverage.

One potential issue in using a subset of markets is that the subset may be biased toward a particular geographic region, agro-climatic zone, population or other feature. To investigate this problem, the sub-population of markets are organized across region, agro-climatic zone, and compared to the overall population of markets for which data are available. Table 3, below, summarizes the number of markets in the original price database, as well as each regions share of the overall population of the country.

Table 3. Distribution of all markets in price database by region

Region	Number of markets in original database	Share	Est. 2010 Population	Share
Maradi	17	22%	3,021,169	20%
Zinder	12	15%	2,824,468	19%
Tahoua	13	16%	2,658,099	17%
Tillabéry	12	15%	2,500,454	16%
Dosso	10	13%	2,016,690	13%
Niamey	5	6%	1,222,066	8%
Agadez	5	6%	487,313	3%
Diffa	5	6%	473,563	3%
Total	79	100%	15,203,822	100%

As shown, the population of Niger tends to be relatively well distributed among the regions, with the largest share falling in Maradi and the smallest in the rural regions of Agadez and Diffa. Table 4, below, summarizes similar information focusing only on the 29 markets that are part of the final price database. The table shows that the sub-set of markets is distributed in nearly the same manner as the larger, 79-market database. The Maradi region is somewhat underrepresented and the Tillabéry region somewhat overrepresented in the smaller database, but the differences are not great.

Table 4. Distribution of selected markets in price database by region

Region	Number of markets in analysis database	Share of sub-population
Tillabéry	7	24%
Tahoua	5	17%
Dosso	4	14%
Maradi	4	14%
Zinder	4	14%
Agadez	2	7%
Diffa	2	7%
Niamey	1	3%
Total	29	100%

Source: Author's calculations

We now turn to the distribution of the 29 markets across the agro-ecological zones, and compare that to the 79-market database across the same zones. Table 5, below, summarizes the two datasets. Similar to the regional-level analysis, the distribution of the analysis database at the agro-ecological level appears to mirror closely the original price database.

Table 5. Distribution of markets by agro-ecological zone

	Markets in original database	Share of total	Markets in analysis database	Share of total
Rainfed agriculture zone	31	39%	10	34%
Southern irrigated cash crop zone	17	22%	5	17%
Agro-pastoral zone	12	15%	5	17%
Niger River irrigated rice zone	5	6%	1	3%
Sub-zones of high work out-migration	5	6%	4	14%
Pastoral zone	4	5%	1	3%
Aïr mountains cultivation zone	2	3%	1	3%
Komadougou River & Lake Chad zone	2	3%	1	3%
Desert	1	1%	1	3%
	79	100%	29	37%

Source: Author's calculations

In addition to the panel-based millet price database, we also create a dyadic matched price database for use in our analysis of market performance. This is accomplished by exporting the price series to MATLAB and implementing a matching algorithm. The matching algorithm creates the number of desired permutations, or in this case:

$$\binom{n}{k} = \frac{n!}{k!\,(n-k)!} = \frac{29!}{2!\,(29-2)!} = 406 \qquad (5)$$

where n is the number of markets, and k is the number of elements in each subset (or unique market pairs). We then match prices from each market pair to arrive at a panel dataset populated by market-pair prices, NDVI deviations, distance and other binary indicators reflecting geographical features. A series of coding checks are conducted on a random subset of data to ensure that data have been accurately matched for each of the 406 market pairs/dyads.

Review of Millet Prices & Price Regimes

Through statistical analysis of the millet price data we can learn more about patterns of annual price variation. Table 6, below, summarizes millet prices at the market-level for the growing season and non-growing season months. Reviewing the table we see that millet prices during the growing season are higher than levels observed from September through April. The same is true for the standard deviations presented. Many factors contribute to the observed volatility. Production shocks, particularly those related to droughts and pest infestations, can greatly affect yields and thus millet supplied to the market. Consumer demand, which peaks just before the onset of the rainy seasons when households own food stocks near depletion, tends to put upward pressure on staple food prices (Cornia, Deotti, and Sassi, 2012). Because both supply and demand drivers may be affected by production shocks, there is a tendency for prices to rise more rapidly in years with negative production shocks.

Whereas other internationally traded staple food prices may be regulated by their degree of integration into international trade markets, millet prices in Western Africa are primarily driven by production in Burkina Faso, Mali, Nigeria, and Niger and there is little evidence that international food prices drive domestic millet prices (Cornia, Deotti, and Sassi, 2012). Moreover, the regional trade that does occur is often unobserved and not adequately captured by regional trade statistics (Brown, Hinterman & Higgins, 2009).

Table 6. Summary of millet prices from markets studied

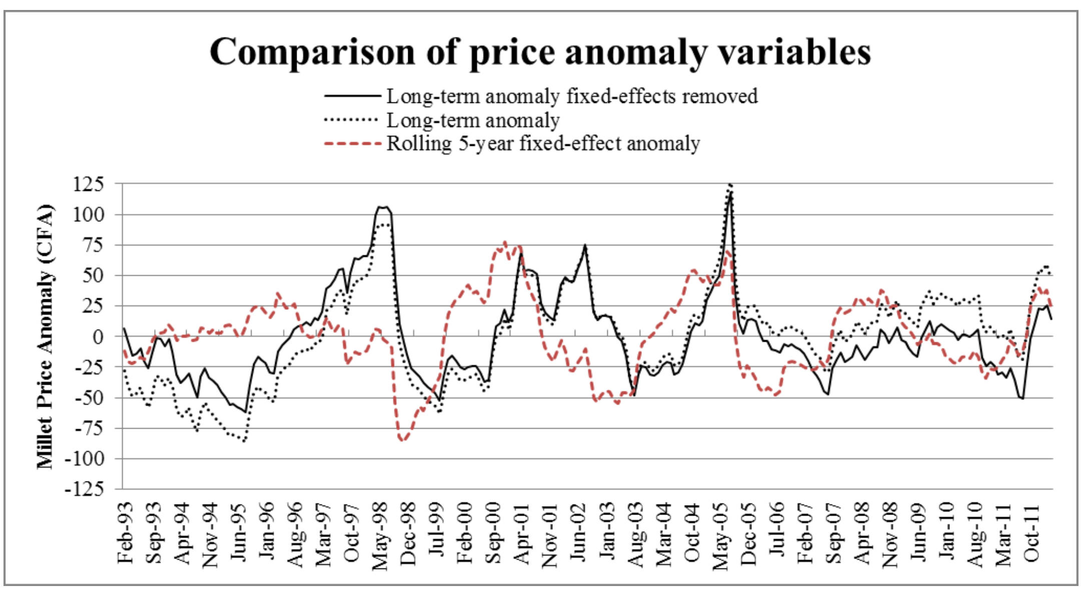
	Overall		**May-Aug**		**Sep-Apr**		
Market	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Obs**
BAKIN-BIRGI	140	44	160	50	131	36	230
KOUNDOUMAWA	145	47	168	53	134	39	226
TCHADOUA	145	43	161	50	137	37	230
TESSAOUA	146	47	166	53	136	41	230
DAN-ISSA	147	48	167	58	138	40	230
DUNGASS	148	51	169	62	137	41	230
MARADI	153	44	170	51	144	37	230
DOGONDOUTCHI	164	43	185	49	153	36	230
BADAGUICHIRI	168	48	191	55	156	39	230
BIRNI KONNI	171	46	191	53	161	38	230
GOURE	171	47	188	56	162	38	230
BOUZA	173	44	193	49	164	38	229
TORODI	177	45	192	51	169	40	230
LOGA	178	46	203	49	166	39	230
GAYA	184	54	207	61	172	46	227
KIRTATCHI	184	48	205	50	174	44	230
TERA	184	47	200	49	176	43	226
FILINGUE	190	50	214	55	179	43	230
AGADEZ	196	47	211	54	189	41	230
DIFFA	197	53	212	60	189	48	230
BALEYARA	198	43	216	48	189	38	230
GOTHEYE	200	55	218	64	191	48	230
COMPLEX/Bonkaney	201	40	214	46	195	35	230
DOSSO	202	48	222	54	191	42	229
ARLIT	205	41	217	45	199	38	230
TAHOUA	209	52	228	61	200	44	227
TCHINTABARADEN	209	51	226	60	201	44	230
OUALLAM	214	51	235	54	203	47	230
N'GUIGMI	216	57	228	63	210	52	230
Total	180	53	198	58	171	48	230

Source: Author's calculations

To investigate the underlying temporal differences in observed price and volatility levels, we create three price anomaly variables to classify marketing-year price regimes. In creating the anomalies we aim to remove the fundamentals of the price signal in order to focus on deviations from what would be considered normal. Our main concern is creating a metric that best captures exceptional deviations (these can also be thought of as bubbles) in millet prices from what fundamentals would predict. We create our first anomaly variable by estimating a fixed-effects model over a rolling five-year window, controlling for monthly effects, temporal effects, and market-specific effects. We then calculate the residuals from the model to obtain one set of price anomalies. Because we use a rolling five-year window for estimation, this metric better accounts for shorter term price fluctuations and may be more appropriate for current food security assessment as it enables a comparison with price deviations from recent periods. To assess how well our short-term price anomaly compares with a longer look back window, we create a second price anomaly which takes the observed millet price in each period and differences them from the long-term monthly mean for each market. This metric enables us to make general comparisons to price deviations from all past periods, regardless of when they occurred. Our final metric blends the two previous approaches to arrive at an intermediate anomaly. To compute the third price anomaly, we first estimate a fixed-effects regression model at the market level on millet prices using monthly binary variables and a monthly trend variable to remove seasonal and temporal effects. We then create our anomaly by calculating the residual for each market.

By construction, each anomaly represents a slightly different perspective regarding the nature of price deviations at a given point in time. For example, the five-year burn-in period of the first anomaly means that it does a poor job of capturing price deviations observed in the early 1990s. This is particularly important for the 1997-98 marketing year which was exceptionally bad in terms of abnormally high price levels. The long-term anomaly variable does not suffer from this problem though, as it is based on a deviation from a longer-term monthly mean. At the same time, the long-term mean can be influenced by extreme values observed in the past that may have no bearing on current price realizations. This may cause the over or under-adjustment of recent anomalies, whereas our rolling-five year anomaly variables will not suffer from this problem as they are continually updated based on the rolling-window. The blend of the two approaches seems reasonable as it mitigates the weaknesses of the each prior approach. Figure 8 compares each of the anomaly variables over time. As shown below, the long-term anomaly does a better job of highlighting extreme deviations from a single historical average. However, the rolling-anomaly appears to be better for comparing prices at any given point in time relative to the past five years, a metric which may be more appropriate for food security analysis and decision making.

Figure 8. Price anomaly comparison over time



Source: Author's calculations

With the anomaly variables created, we then propose a typology for marketing-year price regimes based on departures from market fundaments. Our regime assignments are based on the following rules:

$$Regime = 0\ if\ a_{jit} \leq 25^{th}\ percentile \text{ (Good)} \tag{6}$$

$$Regime = 1\ if\ 25^{th}\ percentile\ < a_{jit} < 75^{th}\ percentile \text{ (Average)} \tag{7}$$

$$Regime = 2\ if\ a_{jit} \geq 75^{th}\ percentile \text{ (Bad)} \tag{8}$$

where a_{jit} is the anomaly from each model (j=1, 2, 3) described above, i indexes the market, t indexes the marketing-season (October-September), and the percentiles refer to the 25th and 75th percentile values of the overall distribution associated with each anomaly. If an average anomaly value for the marketing-seasons is less than the value of the 25th percentile associated with the overall anomaly value for a given market, then that marketing year is categorized as a "Good" marketing year for the respective market. The process is repeated for marketing-year anomaly values falling between the 25th and 75th percentile ("Average" years), and those above the 75th percentile ("Bad" years).

Table 7, below, summarizes the result of this exercise. Our final regime characterization is based on the results from the third anomaly model (fixed-effect long-term 1993-2012). The motivation for categorizing growing years into different regimes is that we want to explore the correlation between NDVI outcomes and market dynamics for each year. By knowing how similar good marketing years are to one another, and how different they are from bad years we hope to glean insight into how we can forecast future outcomes based on observed price levels and NDVI.

Table 7. Millet price anomaly by regime type

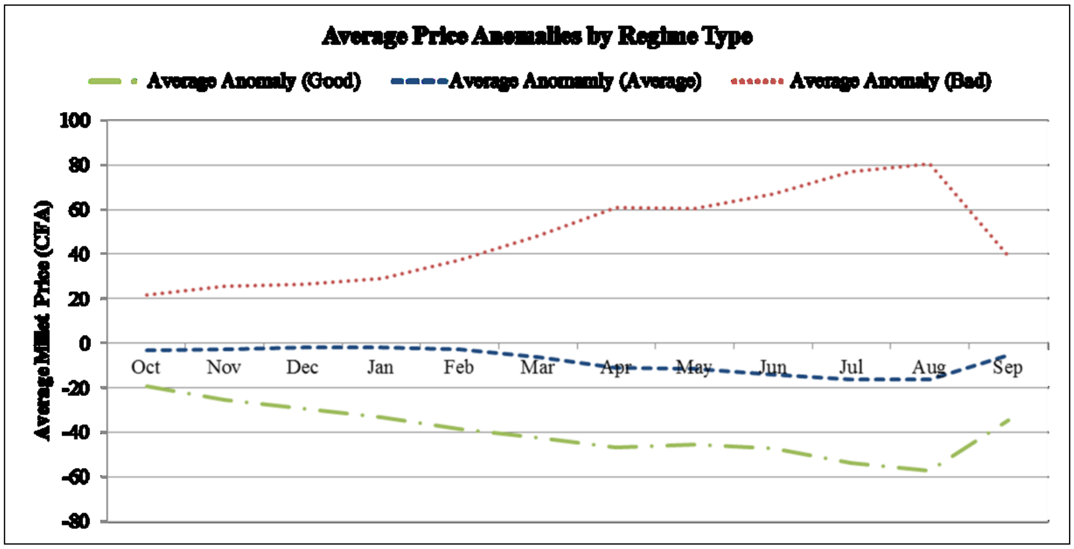
Marketing Year	Cumulative 5-year fixed-effect anomaly	Long-term anomaly (1993-2012)	Fixed-effect long-term (1993-2012)	Regime Type	Good	Average	Bad
1992-93	-15.47	-44.83	-12.05	Average	5	24	0
1993-94	1.88	-53.23	-23.49	Good/Average	11	18	0
1994-95	6.08	-72.75	-46.54	Good	28	1	0
1995-96	23.34	-35.13	-12.45	Average	0	29	0
1996-97	2.76	10.25	29.4	Bad	0	4	25
1997-98	-11.01	63.64	79.26	Bad	0	0	29
1998-99	-56.49	-41.3	-29.5	Good/Average	15	14	0
1999-00	34.47	-32.81	-24.26	Good/Average	13	16	0
2000-01	53.70	31.08	36.05	Bad	0	3	26
2001-02	-17.01	40.11	41.6	Bad	0	2	27
2002-03	-46.06	-1.47	-3.51	Average	0	29	0
2003-04	15.08	-19.46	-25.02	Good/Average	7	22	0
2004-05	47.02	53.06	43.96	Bad	0	2	27
2005-06	-36.31	13.46	0.83	Average	0	26	3
2006-07	-20.07	-7.23	-23.39	Good/Average	14	14	1
2007-08	26.12	6.88	-12.81	Average	2	26	1
2008-09	9.94	21.19	-2.03	Average	0	27	2
2009-10	-14.99	30.25	3.5	Average	0	29	0
2010-11	-17.64	-0.52	-30.8	Good/Average	19	10	0
2011-12	33.06	47.69	15.41	n.a.*	-	-	-

*Data missing for most of 2012. All values reported in 2008 CFA.

Source: Author's calculations

One way to visualize price anomaly differences from the various marketing years is to plot the average value for each regime at each month of the marketing season. As discussed earlier, many predictable events have a bearing on how prices evolve throughout a marketing season. Once we control for these predicable events, as we have done through the creation of anomalies, we can peel back additional details on what characterizes good years from bad years. Figure 9, below, compares the average anomaly values for each price regime. Of interest to us is the fact that during good price regimes, anomalies are well below average and the magnitude of the anomaly increases each month of the marketing seasons, but at a smooth pace. On the other hand, average price anomalies in bad years follow a different pattern and tend to increase continuously throughout the year, with noticeable jumps from one month to the next. For example, by February, average price anomalies from bad regimes are already 40 CFA from their expected value and the figure climbs to 60 CFA by April and May. At the peak of the hungry season, price anomalies reach a high point at 80 CFA above their expected value.

Figure 9. Average millet prices by regime and marketing season

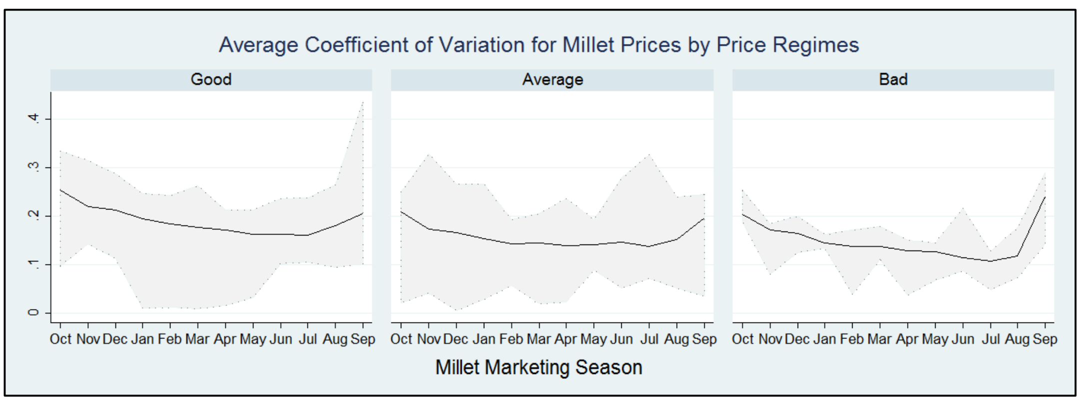


Source: Author's calculations

It is also important to note that the general pattern of price anomalies in bad years is not a mirror reflection of good years. Large deviations may be observed as early as April in bad marketing years, whereas they remain within a narrow band in good years. Because the consequences of these price deviations are magnified during the lean season, it is important to understand how markets function during these times and to determine whether or not NDVI can be exploited to forecast market behavior and price levels.

Another way to analyze general patterns of market performance across the different types of price regimes is to consider the minimum, maximum and average coefficients of variation across the entire market. In an ideal world where markets are well integrated and transactions costs fixed, the standard deviation of prices across regions should reflect transportation costs. Thus, when prices are higher, say due to production shocks, we would expect that spatial arbitrage opportunities will drive the standard deviation of prices to be lower than in normal times (O Grada, 1997). One possible way to infer the nature of market behavior is to consider the coefficient of variation of prices across the entire market. If markets are segmented, we would expect the coefficient of variation to be larger than in the case where markets are well connected. Figure 10, below, presents the average, monthly coefficient of variation for millet prices across the three types of regimes created. The gray bars represent the minimum and maximum for a given month of a given regime.

Figure 10. Coefficient of variation by price regime



Source: Author's calculations

The general story told by the coefficients of variation is that early in marketing seasons the price signal relative to the price noise is larger indicating uncertainty across markets. This is intuitive as there is substantial information flowing to markets during the harvest months due to the unknown quality and quantity of food available to the market. As one would expect, in bad years the relative speed at which this information makes its way into the market appears to be somewhat faster as depicted by the steeper negative slope in the third figure and the narrower upper and lower bounds. The general shape of the coefficient of variation line suggests that market performance improves throughout the year as price signals narrow in terms of their dispersion. However, the abrupt jump from August to September reveals the impending uncertainty of the harvest. At this moment, NDVI may add value by revealing timely and accurate information on the vegetation production conditions of a village, a region, or a neighboring country. Turning to the first figure, on the left, the wide boundaries of dispersion are more indicative of a fragmented market structure. As one might expect, the middle figure is a blend of the two extremes and represents average conditions. In the following section, we investigate the structure of the markets in more detail by looking at pairwise price correlations and Granger-causality tests.

Time Series Properties of Millet Price Data

Failure to account for unit roots in time-series data can seriously distort statistical inference and may lead in improper conclusions being drawn. To test for unit roots in each of the 29 markets selected for analysis we use a procedure outlined by Enders (1995), who suggests estimating the least restrictive model possible first (usually one with a trend and drift term) and then incrementally increasing the restrictions in the model if unit roots are detected. Enders' reasoning is based on the fact that most unit root tests have low power to reject the null hypothesis (near observation equivalence problem), and thus if it is initially rejected, there is little reason to proceed with additional restrictions in the in the model. Formally, we use the augmented Dickey-Fuller (1979) (ADF) test to check for unit roots:

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_1 t + \sum_{p=1}^{3} \beta_p \Delta y_{t-p} + \varepsilon_t \qquad (9)$$

where the Δ indicates a first-differencing of the data, p is the lag order (3 in our specifications), and α is the coefficient on the time trend. The above regression is ran and we test the null hypothesis, that the data contain a unit root, by testing whether or not $\gamma = 0$. The results of the ADF test, presented below in Table 8, suggest that the individual price series for each markets does not contain a unit root. I also test for panel unit roots and find the panel to be stationary.

Table 8. Summary of unit root tests following Enders (1995)

Market ID	Market Name	Test Statistic ($\gamma = 0$)	Critical Value 1%	Critical Value 5%	Critical Value 10%
325001	AGADEZ	-14.181	-4.003	-3.435	-3.135
325003	ARLIT	-14.551	-4.003	-3.435	-3.135
325004	BADAGUICHIRI	-15.447	-4.003	-3.435	-3.135
325005	BAKIN-BIRGI	-14.656	-4.003	-3.435	-3.135
325006	BALEYARA	-14.728	-4.003	-3.435	-3.135
325008	BIRNI KONNI	-14.810	-4.003	-3.435	-3.135
325009	BOUZA	-15.247	-4.003	-3.435	-3.135
325011	DAN-ISSA	-14.232	-4.003	-3.435	-3.135
325012	DIFFA	-14.016	-4.003	-3.435	-3.135
325013	DOGONDOUTCHI	-15.260	-4.003	-3.435	-3.135
325014	DOSSO	-14.721	-4.003	-3.435	-3.135
325015	DUNGASS	-15.424	-4.003	-3.435	-3.135
325018	FILINGUE	-15.551	-4.003	-3.435	-3.135
325019	GAYA	-14.777	-4.003	-3.435	-3.135
325020	GOTHEYE	-15.473	-4.003	-3.435	-3.135
325022	GOURE	-14.591	-4.003	-3.435	-3.135
325027	KIRTATCHI	-15.157	-4.003	-3.435	-3.135
325030	KOUNDOUMAWA	-15.007	-4.003	-3.435	-3.135
325031	LOGA	-15.633	-4.003	-3.435	-3.135
325034	MARADI	-14.607	-4.003	-3.435	-3.135
325036	N'GUIGMI	-14.451	-4.003	-3.435	-3.135
325043	OUALLAM	-15.355	-4.003	-3.435	-3.135
325049	TAHOUA	-15.037	-4.003	-3.435	-3.135
325051	TCHINTABARADEN	-14.647	-4.003	-3.435	-3.135
325053	TERA	-14.691	-4.003	-3.435	-3.135
325054	TESSAOUA	-15.094	-4.003	-3.435	-3.135
325129	TCHADOUA	-14.725	-4.003	-3.435	-3.135
325132	TORODI	-14.356	-4.003	-3.435	-3.135
325134	COMPLEX/Bonkaney	-14.414	-4.003	-3.435	-3.135

Source: Author's calculations

Price Correlation Analysis

With the time-series properties of our dataset diagnosed, we return our attention to the spatial relationships in our data. As a starting point for our analysis we consider the degree of millet price correlation across markets. In its simplest form, price correlation can provide insight into how well millet prices move in tandem or how well markets appear to be integrated. Table 9, below, summarizes the analysis.

Table 9. Summary of rolling price correlations

Marketing Year	3-month rolling correlation		1-year rolling correlation		10-year	
	Diff. Dept.	Same Dept.	Diff. Dept.	Same Dept.	Diff. Dept.	Same Dept.
1993-94	0.321	0.357	0.461	0.516		
1994-95	0.247	0.266	0.573	0.588		
1995-96	0.433	0.483	0.566	0.607		
1996-97	0.489	0.549	0.679	0.747		
1997-98	0.492	0.558	0.743	0.781		
1998-99	0.222	0.301	0.792	0.831		
1999-00	0.156	0.225	0.368	0.518		
2000-01	0.517	0.581	0.716	0.760		
2001-02	0.442	0.463	0.764	0.777		
2002-03	0.437	0.476	0.735	0.787	0.886	0.917
2003-04	0.418	0.502	0.759	0.827	0.880	0.916
2004-05	0.643	0.694	0.752	0.771	0.865	0.906
2005-06	0.371	0.444	0.796	0.844	0.853	0.902
2006-07	0.275	0.345	0.578	0.682	0.851	0.904
2007-08	0.381	0.445	0.611	0.635	0.847	0.897
2008-09	0.421	0.506	0.547	0.696	0.822	0.875
2009-10	0.376	0.461	0.572	0.708	0.790	0.854
2010-11	0.265	0.321	0.674	0.734	0.769	0.820
2011-12	0.529	0.533	0.507	0.495	0.764	0.819
Total	0.385	0.424	0.648	0.695	0.833	0.880
Overall Correlation	0.390		0.654		0.838	

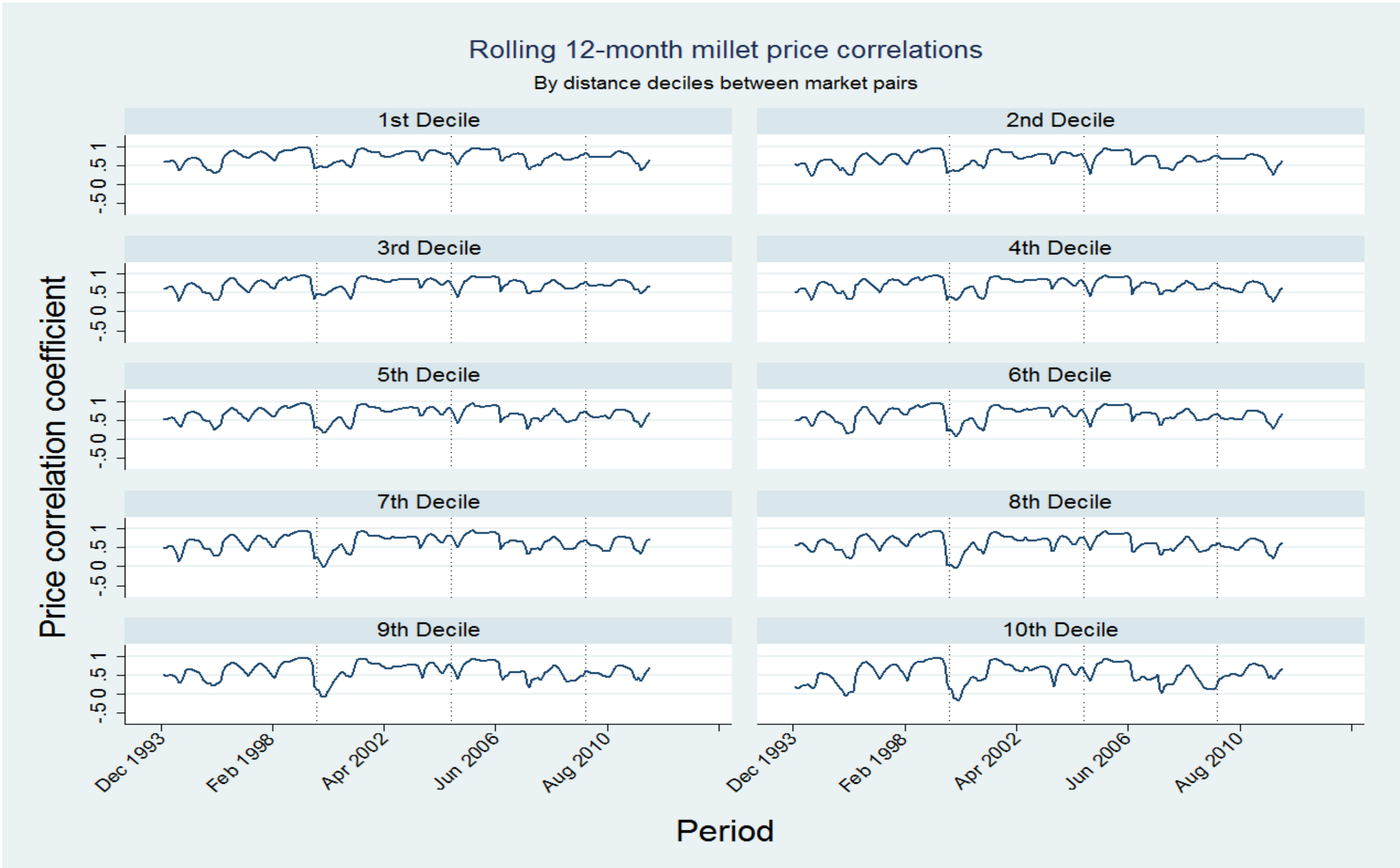
Source: Author's calculations

Our hypothesis underlying the analysis is that prices in well-integrated markets should display reasonably large, positive correlation coefficients whereas in a segmented market structure, we would expect lower or even negative correlation coefficients unless millet was so abundant that prices hit a floor across the region and trading completely stopped. In the latter scenario, we would expect correlations to be positive due to prices all approaching the floor. Relying on correlation analysis on its own to draw conclusions concerning market performance can pose problems (as discussed above). However, when used in conjunction with other spatial price analysis tools, price correlations can help triangulate conclusions that can be drawn about general market integration over time and space.

We use a series of correlation metrics in order to analyze market integration in the short-term (3-month), medium-term (12-month) and long-term (10-year). A few interesting patterns emerge from the table. First, working bottom to top we see that the overall correlations are 0.39 for the short-term, 0.65 for the medium-term, and about 0.84 for the long-term. The medium-term figures are consistent with the price correlations calculated by Aker (2010b). However, the short-term correlations suggest that price transmission is far from instantaneous, which may be due to lack of information flows, late shipments, general uncertainty or other trade frictions common in developing countries.

Focusing on the 2004-05 marketing season, the 3-month rolling price correlations are the highest of all years analyzed. This may well be suggestive of a market structure in which price signals were transmitted faster than average due to shortages in the market or simply bad news traveling at a faster rate than normal or good news. If we contrast this outcome with the 3-month rolling price correlations for the 1999-2000 marketing season, we observe correlations of 0.16, or levels indicative of fragmented markets. To further investigate these extreme outcomes, we account for the distance between each market pair and plot the evolution of price correlations. Figure 11 presents the resulting figure. If the price transmission relationships are stable over space and time, we would expect a horizontal line for the distance deciles. This is clearly not the case.

Figure 11. Summary of rolling 12-month millet price correlations by distance deciles

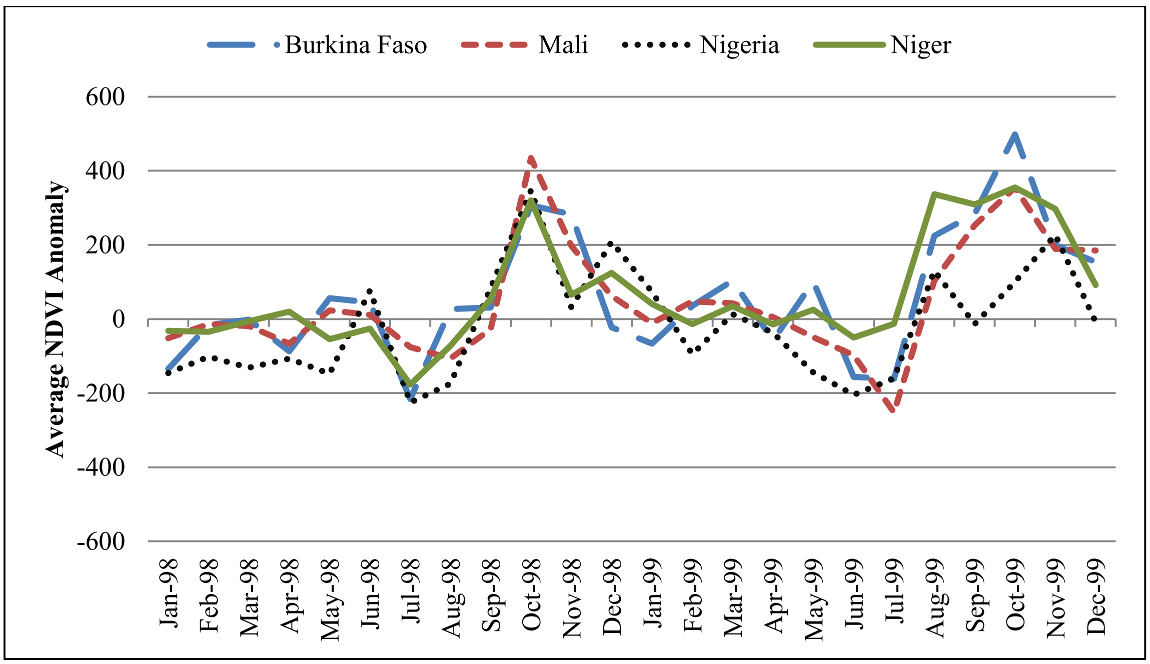


Dotted lines indicate harvest periods (Oct. 1999, Oct 2005, Oct 2009). Source: Author's calculations

The graphical depiction of the rolling price correlations demonstrate that levels of market integration, at least as measured by correlations alone, is far from static and appears to ebb and flow in terms of the speed at which price signals adjust across time and space.

One noticeable trough is observed around the harvest of 1999, suggesting segmentation among markets over the prior 12 months (the 1998/99 marketing year). To investigate how NDVI outcomes correlate with this fracturing in market ties, we plot the average NDVI anomalies from January 1998 through December of 1999 for Niger and its neighboring countries, shown below in Figure 12.

Figure 12. Summary of NDVI outcomes across regions 1998-1999



Source: Authors calculations

Initially, what stands out in the graphic are the above average NDVI outcomes in October of 1998, and then again in August, September and October of the following year. Not only did Niger NDVI spike, but all of the neighboring countries also appear to have above average NDVI outcomes for both 1998 and 1999. We interpret these above average vegetation production conditions as being suggestive of an exceptional growing season and plentiful millet harvest across the entire Sahelian region. What this could suggest is that spatial arbitrage opportunities were likely far and few for millet products during the second half of the 1998/1999 marketing season. Moreover, the back-to-back positive NDVI outcomes for the entire region likely reduced the incentives for millet trade, resulting in many fragmented markets where prices followed local paths rather than a primary signal emerging from the overall market. This outcome is particularly interesting because it demonstrates the additional inference that one can start to make by cross-referencing NDVI outcomes with indicators of market integration. In order to peel back another layer on what may be driving price transmission signals, we turn our attention to an analysis of Granger-Causality testing in the next section.

Granger-Causality Tests

While Granger-causality cannot reveal the exact casual mechanism of how price transmission signals spread across all markets simultaneously, it can help tell us whether or not a particular market leads or lags in price discovery. We test each market pair for Granger-causality using a series of bivariate regressions. Because we have 29 markets, a vector autoregressive model (VAR) is not feasible due degrees of freedom constraints and the unknown structure of all potential restrictions needed to model correctly all market interactions.[17] For the analysis we estimate the following model in levels:

[17] A single lag VAR for our 29 markets would require the estimation and interpretation of over 840 parameters. Future research may consider panel-based Granger-causality tests.

$$P_{it} = c_1 + \sum_{i=1}^{k} \alpha_i P_{i,t-i} + \sum_{i=1}^{k} \beta_i P_{j,t-i} + u_t \qquad (12) \qquad (10)$$

where P_{it} and P_{jt} are the prices in markets i and j at time t, and k is the lag order. To assess the dynamics of Granger-causality relationships, we conduct both static and rolling tests, setting the lag lengths at 3 months to make comparisons simple.[18] To test for Granger-causality we conduct an F-test on the following null hypothesis using the coefficients from above:

$$H_o = \beta_1 = \beta_2 = \dots \beta_k = 0 \qquad (13) \qquad (11)$$

We do this by estimating the following restricted model on market *i* prices only.

$$P_{it} = c_1 + \sum_{i=1}^{k} \theta_i P_{i,t-i} + e_t \qquad (14) \qquad (12)$$

Then we calculate the sum of squared residuals from the restricted ($RSS_0 = \sum_{t=1}^{T} \hat{e}_t$) and non-restricted model ($RSS_1 = \sum_{t=1}^{T} \hat{u}_t$) for use in a joint F-test, depicted below where q is the number of parameters in the model and T is the number of time periods:

$$s_1 = \frac{(RSS_0 - RSS_1)/q}{RSS_1/(T - 2q - 1)} \sim F_{p,T-2q-1} \qquad (13)$$

If the calculated test statistic is greater than the specified critical values (normally 1% for this analysis) we can reject the null hypothesis and can conclude that market *j* Granger-causes market *i*. To test if market *i* Granger-causes market *j*, the process is repeated with data from market *j* placed on the left-hand side of the regression and the α coefficients are checked for joint significance.

[18] Further analysis could be conducted on the lag length to determine how robust results are to varying parameters in the estimating equation.

Our review of millet prices revealed substantial variation in terms of the price level, as well as variance throughout the year. Moreover, the rapid price rise in the summer of 2005 could have been associated with a structural change in the underlying dynamics of millet markets and trading patterns. In order to investigate how periods of volatility affect market-pair price dynamics, we conduct a series of rolling Granger-Causality tests. For the rolling tests we select a window of millet price data (120 periods or 10 years) for each market pair and we test for Granger-Causality. We then iterate forward 1 month, and repeat the same test using a 120 period window. We repeat the process for each market-pair until our 120 period window reaches the end of our data (occurring in March 2012). In total, we estimate over 100 rolling windows for each market pair, across all market-pairs.[19] The purpose of the exercise is to determine the stability of the results overtime and gain a sense of how network ties may change across space and time.

Granger-Causality Results

A summary table of the results for the static test is presented below in Figure 13. Green squares represent dyads with significant test statistics and white ones reflect insignificant test statistics, indicating that the null hypothesis could not be rejected at 1% level.

[19] We do not explicitly make an alpha adjustment for critical values given the multiple outcomes (i.e. Bonferroni correction), but we do require statistical significance to be at 1% for the relationship to be considered statistically valid.

Figure 13. Granger-causality results for all market pairs (static)

Granger Causality: Static Results (3-lag specification)

1 = statistically signficant relationship

	DIFFA	GOTHEYE	N'GUIGMI	AGADEZ	ARLIT	TORODI	BAKIN-BIRGI	LOGA	GOURE	KIRTATCHI	OUALLAM	TERA	DOSSO	COMPLEX/Bonkaney	BALEYARA	FILINGUE	TAHOUA	KOUNDOUMAWA	TCHINTABARADEN	DUNGASS	DOGONDOUTCHI	BIRNI KONNI	BADAGUICHIRI	DAN-ISSA	BOUZA	GAYA	TESSAOUA	TCHADOUA	MARADI
GOTHEYE	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OUALLAM	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N'GUIGMI	1	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
TORODI	1	1	1	1	1	0	0	1	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AGADEZ	1	1	1	0	1	1	1	1	0	1	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1
BAKIN-BIRGI	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
COMPLEX/Bonkaney	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0
GOURE	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
DOGONDOUTCHI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
FILINGUE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0
KIRTATCHI	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	0	0	1	1	1	0	1	1	0	0	0	0
DIFFA	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	0
DAN-ISSA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0
TERA	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	0
ARLIT	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	0
BIRNIKONNI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	0	0
BOUZA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0
DOSSO	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0
DUNGASS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	0	0
TCHINTABARADEN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	0	0
LOGA	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1
BALEYARA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0
BADAGUICHIRI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1
GAYA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0
TAHOUA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0
KOUNDOUMAWA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
MARADI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
TESSAOUA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
TCHADOUA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1

<--- Market Granger Causes--->

<--- Market is Granger Caused--->

Source: Author’s calculations

The layout in the figure above reads left-to-right for Granger-causing results (for example, prices from Gotheye are not useful in forecasting price movements in any other markets), and top-to-bottom for Granger-caused results (prices from Gotheye tend to lag behind prices from all other markets). The static Granger-caused results clearly show that millet prices in certain markets lag behind others, and that a few markets appear to be reference points of price discovery. For example, Agadez, Gotheye, N’Guigimi and Ouallam tend to be Granger-caused, or millet prices lag behind, whereas markets such as Maradi, Tessaoua, and Tchadoua tend to not be Granger-caused (reflected by the large number of white space vertically below the market), indicating that millet prices in the respective market pairs tend not to lead prices from these reference markets. Turning to the Granger-causing results, we see that Agadez, Gotheye, and Ouallam Granger-cause few markets whereas Maradi, Tahoua, Tessaoua, and Tchadoua tend to Granger-cause many.

Generally, the results suggest that markets not connected to main roads or semi-isolated are weakly integrated, or integrated with a substantial lag, whereas the Granger-causing markets are the main points of price discovery, and likely emergence points for price shocks. Most of the dominant Granger-causing markets lie in production zones which is consistent with Aker's (2010b) conclusion. When we cross reference the major Granger-causing markets with Table 10, which reports the number of productive, SPAM-filtered NDVI pixels surrounding each market, we see that many of the Granger-causing markets are in geographic areas with large potential for millet production, whereas most of the Granger-caused markets tend to be in rather isolated agro-ecological and infrastructural zones, with low potential for millet production. Gotheye (and somewhat Tera) appears to be an anomaly here as it is surrounded by productive lands, yet price signals from this location have little use in helping forecast prices from other markets. That aside, the results generally support the notion that price shocks are likely to be driven by production/supply shocks emerging in the main production zones rather than demand shocks from urban or rural areas. Moreover, the results also suggest the need to closely monitor peripheral markets because information and supplies may only flow to these places with a substantial delay.

Table 10. Summary of markets and NDVI pixels falling in selected buffers

Market	NDVI 20 km	NDVI 50 km	NDVI 100km	Livelihood Zone
TERA	25	106	448	Rainfed agriculture zone
BIRNI KONNI	21	101	454	Southern irrigated cash crop zone
DUNGASS	19	123	479	Southern irrigated cash crop zone
TESSAOUA	19	118	487	Rainfed agriculture zone
DIFFA	18	122	438	Komadougou River & Lake Chad cash crop zone
MARADI	18	117	484	Southern irrigated cash crop zone
BAKIN-BIRGI	18	116	446	Agro-pastoral zone
BALEYARA	18	116	446	Sub-zones of high work out-migration
TCHINTABARADEN	18	86	248	Pastoral zone
TCHADOUA	17	122	488	Rainfed agriculture zone
GAYA	17	116	446	Southern irrigated cash crop zone
KOUNDOUMAWA	17	115	490	Rainfed agriculture zone
DOGONDOUTCHI	17	115	471	Rainfed agriculture zone
GOTHEYE	17	107	379	Niger River irrigated rice zone
GOURE	16	117	446	Agro-pastoral zone
DAN-ISSA	16	113	483	Southern irrigated cash crop zone
LOGA	16	108	449	Sub-zones of high work out-migration
BADAGUICHIRI	16	95	411	Sub-zones of high work out-migration
BOUZA	15	102	442	Rainfed agriculture zone
FILINGUE	14	107	386	Agro-pastoral zone
TAHOUA	14	102	390	Agro-pastoral zone
DOSSO	14	86	404	Rainfed agriculture zone
COMPLEX/Bonkaney	13	89	382	Rainfed agriculture zone
OUALLAM	9	86	326	Sub-zones of high work out-migration
TORODI	9	64	377	Rainfed agriculture zone
KIRTATCHI	6	72	358	Rainfed agriculture zone
ARLIT	6	10	16	Desert
AGADEZ	3	19	29	Aïr mountains cultivation zone
N'GUIGMI	1	25	131	Agro-pastoral zone

Source: Author’s calculations

This initial analysis is based on a snapshot of the data over a fixed period of time. Varying the lag structure or the included covariates in the model could well affect the stability results. To get a sense of the temporal robustness of these initial findings, we construct a monthly, rolling 10-year window and calculate the Granger-causality test statistics for 110 points in time, for each market-pair. Figure 14 summarize the results and can be thought of as a dynamic assessment of the stability of the lead/lag structure discussed above.

Figure 14. Summary Granger-Causality results (rolling regression, 3-month lag)

Granger Causality: Rolling Results for 110 Periods (3-lag specification)

Number of periods in which statistically significant relationship is detected between dyads

<--- Market is Granger Caused---> / <--- Market Granger Causes--->	AGADEZ	N'GUIGMI	TORODI	GOTHEYE	ARLIT	DIFFA	TERA	LOGA	GOURE	BAKIN-BIRGI	COMPLEX/Bonkaney	DOSSO	KOUNDOUMAWA	TCHINTABARADEN	TAHOUA	BALEYARA	OUALLAM	BOUZA	DUNGASS	BIRNI KONNI	BADAGUICHIRI	KIRTATCHI	GAYA	DAN-ISSA	FILINGUE	DOGONDOUTCHI	MARADI	TESSAOUA	TCHADOUA
GOTHEYE		2															1					1			60	1			1
OUALLAM	27	34	7	2	26	27			5	14												1			1	1			
KIRTATCHI	13	10	11	11	10	10		11	10	4				1	1	1	10	1							102				1
DOGONDOUTCHI	29	13	15	15	14	14	14		14	10			1			13	14			11		109			2		2	1	1
FILINGUE	11	38	9	9	26	8	8	103	8	9			8	4			9					107							27
AGADEZ		68	86	66		53			5	14			28				7	22				2			3	1	33		1
N'GUIGMI	80		78	81	43	64	69										1		6			1			1	1			1
TORODI	78	110		42	18	48	24	41	73							41	2					1	4		2	1			1
ARLIT	69	110	51	38		7	1	23		8			4		56	3	36	26			24	3			7	1		31	1
DIFFA	110	110	70	84	110		85	55		17	29		39	9	65	7	36	1	2	2	2	12			1	1			1
BAKIN-BIRGI	110	102	99	110	110	110	74	31	31		31	31		9	31		36					2			1	2			7
COMPLEX/Bonkaney	110	110	110	110	110	107	54	99	11	40		49	1		31		36					12		1	2	2			1
TCHINTABARADEN	110	108	110	110	110	103	35	76	57	16	104	65			31	36	36			10		12			2	2			1
LOGA	110	8	69	54	96	108	6		110	44	5	65	41	27	67	2	36	32	4	68		12	49		3	8	69	37	6
GOURE	110	109	110	110	110	108	110	92		100	96	11	94	40	31	1	36					12			1	1			1
TERA	109	110	110	110	78	79		66	64	64	49	43	11	57	79		36	2		50	45	12	40	42	10	7	6		5
DUNGASS	110	110	110	110	110	105	110	31	43	95	63	29	110	49	30	66	36	8		14	31	12		4	1	2		2	1
DOSSO	110	110	110	109	110	110	110	99	79	81	104		64	50	69		36	11		38	20	6			1	2			1
GAYA	110	109	110	110	110	110	110	86	110	89	84	108	95	45	30	22	36	15	72			12		11	2	16		7	1
BOUZA	110	110	110	76	110	110	110	99	109	110	76	109	99	109	31	92	36			4		12	4		10	8			1
KOUNDOUMAWA	110	110	110	110	110	110	110	108	110	98	110	110		67	79	110	36	18		54	12	12			10	16			1
BIRNIKONNI	110	110	110	110	110	110	110	105	110	110	110	101	110	110	31	24	36	46	62		22	12			1	15			1
DAN-ISSA	110	110	110	110	110	110	110	110	110	110	110	83	110	110	40	19	36	19	110	3		12			8	16		3	1
TAHOUA	110	106	110	110	110	110	110	83	110	110	110	110	110	110		69	36	56		1	45	12	27	22	5	16		7	2
BADAGUICHIRI	110	109	110	110	110	110	110	103	110	110	110	108	106	110	31	109	36		61	25		12		1	9	16	11		10
BALEYARA	110	110	110	110	110	110	110	110	110	110	110	110	90	110	110		36	97	36	81	81	14	78		10	16			1
TCHADOUA	105	105	105	105	105	105	105	101	105	105	105	105	105	105	105	105	36	104	96	73	105	12	36	84	10	16	3	7	
MARADI	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	36	109	103	84	110	12	42	12	10	16		8	1
TESSAOUA	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	110	36	110	104	110	110	12	100	108	10	16	43		12

<--- Market Granger Causes--->

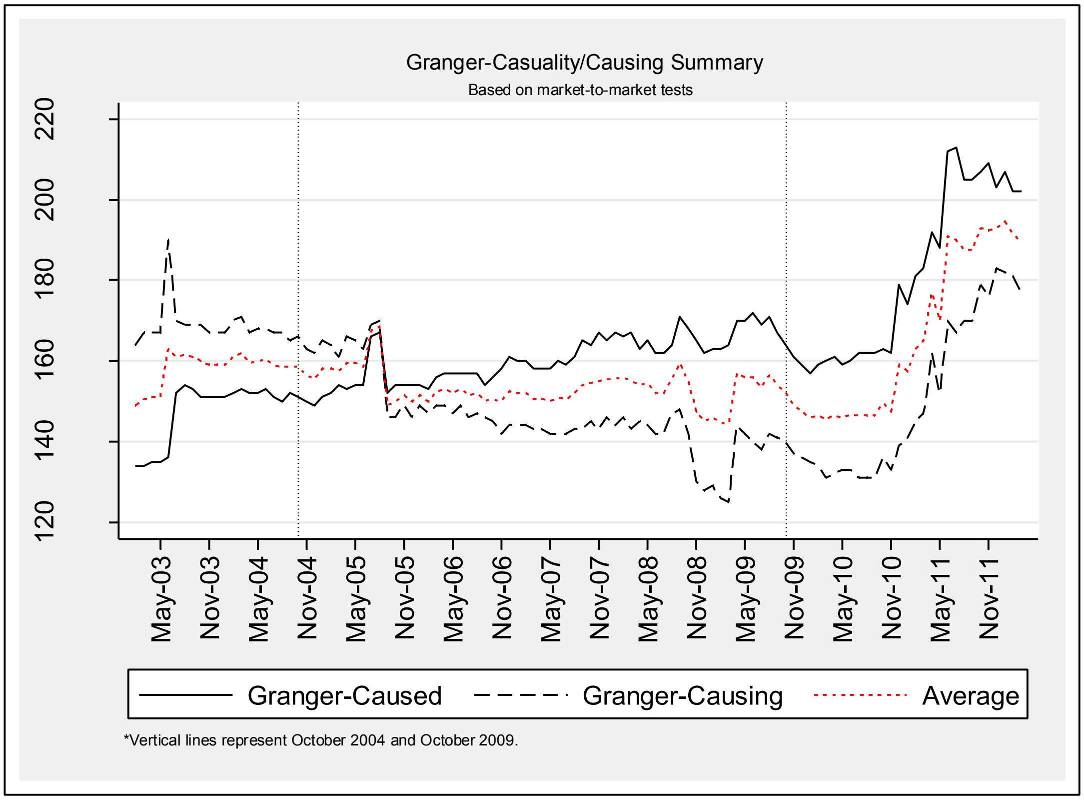
<--- Market is Granger Caused--->

Source: Author’s calculations

The figure in each grid represents the total number of times that a market Granger-causes/is caused, based on a statistical cutoff of 1 % (p-value of 0.01). If the matrix were to be completely green or white, we interpret this as being indicative of a stable, long-run relationship in Granger-causality dynamics. However, the shades of green suggest dynamic linkages between market pairs, at least in a statistical sense. The periphery markets discussed above, Agadez and N’Guigimi, appear to have somewhat stable long-term relationships with their respective Granger-causing markets. However, Ouallam (and to some extent Tahoua and Tchadoua) appears to have a less stable relationship which suggests that, at least in the statistical sense, the market is not as isolated as one may conclude from static analysis. Gotheye has a similar outcome, where the figure shows that during certain periods it actually Granger-causes Filingue for 60 periods. This may be due to its location in a semi-productive zone, proximity to flow points of Tera and Nimary, or changing trade dynamics. The varied colors suggest that the trade networks, at least as measured by price leads and lags, within Niger are dynamic. This should come as no surprise as our price regime and correlation analysis portrayed a picture of a market structure that exhibits great ebbs and flows in market integration and segmentation. One of the major takeaways from this analysis is that models that fail to account for these dynamics of market structure may to misestimate prices and/or the influence of local and national prices on a single market, because these evolve over time and do not exhibit a stable, uniform pattern.

While the figures above are informative for making comparisons between market-pairs, another way to look at the dynamics is to consider the total number of markets that Granger-cause and the number of markets that are Granger-caused at each point in time. Figure 15, below, summarizes the results of this exercise for all market pairs under consideration. In an ideal situation where markets are perfectly integrated (prices are simultaneously determined), we would expect the number of Granger-causing markets roughly to be equal to the number of Granger-caused markets.

Figure 15. Rolling Granger-Causality results by period (3-month lag)



Source: Author's calculations

The figure above suggests that this is not the case. In fact, of the 406 potential pairs that may exhibit Granger-causality relationships, the actual number falls between about 130 and 220 across the entire period of analysis. Between May 2005 and November 2005 the total number of market-pair relationships that were classified as being Granger-caused, based on the statistical properties of the millet prices, was below the number of market-pair relationships that were classified as Granger-causing. Post 2005 harvest, the upward trend in Granger-caused relationships increases slightly until August 2010 (period 350), where after that the number of market pairs with statistically significant Granger-caused results grows rapidly. The graph suggests that market integration is improving as the number of Granger-causing and Granger-caused markets are growing at similar paces post-May 2010. What is not clear from the graphic is if this growth is caused by a few markets emanating leading price signals to the rest of the market, or if improved communications and trade networks are causing gradual improvements among all markets. Given the dramatic expansion in cell phone use over the last 10 years, is plausible that increased information flows and commercialization have improved spatial and inter-temporal arbitrage opportunities in cereal markets.

Summary of Price Differences

To close out our descriptive analysis of market performance, we consider summary statistics from our price dispersion database, which calculates the spatial price spread (absolute value of the price difference) between all dyads. O Grada (2007) points out that the Law of One Price, under constant transportation costs, implies that food price volatility across markets should decline during famines. While we cannot ensure that transportation costs are constant across our period of analysis, we can look at simple patterns in price dispersion to see if such an argument is supported. On average, if price spreads between markets are large, we interpret this as a sign of a fragmented market structure and if dispersion is low, we interpret this as evidence that markets are well-functioning.[20] Table 11 summarizes average price dispersion by marketing year.

[20] Of course a full analysis of price dispersion would control for buyer and seller characteristics as well as product heterogeneity, information costs, and other factors that may affect dispersion. We do not have data on any of these factors, thus they are omitted from analysis and discussion.

Table 11. Average millet price differences between markets (absolute value)

	All market pairs		Market pairs in same region	
Marketing Year	Mean	Std. Dev.	Mean	Std. Dev.
1992-93	32.48	24.07	22.89	18.74
1993-94	33.37	23.59	21.23	16.28
1994-95	27.97	20.05	18.62	14.38
1995-96	29.97	22.28	22.12	19.43
1996-97	34.16	24.97	28.90	21.90
1997-98	40.07	30.83	28.26	22.31
1998-99	31.46	22.31	21.84	16.47
1999-00	27.49	21.45	22.40	20.35
2000-01	36.15	27.05	29.70	23.85
2001-02	36.16	28.30	31.28	24.40
2002-03	36.07	25.95	24.32	19.74
2003-04	28.41	20.69	22.17	16.59
2004-05	40.82	31.34	34.49	25.67
2005-06	36.80	27.86	21.89	18.18
2006-07	34.93	27.85	23.13	19.59
2007-08	38.01	30.29	26.96	21.64
2008-09	39.94	29.29	29.72	22.38
2009-10	31.87	24.87	24.79	19.11
2010-11	35.79	25.75	28.29	20.87
2011-12	32.42	22.94	22.40	15.88
Total	34.29	26.21	25.38	20.63

Source: Author's calculations

When interpreting these initial results it is important to remember that they do not control for other fixed-factors which may affect the magnitude of dispersion (product heterogeneity, monopoly pricing, variable transportation costs, buyer and seller characteristics, see Hopkins 2008 for a full discussion). However, an initial glimpse into average dispersion may provide some initial insights into how market performance changes over time in Niger. Price dispersion appears to be a little higher than average following periods of below average NDVI outcomes (1997-98, 2004-05, and 2008-09), whereas years with above average NDVI outcomes (1993-94, 1998-99, and 2002-03) is about normal. However, when we compare the price spreads from market dyads in the same region to all market pairs we see that markets presumably closer to one another have lower price spreads. These preliminary remarks should be taken with caution as they are based on unconditional statistical averages of annual, dyadic-based price differences. In our empirical approach we control for time invariant heterogeneities that may influence this metric and consider how NDVI shocks affect changes in price spreads across environmentally stressed and unstressed markets.

Chapter 6: NDVI & Millet Production Data

This chapter reviews the remote sensing concepts underlying the vegetation index used in this study (NDVI) and the various procedures used for processing the data. The second half of the chapter includes a preliminary analysis of the NDVI data and highlights the changing nature of phenological events associated with the millet growing seasons in Niger.

Overview of Remote Sensing and Vegetation Indices

In large underdeveloped regions, remote sensing can be a cost-effective and especially useful means for deriving consistent and objective information regarding changes in vegetative cover and environmental conditions. Remotely sensed data, by definition, are data that are observed and measured from a distance, often using aerial platforms such as satellites or aircraft. Generally, remote sensing involves using sensors to detect how much energy is absorbed, reflected or transmitted by a surface, captured by electromagnetic radiation, from many parts of the electromagnetic spectrum including visible light, infrared and ultraviolet light. Because patterns of reflectance and absorption over different wavelengths varies across Earth surface materials, one can use spectral signatures to distinguish among soil, water, vegetation and other land covers. Vegetation, in particular, has a spectral signature that allows scientist to distinguish it readily from other Earth surface materials.

Nicholson (2011) notes that the spectral signature of vegetation is unique in that "while most natural substances show a gradual increase in reflectivity with wavelength in the solar bands of the spectrum, green vegetation shows a dramatic increase between the red and near-infrared wavelengths (pp. 12).” Using the differential reflection between the two spectral bands, scientists have developed a number of indices to monitor and track vegetation. The most commonly used index is the normalized difference vegetation index which can be defined as:

$$NDVI = \frac{CH_2 - CH_1}{CH_1 + CH_2}$$

where CH_1 is the reflectance in channel 1 of the electromagnetic spectrum (0.6-0.7µm), or the visible/red portion and CH_2 is the reflectance in channel 2 (0.7–1.1µm), or the near-infrared portion. Nicholson (2011) notes that, “NDVI ultimately is a measure of the total absorption of photosynthetically active radiation (PAR), but in semi-arid regions it correlates well with such parameters as percentage surface cover, biomass, and leaf areas index as well as rainfall (pp. 12).”

Numerous studies conclude that NDVI is strongly correlated with net primary production, crop yields (Tucker, 1985, Prince 1991, Rasmussen, 1997, 1998; also see Table 1 in Funk and Budde, 2009) and even precipitation (Nicholson, 1994; Tucker and Nicholson, 1999). In regions with stable agricultural management, much of the interannual variability of yield can be explained through vegetation index data derived from the Advanced Very High Resolution Radiometer (AVHRR). Differences in yield due to non-weather parameters such as use of high yielding crop varieties, agricultural inputs such as fertilizer, pesticides and herbicides, and the use of variable rate application of these inputs cannot be easily seen from space. Although the use of NDVI as a correlate to yield is widespread in both developed and developing countries, it cannot capture significant changes in agriculture management or the impact of weather on crops with different genetic potential (Bin, 2013;

Haboudane, 2004).

While there appears to be no single, ideal NDVI metric for modelling crop yields, a variety of approaches have been documented. In their review of NDVI-yield studies, Funk and Budde (2009) report that mid-to-late season NDVI tends to capture yield better than seasonal integrations of maximum NDVI values. They also note that phenological adjustments, such as start of season, may also be made to assist analysis of NDVI. Crop masks are also used to reduce the influence of non-agricultural vegetation signals, and the subtraction of pre-season NDVI values (Rasmussen, 1997) has also been shown to increase estimation accuracy.

In the context of Western Africa, Rasmussen (1992) finds that in Burkina Faso millet yields can be estimated from regression models that use an integral of AVHRR NDVI from the phonological stage of the reproduction period of millet. In Senegal, Rasmussen (1997) reaches a similar conclusion noting that yield variance for millet is best explained using an NDVI integral corresponding to the reproduction period of the plant. The study also advocates for the use of soil and vegetation classes as covariates in NDVI crop forecasting models, as well as the application of pre-rainy season NDVI to control for non-crop vegetation that may be found in agricultural lands. Later work (Rasmussen, 1998) suggests that the inclusion of environmental variables (livestock density) to the millet yield-integrated NDVI model improves the level of explained yield variance. However, both studies are based on small sample sizes (ranging from 12 to 27 observations). Throughout our study we primarily use NDVI as a proxy for agricultural millet production, and thus millet availability. Since there has been little change in the agricultural system in Niger during the period of this study, we do not need to take into account changing seed varietals or large scale increases in agricultural inputs. This study does attempt to reduce the influence of non-agricultural vegetation signals in the NDVI by applying Harvest Choice crop masks, as discussed below.

Remotely Sensed Data Properties and Potential Sources of Error

While NDVI data may not suffer from the common problems that plague the collection and processing of economic data in developing countries, the manner in which the remotely sensed data are collected and processed gives rise to other potential sources error, inconsistency or mis-measurement. Data resolution can affect the level of detailed analysis that may be conducted on remotely sensed data. The spatial, spectral, radiometric, and temporal resolution of the remote sensing instrument will affect the information that can be derived and ultimately the vegetation indices that can be computed.[21] Spatial resolution, or the ground surface area that falls into a pixel being monitored, determines the spatial detail of remotely sensed data. Remotely sensed data that has coarse spatial resolution will limit the level of geographic specific analysis that can be conducted. Spectral resolution, or the number and width of spectral bands that are defined by a sensor, will determine the range of spectral discrimination (or range of vegetation indices). Data used throughout this study are derived from the AVHRR sensor, which is a broad-band scanner with five bands.[22] Radiometric resolution refers to the ability of a sensor to discriminate small differences in the magnitude of reflected or emitted energy. The AVHRR instrument has a high 10-bit radiometric resolution, which store sensor data

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[21] See Sanderson (2000) or Canada Center for Remote Sensing (2007) for a basic overview.
[22] http://pubs.er.usgs.gov/djvu/FS/2005_3114.pdf

into 1024 levels per sensor pixel value.[23] Finally, the temporal resolution of a sensor, or the frequency with which a sensor passes over the same swath of Earth's surface, may determine how precisely one can track changes in patterns of light reflectance and absorption. Temporal resolution is important to this study as we are interested in changes of maximum NDVI values on a month-to-month basis.

Even if remote sensing instruments have adequate resolution among the domains described above, other factors such as atmospheric effects, off-nadir viewing, and instrument precision and calibration can result in deviations in NDVI values that are not related to vegetation dynamics (Goward et al., 1991). Atmospheric effects, such as water vapors and aerosols, and clouds can distort measurements of sensors and need to be accounted for in processing spectral signals. Rasmussen (1998) describes how cloud masking procedures can lead to a severe deterioration in the measured correlation among integrated NDVI values and millet yields. Corrections are needed to account for the measurements because the AVHRR satellites have orbital drift in the instruments from before the year 2000. The satellite drift changes the time of overpass from early in the afternoon to later and later times as the orbit degrades. Soil effects in arid and semi-arid regions can also have a large impact on the vegetation indices due to light scattering and may result in inaccurate NDVI values (as reviewed in Nicholson, pp. 12, 2011). To address many of these perturbing influences, the Maximum Value Composite (MVC) technique developed by Holben (1986) is commonly applied to NDVI data. To create a consistent and comparable times-series of NDVI, data adjustments are also made to account for the calibration and temporal performance of the observations.

AVHRR NDVI Data

The AVHRR NDVI data used in this study are from the NASA Global Inventory Monitoring and Modeling Systems (GIMMS) group at the Goddard Space Flight Center. The data are the combination of data from six AVHRR instruments on-board five different NOAA satellites and have been processed and adjusted to account for potential sources of inconsistencies, error, and/or other perturbing factors (see Tucker et al. 2005 for complete discussion). This data was used because it was the only sensor that has continuously available and corrected observations from 1981 to the present. The NDVI data are an 8-km equal-area dataset from July 1981 through December 2011. The data are formed based on maximum value NDVI composites (Holben, 1986) with a 15-day composite NDVI for Africa. The fifteen data composite takes the maximum value from days 1 to 15, and the days 16 to the end of the month. The technique also addresses atmospheric corrections for volcanic effects, provides cloud screening, and minimizes atmospheric and directional reflectance effects (Tucker et al., 2005). With regard to orbital drift and sun-target-sensor geometry, the data were corrected using a solar zenith angle correction based on Pinzon et al. (2005). The GIMMS also group carried out numerous radiometric calibration assessments to ensure precision within and among surface trend data from the different instruments. Robustness checks were made on the combined data series by comparing values with targets through time. Dr. Molly Brown of NASA provided bi-monthly subsets of the GIMMS group processed data to the study using latitude and longitude boundaries covering 12°W - 15°E and 12°N - 25°N. Over 93,600 pixels covering 365 months (July 1981-December 2011) were provided to the study.

To construct the NDVI anomalies used in the study we first pass the raw AVHRR NDVI data through Harvest Choice's spatially explicit Spatial Production Allocation Model database[24] (SPAM), which contains estimates of crop distribution (Yu et al., 2000). The Spatial Production Allocation Model uses a cross-entropy minimization approach, that accounts for prior knowledge regarding actual crop distribution and factors that influence the distribution, to estimate plausible disaggregated estimates of crop production distribution on a pixel basis (MapSpaM, 2010). The SPAM database contains four types of crop distribution estimates, harvested area, physical area planted, production, and yield. The model incorporates spatially explicit input data including crop production statistics from the Food and Agriculture Organization (FAO), aggregated land cover and land use data from Boston University-MODIS Land Cover, Joint Research Center Global Land Cover2000 Project (JRC GLC2000) and United States Geological Survey Global Land Cover Characteristics (USGS GLCC), biophysical crop suitability assessments from the FAO and International Institute for Applied Systems Analysis (IIASA) in the form of agro-ecological zones, population density estimates from Gridded Population of the World (GPW) Version 2, and distances to urban centers and any prior knowledge concerning the spatial distribution of crop systems in a country (MapSpaM, 2010). The data are in the form of 5 x 5 minutes crop distribution maps.

[24] http://mapspam.info/

Table 12. Summary of NDVI filtering and processing

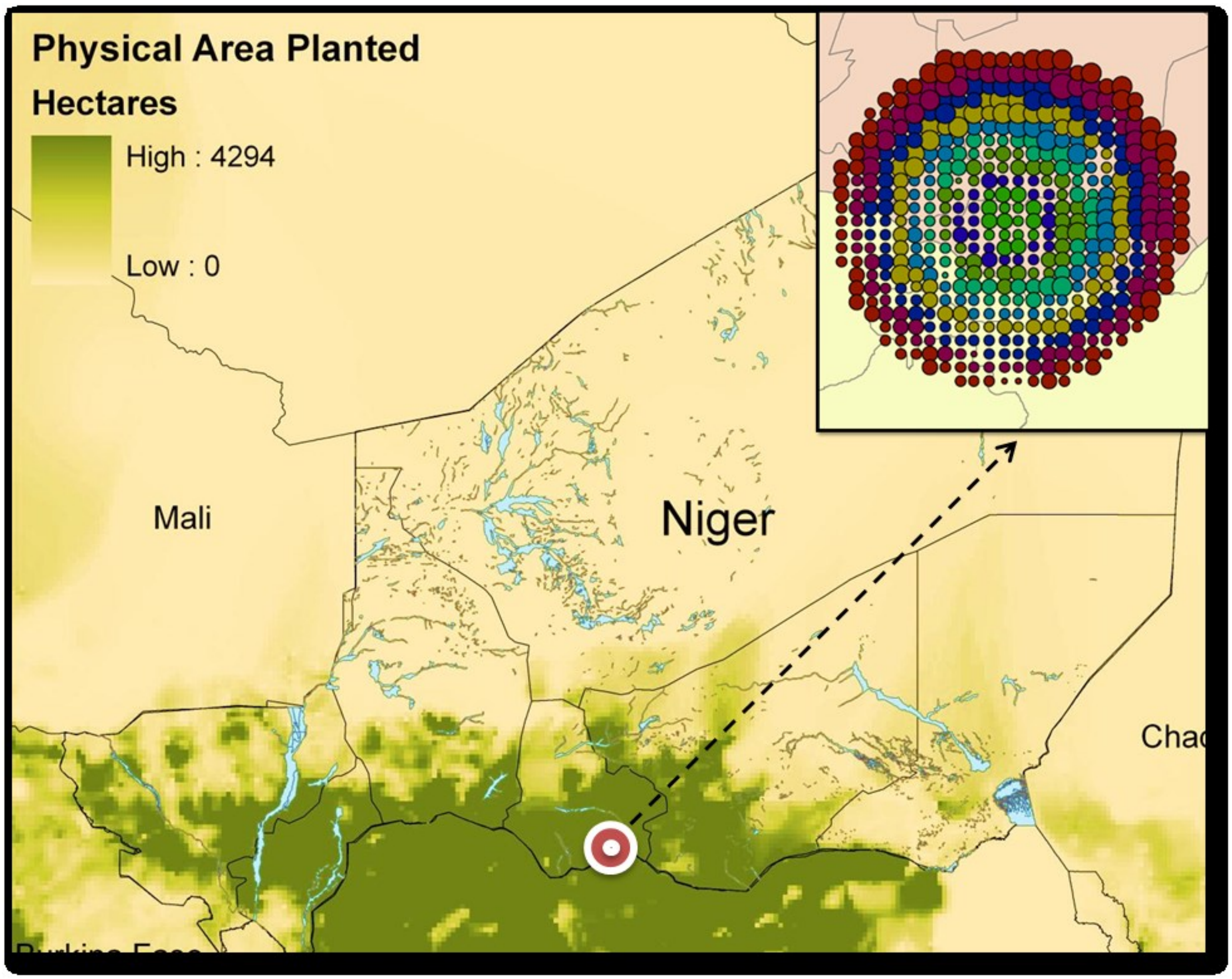
Data Product	AVHRR NDVI	SPAM (Production Maps)
Time series	July 1981-December 2011	Based on year 2000 inputs
Data projection	8km x 8km resolution Geographical coordinates	9km x 9km resolution*
Raw pixel number	93,661 x 365 periods	n.a.
Pixel numbers after filtering	33,296 x 365 periods	n.a.

Source: Author's calculations; * Maps are 5 X 5 minute or about 9km X 9km on the equator.

Specifically, we use the physical area planted variable from SPAM to tag pixels containing millet producing plots from those with no plausible production estimates. This initial filtering reduces the number of NDVI pixels considerably. The effect of the filtering exercise should help reduce distortions introduced into the NDVI signal by non-productive areas. However, the method will not completely isolate millet production regions as other crops and vegetative cover may also be grown within the same pixel. The SPAM maps also likely contain some measurement error. Once filtered, we create a series of buffers, in 10 kilometer increments, around each of the 29 markets in the study. As some markets are located near one another, the market-level buffers may include overlapping pixels. We use 10 kilometer increments in order to be able to test the sensitivity to area of NDVI pixels used and to allow for varying extent of an area surrounding a given market. The smallest buffer we calculate is 20 kilometers and the largest is 100 kilometers. Figure 16 below, shows a map of millet producing zones in Niger. On the left-hand side of the figure we present the distribution of the SPAM data and on the right hand side we present the market buffers for a selected market in Southern Niger. At the center of the picture is the market and the ring of concentric circles represents the NDVI buffer. The size of the circles in the buffer indicates the intensity of millet production contained within each pixel. The color of the circles are associated with the size of the buffer (dark red = 100 km). This figure represents how the study filters the data at the market level.

NDVI Buffers are calculated by taking the location of each market and calculating concentric circles around each market. We keep all pixels that are tagged millet producing zones and record weights on the intensity of production. Larger buffers reflect a greater cultivated area. Table 13, below, summarizes the average values of raw NDVI at the regional level composed of all 50 kilometer buffers from the 29 markets. Niger has seven major administrative regions and the capital, Niamey, includes a capital district.

Figure 16. NDVI Buffers by millet physical area planted intensity from SPAM



Source: Author's calculations

Table 13. Summary of raw NDVI values by region using 50 kilometer buffer (July 1981 – December 2011)

Region	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Agadez												
mean	1,320	1,308	1,291	1,227	1,401	1,281	1,242	1,514	1,678	1,278	1,299	1,308
std. dev.	157	149	148	154	271	241	276	507	481	222	190	161
coef. var.	0.12	0.11	0.11	0.13	0.19	0.19	0.22	0.33	0.29	0.17	0.15	0.12
Diffa												
mean	2,286	2,183	2,168	2,073	2,348	2,277	2,987	3,947	3,620	2,525	2,456	2,385
std. dev.	174	160	156	175	200	304	663	705	674	369	241	217
coef. var.	0.08	0.07	0.07	0.08	0.09	0.13	0.22	0.18	0.19	0.15	0.10	0.09
Dosso												
mean	2,647	2,465	2,298	2,123	2,487	2,713	3,433	4,253	4,516	3,659	3,139	2,881
std. dev.	403	349	292	339	486	831	974	928	973	983	703	522
coef. var.	0.15	0.14	0.13	0.16	0.20	0.31	0.28	0.22	0.22	0.27	0.22	0.18
Maradi												
mean	2,471	2,300	2,210	2,018	2,256	2,217	2,909	3,771	3,987	3,320	2,905	2,662
std. dev.	205	173	181	185	228	316	455	469	469	485	347	256
coef. var.	0.08	0.08	0.08	0.09	0.10	0.14	0.16	0.12	0.12	0.15	0.12	0.10
Niamey												
mean	2,225	2,068	1,968	1,812	2,035	2,079	2,585	3,340	3,501	2,746	2,529	2,354
std. dev.	143	172	136	169	261	277	340	254	216	258	172	128
coef. var.	0.06	0.08	0.07	0.09	0.13	0.13	0.13	0.08	0.06	0.09	0.07	0.05
Tahoua												
mean	2,106	2,011	1,931	1,766	2,045	1,918	2,433	3,290	3,443	2,646	2,353	2,221
std. dev.	226	207	193	192	229	263	358	443	509	499	346	264
coef. var.	0.11	0.10	0.10	0.11	0.11	0.14	0.15	0.13	0.15	0.19	0.15	0.12
Tillabéry												
mean	2,103	1,977	1,892	1,757	2,009	1,990	2,448	3,168	3,304	2,539	2,335	2,204
std. dev.	408	377	322	336	403	609	811	934	942	774	587	473
coef. var.	0.19	0.19	0.17	0.19	0.20	0.31	0.33	0.29	0.29	0.30	0.25	0.21
Zinder												
mean	2,307	2,191	2,140	2,012	2,275	2,203	2,859	3,643	3,694	2,926	2,624	2,470
std. dev.	298	258	269	288	284	349	605	648	591	556	424	349
coef. var.	0.13	0.12	0.13	0.14	0.12	0.16	0.21	0.18	0.16	0.19	0.16	0.14

Color ramp = coefficient of variation for NDVI
Source: Author’s calculations

To ease in interpreting the table, the normalized measure of dispersion (coefficient of variation calculated from monthly values from July 1981-December 2011) is shaded for each month and region using a green bar. The length of the bar indicates the coefficient of variation of NDVI outcomes for a given month. Dosso and Tillabery appear to exhibit the greatest variability, particularly during the growing season (May-October), whereas Maradi and Tahoua have lower levels of dispersion.

With our data filtered and buffers created, we construct a rolling 11-year NDVI anomaly around each market. Eleven years was selected in order to match the NDVI data with the post-1993 price data.[25] Each NDVI anomaly is estimated by calculating the monthly average of all NDVI pixels within a given buffer and regressing the resulting value on a set of monthly dummy variables and a time trend, and a squared time trend. The information not absorbed by the predictable factors in the regression captures the deviation (anomaly) from the expected value, at each point in time. To ensure that the anomaly does not incorporate more information than is available at a given point in time (as would be the case if we were to use the entire time series to construct the anomalies), we use a rolling regression model which incorporates moving window of monthly NDVI data from the previous 11 years. Given that we are primarily interested in forecasting market performance, we seek a variable, that at each point in time, only contains as information as is available to an analyst at that moment in time.

To aid in our preliminary analytical description of the NDVI data we create a set of NDVI ranking variables at the market level, and then average them into a single ranking system. The ranked values consider how NDVI anomalies rank across time

[25] Recall, our NDVI data span July 1981 through April 2012, whereas our price data run 1993-2012.

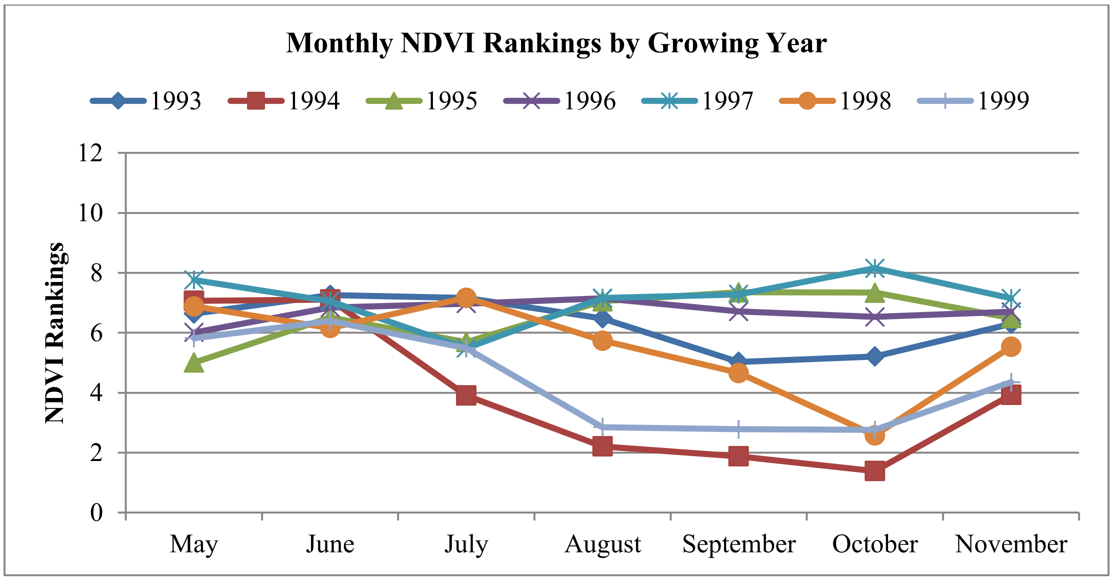
and within the same growing seasons. The results from this exercise are described below and demonstrate the annual variability in the NDVI data.

Analysis of NDVI Rankings

In order to get a sense of how an observed NDVI outcome compares to past outcomes we create a set of monthly rankings for each NDVI anomaly, focusing on NDVI for May-November. The first ranking, depicted in Figure 17, is created by taking all monthly NDVI outcomes from the previous years and ranking them against each other in a rolling manner. For example, the May 2003 NDVI ranking is calculated by looking at all NDVI anomalies for May 1992-2003 and assigning 2003 a ranking from 1 to 12, with 1 being far above average (the highest average NDVI value observed over the 12 year span) and 12 being far below average. The analytical advantage of such a ranking system is that each rank can be used to make assessment as to how current levels compare to historical values.

In analyzing the rankings, we break the data into three time segments that demonstrate similar NDVI patterns. Figure 17, below, depicts the rankings for 1993-1999 for the months of May through November. Working left to right, it is readily apparent that each May and June, over the past 6 years, is about the same in terms of their average ranking. As we move to July, we start to see a divergence in the outcomes with average NDVI from July of 1994 looking rather different from other years. As we continue to transition through the growing season, the patterns of NDVI in 1994 and 1999 take on a much different path than other years. By October, the years 1994, 1998 and 1999 have distinguished themselves as having much better average NDVI outcomes than the twelve years prior. What is also interesting is that the NDVI signal appears to be the highest ranked in October for those three years. These later than average anomalies may be suggestive of a growing season that is different from normal. However, we need to compare NDVI within the growing season to confirm this point.

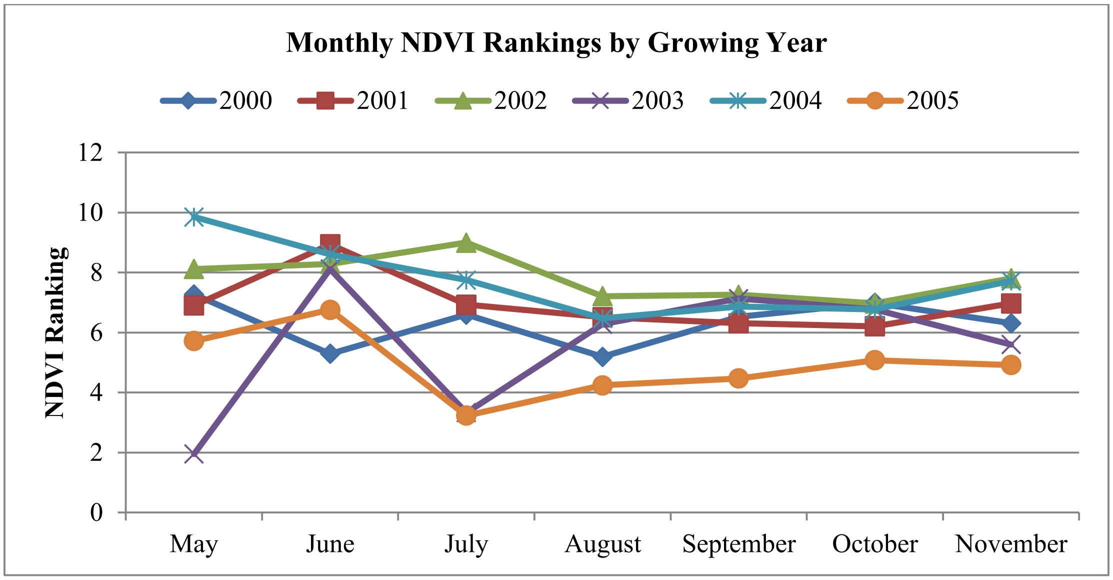
Figure 17. NDVI monthly rankings by growing season 1993-1999 (1=best, 12=worst)



Source: Author's calculations

Moving towards the middle part of NDVI sample, shown in Figure 18, the outcomes appear to change quite a bit. The month of May looks remarkably different from year to year with 2004 being the worst of the batch and 2003 being the best. The high ranking for May 2003 NDVI suggests an early start to the growing season. June NDVI rankings are different from the previous figure in that they are more widely distributed and, for the most part, worse than average when compared to each 12-year cohort. July NDVI rakings follow a somewhat similar pattern but 2003 and 2005 appear to have had much better average NDVI outcomes. The remaining months fit in a tighter distributional window and appear to be mostly average, except for 2005 outcomes.

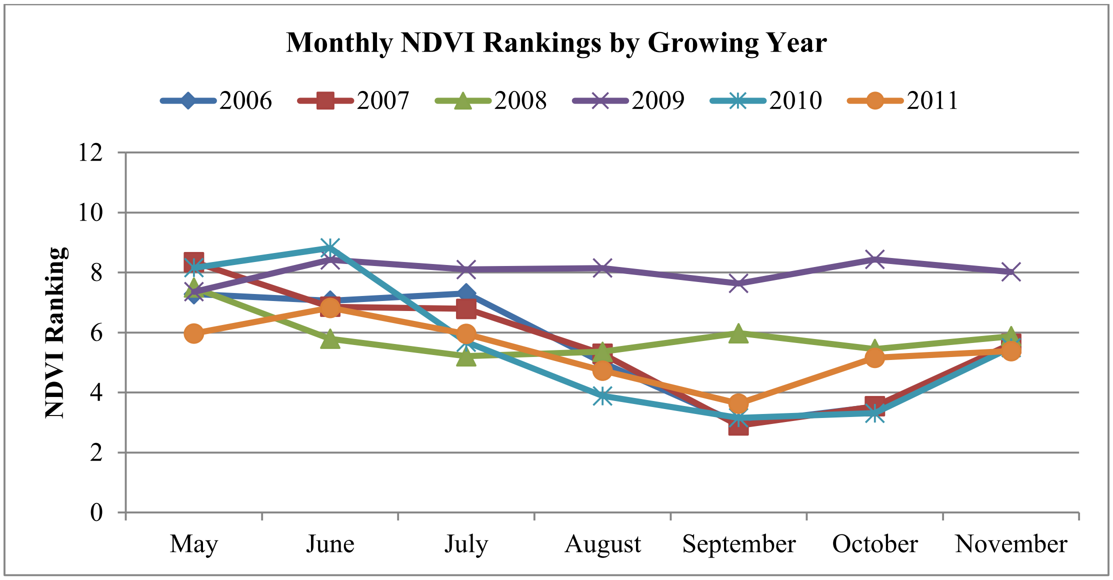
Figure 18. NDVI monthly rankings by growing season 2000-2005 (1=best, 12=worst)



Source: Author's calculations

Moving to the final graphic for the year-by-year comparison we see outcomes that are more in light with what we observed for1993-1999. The early part of the growing season appears to fit within a small distributional window and, on average, may be slightly worse than each month from the respective 12-year comparison group. Where things take a different turn is in August, September and October, with each of these months being somewhat above average for 2006-2011. NDVI outcomes for 2009 are the exception here, with each month taking on a ranking of 8 or higher. The years 2007, 2010, and 2011 appear to have late green-ups as shown by the low rankings for September and October.

Figure 19. NDVI monthly rankings by growing season 2006-2011 (1=best, 12=worst)

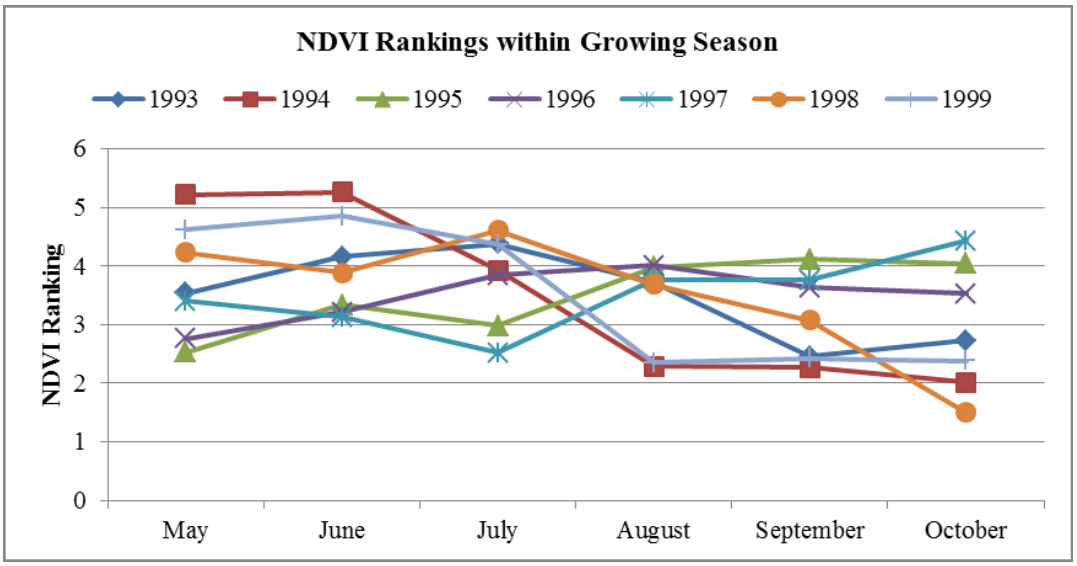


Source: Author's calculations

While the twelve-year comparison is useful for assigning rankings on a historical basis, it tells us little about how concurrent monthly NDVI outcomes compare to each other. That is, we may also be interested in knowing within a growing season how May NDVI outcomes compare to July NDVI outcomes, and so forth. To create this metric we assign a value of 1 to 6 to each month (with 1 being the best and 6 being the worst) within a single growing season based on the average NDVI rankings from all markets. The primary disadvantage of this metric is that one needs data from the entire growing season to construct a seasonal ranking. The results of this exercise are presented in Figure 20 - Figure 22.

Starting with the figure immediately below, we see a different pattern play out in the rankings. NDVI from 1994 is probably the clearest example of a year in which NDVI anomalies increasingly improved throughout the growing season as shown by the downward sloping line. Following a similar pattern was also 1999 and to a certain degree, 1998. On the other hand, 1995 NDVI rankings depict a story of a growing season that was either off to a good start in the beginning, as shown by the low rankings for May and June, or a year that simply had below average NDVI outcomes which were increasingly worse throughout the year. If we cross reference this year with the figure above for the same corresponding time we learn that 1995 was a below average year overall and a point reflected in the price data.

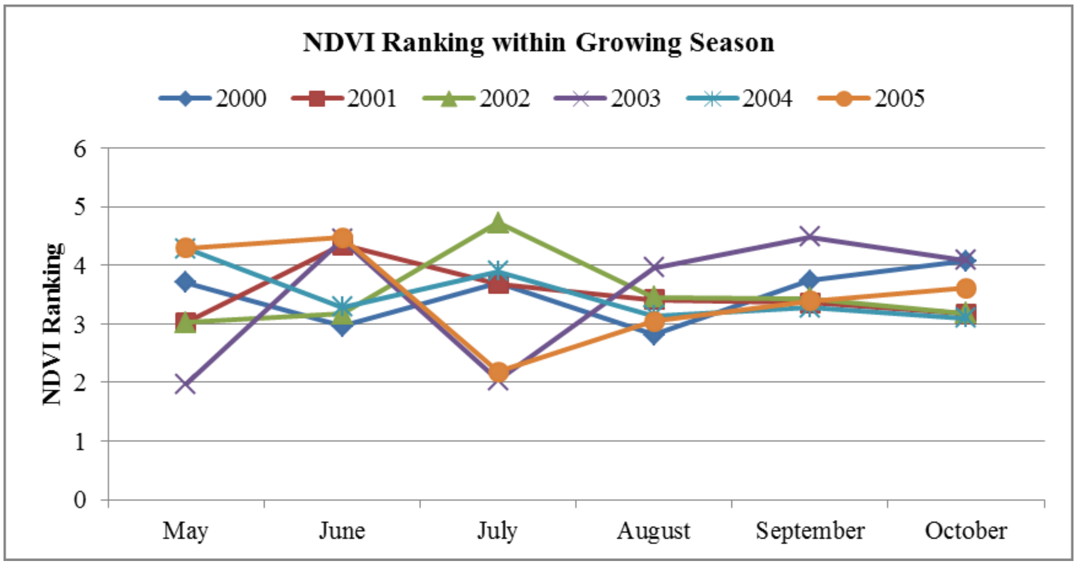
Figure 20. NDVI Rankings within growing season 1993-1999 (1=best, 6=worst)



Source: Author's calculations

Transitioning to the second cluster of time, 2000-2005 shown below, the pattern of NDVI outcomes is different from above, with the months of May and July taking on widely different rankings. If we cross-reference the rankings for 2005 from above, a nice story unfolds. May and June of 2005 take on NDVI rankings higher than any other months, suggesting that average NDVI was at its lowest levels during these months, relative to the other months of the growing season. However, looking at the annual rankings from above, we see that these NDVI levels were average, for each month, compared to the NDVI rankings for the previous 12-years. By July we observe a month with the best ranked NDVI outcome for the entire growing season, and when cross-referenced with Figure 18 above, it is a month with one of the best ranked outcomes over the past twelve years. From these two different perspectives, we can confidently conclude that NDVI from July of 2005, average across our 29 markets in Niger, was much higher than one would have expected.

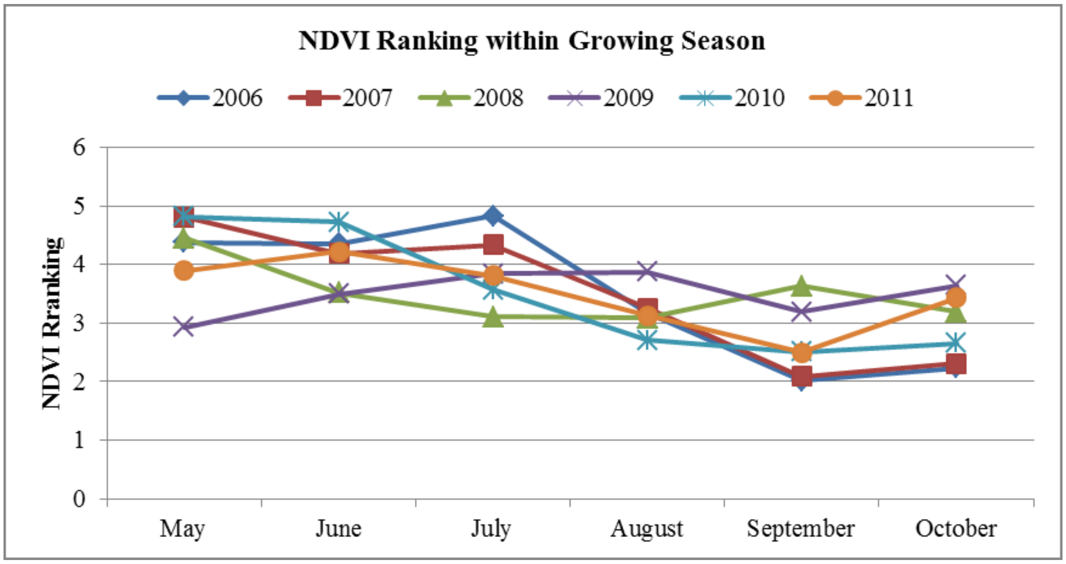
Figure 21. NDVI Rankings within growing season 2000-2005 (1=best, 6=worst)



Source: Author's calculations

The final figure, below, presents seasonal NDVI rankings for 2006-2011. The main observation that can be made from this figure is that the downward sloping shape of each year's ranking suggests NDVI outcomes increase, on average, from month-to-month throughout the growing season. While NDVI rankings for 2009 appear to be about the same for each month, when we cross-reference these values with those from the annual rankings above, we can see that on average, each month had similar NDVI outcomes, but these outcomes were bad across the board. This point highlights the importance of using the two proposed ranking metrics in tandem to determine not only what NDVI outcomes look like within a growing seasons, but also to how the monthly NDVI rankings look overtime.

Figure 22. NDVI Rankings within growing season 2006-2011 (1=best, 6=worst)



Source: Author's calculations

From an econometric modeling perspective these graphs provide a few insights into the evolving nature of NDVI outcomes. The graphs show that NDVI anomalies are dynamic both inter and intra-annually. What the metrics above do not reflect is how the spatial distribution of these patterns play out, which introduces an additional dimension to consider when trying to model millet price outcomes with NDVI. However, when rankings are averaged across space, we can get a sense of what a year looks like relative to past years and whether or not NDVI outcomes for a given month look substantially different from what we would expect.

The advantage of our inter-annual NDVI ranking metric is that we can detect anomalous months early in the growing season. NDVI outcomes that are far above average early in the growing season are of direct use to food security analysts as they suggest an early start to the growing season which in turn means earlier offloading of cereal stocks by traders and less pressure on credit and cereal constrained households. For modeling, this point is important because the normal price spike we expect in

July and August will be less marked due to the additional supply to the markets and the impending early harvest.

On the other hand, in years where NDVI anomalies do not peak until late in the year (1998 for example) the story is different, as is the appropriate ranking metric. In these circumstances, both rankings should be analyzed to determine what the late part of the growing looks like compared the past, and how September and October NDVI outcomes rank compared to those from June, July and August. From a pure modeling perspective, the failure to account for a late green-up, would likely lead to incorrect price predictions and market performance assessments (because of the assumption of a poor harvest) when peak NDVI (a proxy for millet production) may have simply shifted to later parts of the growing season. In these situations, an econometric model should be flexible enough to account for late green-ups and have the ability to recalibrate its prediction mechanism to account for shifting of phenological events of the growing season and the potential impact on market performance. This latter lesson suggests that traditional, fixed lag structures for NDVI variables and price data may not be appropriate inputs to a price forecasting model. More flexible methods should be explored -- particularly ones with learning algorithms that account for spatial, inter and intra-annual dynamics of vegetation production conditions and that can historically contextualize current NDVI outcomes as they relate to millet price outcomes.

NDVI Outcomes and Millet Production

Next, we consider the relationship between NDVI anomalies and official millet production outcomes to test some of our initial impressions about the seasonal variation in NDVI outcomes. One of the most influential and successful models for estimating agricultural supply response is the Nerlovian model (Nerlove, 1958) which estimates output as a function of price, output adjustment and other exogenous covariates. Due to data limitations and our desire to understand the links between NDVI and observed production, we resort to a linear fixed-effects regression model.

Previous studies that have analyzed the relationship between NDVI and crop yield in Niger include Maselli et al. (1991) and Wylie et al. (1991), who use NDVI to predict total herbaceous biomass in Niger over 1986-1988. Rasmussen (1992) and Groten (1993) consider a similar relationship for areas of Burkina Faso, with the latter study finding that NDVI signals from the month of August to be highly correlated with millet yields. Other studies have used maximum NDVI deviation from June through September (Brown et al. 2009), the summation of NDVI deviations over the growing season (Jiang et al., 2004; Rasmussen, 1998) and the maximum deviation from the growing season (Fuller, 1998) to analyze the relationship between NDVI outcomes and crop production or yields. In reality, the growth of millet is a function of numerous factors including water, sunlight, temperature, and soil fertility. Our simplified analysis considers the relationship among pixel-level, regionally aggregated NDVI anomalies and official millet production estimates. We use monthly NDVI anomalies, aggregated to the regional-level, and limit our dataset to areas of intensive millet production.[26] The purpose of the exercise is to determine how well our NDVI anomalies correlate with production outcomes.

[26] Niamey and Agadez have extremely low millet production figures and including them in the analysis only introduces additional noise. Regions included in the analysis are Dosso, Maradi, Tahoua, Tillabery and Zinder.

To account for any time-invariant, unobserved region-level heterogeneities that may influence production outcomes, such as soil type, we estimate a fixed-effects model shown below in equation 14. We test combinations of NDVI variables in order to assess the how NDVI from different stages of the growing season correlate with production outcomes. Our basic model is as follows:

$$Millet\ Production_{it} = \alpha + \beta_1 NDVI_{it} + \varphi X'_{it} + \delta_i + \theta_t + \varepsilon_{it} \qquad (14)$$

where $Millet\ Production_{it}$ is the first differenced value of millet produced in region i at time t, $NDVI_{it}$ is the corresponding NDVI anomalies/levels that were observed across regions, X'_{it} represents a vector of other NDVI variables (lagged NDVI values from October of the previous year, and off-season NDVI outcomes) and the remaining variables are α, an intercept, δ_i a region fixed-effect, and θ_t a time variable to account for unobserved temporal changes that may affect millet production. The model is estimated with a fixed-effects estimator using robust standard errors.

In modeling the relationship between NDVI outcomes and millet production, we test if an increase in NDVI is correlated with an increase of total production of millet, as opposed to an increase in non-crop vegetation. We use first differences to address the potential non-stationary of the millet production data.[27] Millet production data at the region level comes from the USAID Niger FEWSNET team stationed in Niamey. The data represents millet production estimates from the Government of Niger for the years 1996-2010.

The three figures below depict bivariate plots for NDVI metrics and production outcomes. The first graphic, Figure 23, plots the average NDVI anomaly

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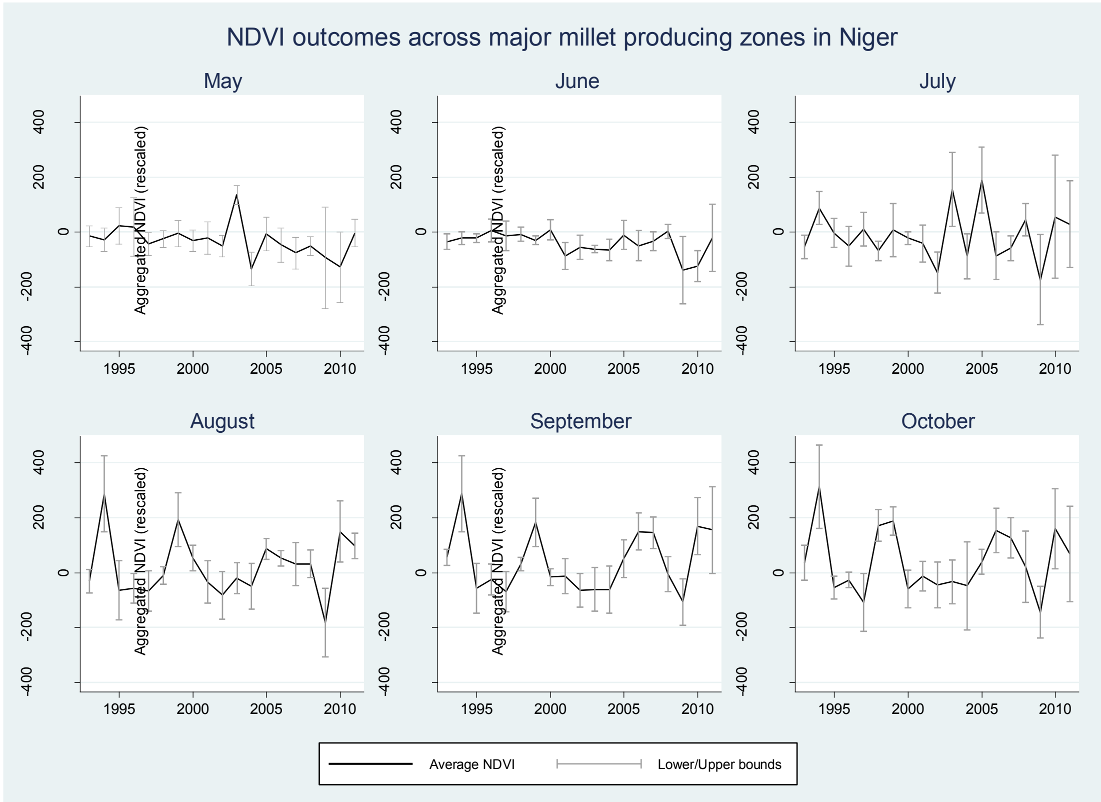
[27] Results from an augmented Dickey-Fuller test on each set of production statics at the department-level could not reject the null hypothesis that the data contained a unit root.

from the five regions for each month of the growing season. The outcomes are centered near zero because they represent the aggregated, demeaned NDVI anomalies from each region for the 14 years of analysis. The vertical bars on the graph represent the upper and lower bounds on the NDVI variables. A review of the graphic suggests that anomalies from May and June have the lowest variability with exceptions occurring in 2009 and 2010. Moving to July through October, we see a much different pattern with much more variability and a somewhat see-saw pattern. However, this pattern is not stable from year-to-year. For August, September and October of 2000-2004, the NDVI anomalies follow a similar shape with a mean slightly below zero. The month that appears to be driving variability is July, which shows large peaks in 2003 and 2005. Even the lower bounds in these years were above what we would have expected across the five regions.

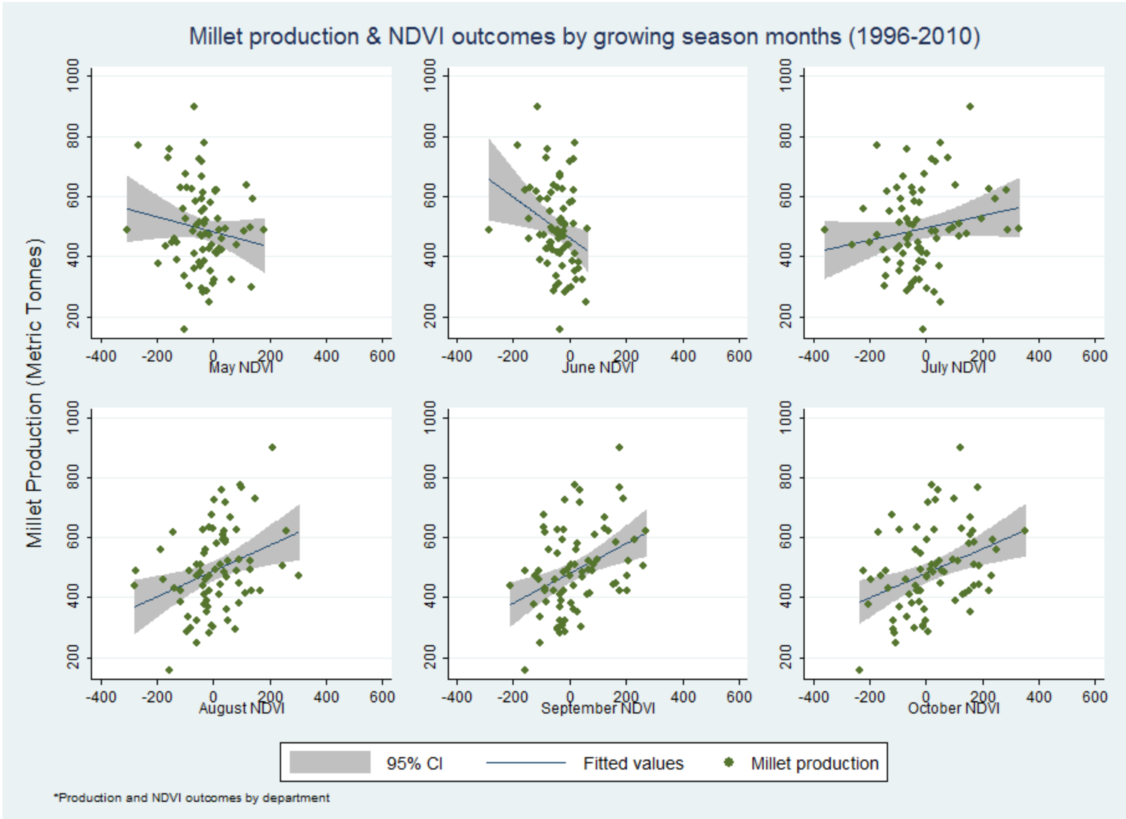
Figure 23. NDVI Anomalies over time



Source: Author's calculations

Figure 24, below, plots NDVI outcomes against the official production stataistcs for each year, by region. Focusing on the monthly NDVI anomalies, we see that NDVI deviations in May and June appear to have little or even negative correlations with production outcomes. Because of this it is difficult to ascertain a priori if May or June NDVI outcomes will be useful in predicting production, even during an early growing season which appear to be rare. Moving to July through October we see that the slope of the fitted correlation line improves compared May and June. This is somewhat expected as the normal growing season starts in July and ends in September or October.

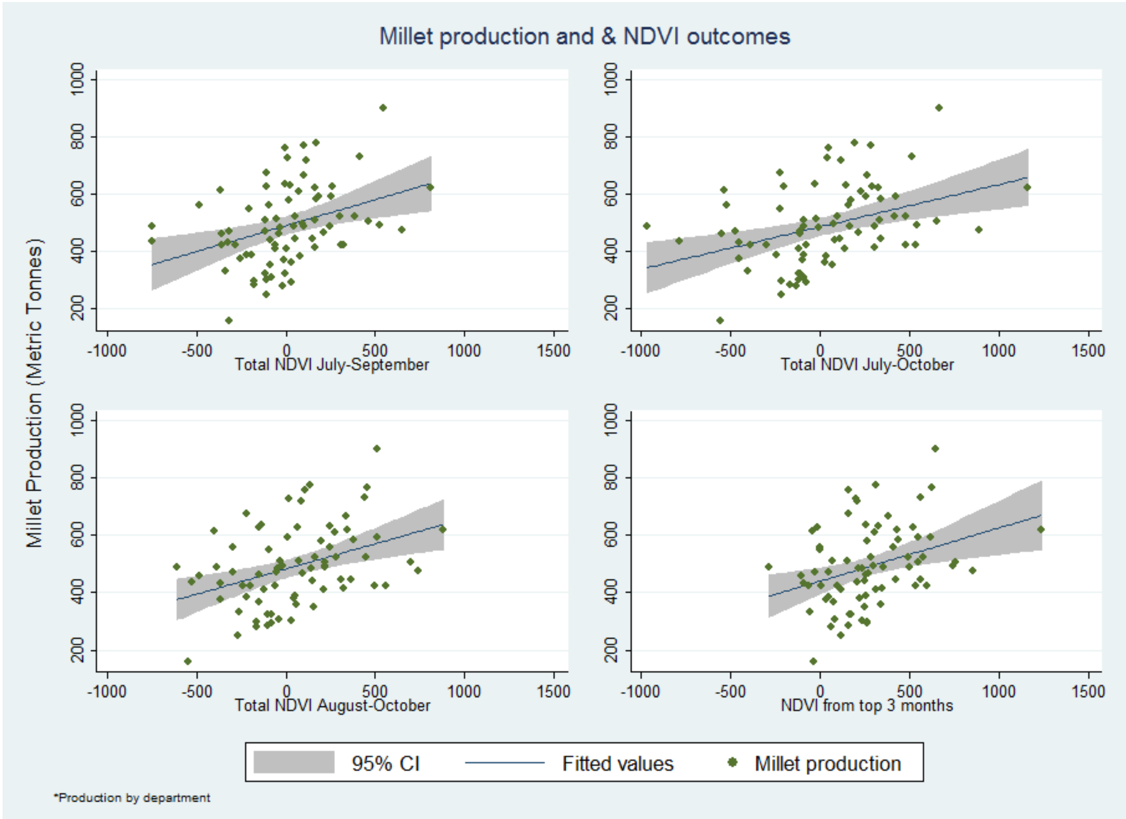
Figure 24. Correlation between millet production and monthly NDVI anomalies



Source: Author's calculations

Figure 25 presents a graph of the data focusing on cumulative NDVI deviations created by taking a combination of top performing NDVI months or different segments of NDVI from consecutive months. The relationships between NDVI and millet production throughout is generally positive, with no clear winner in terms of which metric, from an ocular analysis, appears to be excessively good at capturing the relationship between NDVI and production. Because these graphs do not control for other confounding factors, we turn to regression analysis to determine the robustness of these correlations.

Figure 25. Correlation between millet production and aggregated NDVI anomalies



Source: Author's calculations

Table 14 and 15 present the results from the modeling exercise. When interpreting the coefficients, one should be aware of the small sample size of the production data and that all NDVI anomalies have been rescaled to reduce the space needed for presentation. The relative value of the coefficient is more important than its actual value (and also explains why the constants take on such large values). The results are generally consistent with our expectations from the graphical analysis and the literature review. NDVI from the primary part of the growing season is statistically significantly and positively associated with millet production outcomes.

The left-hand side presents results for a month-by-month analysis of NDVI on production outcomes. It shows that August NDVI (and sometimes June) appears to be the best predictor of production outcomes in terms of the size of the coefficient. The right-hand side of the table presents the results for specifications estimated with the full set of NDVI covariates. NDVI from August still appears to have the strongest correlation with production outcomes, even after controlling for other months NDVI. Interestingly, the final specification reveals that NDVI anomalies from June have a statistically significant and positive relationship with production outcomes while positive NDVI anomalies in September appear to have an inverse relationship with production outcomes. Lagged NDVI values from the previous growing season have a negative effect on production indicating a year-to-year see-saw motion in production, and NDVI anomalies from the non-growing months (NDVI off season) appear have a positive relationship with crop production.

Table 14. Regression results for first differenced millet production and monthly NDVI outcomes

	Major Production Zones					
Dependent variable	Prod.	Prod.	Prod.	Prod.	Prod.	Prod.
October NDVI						4.27***
						1.165
September NDVI					3.28**	
					1.296	
August NDVI				4.43***		
				1.321		
July NDVI			2.36*			
			1.227			
June NDVI		8.61***				
		3.196				
May NDVI	0.68					
	1.973					
Lagged top 3 months NDVI	-4.18***	-4.85***	-3.93***	-4.15***	-4.06***	-3.72***
	0.607	0.637	0.643	0.576	0.566	0.547
NDVI off season	1.99***	1.71**	2.22***	1.75***	1.65**	1.33*
	0.747	0.693	0.717	0.657	0.761	0.76
Year	24.77	73.48*	16.94	21.13	8.85	19.48
	42.72	40.72	39.44	35.04	39.56	33.22
Constant	-48291	-145,326*	-32656	-41074	-16539	-37949
	85,597	81,539	79,087	70,274	79,268	66,536
Observations	70	70	70	70	70	70
R-squared[a]	0.369	0.448	0.408	0.485	0.429	0.509
Number of regions	5	5	5	5	5	5

Stars represent significant level (*** = 1 percent, ** = 5 percent, * = 10 percent); All results based on fixed-effects model with robust standard errors). a - R-squared statistic calculated using Stata's areg regression command. All production values are estimated in ‘000s of metric tonnes.

Table 15. Regression results for first differenced millet production and monthly NDVI outcomes full specification

	Major Production Zones					
Dependent variable	Prod.	Prod.	Prod.	Prod.	Prod.	Prod.
October NDVI						6.72***
						1.792
September NDVI					-1.47	-8.93***
					1.868	2.863
August NDVI				4.93***	6.41***	6.88***
				1.705	2.338	2.372
July NDVI			1.86	-2.02	-2.51	-0.93
			1.46	1.937	1.886	1.562
June NDVI		9.26***	7.56*	8.61**	8.59**	5.27*
		3.48	3.925	3.636	3.695	3.028
May NDVI	0.68	-1.24	-2.69	0.14	0.21	-2.37
	1.973	1.801	1.83	1.872	1.835	1.68
Lagged top 3 months NDVI	-4.18***	-5.00***	-4.75***	-5.00***	-5.10***	-4.44***
	0.607	0.617	0.703	0.717	0.753	0.723
NDVI off season	1.99***	1.80**	2.13***	1.22	1.26	1.49**
	0.747	0.688	0.702	0.796	0.785	0.724
Year	24.77	68.65	45.31	78.42*	84.76*	68.08
	42.72	41.973	41.48	41.71	43.20	41.19
Constant	-48291	-135639	-89053	-155,267*	-167,925*	-134939
	85,597	84,035	83,023	83,435	86,425	82,392
Observations	70	70	70	70	70	70
R-squared[a]	0.369	0.452	0.465	0.544	0.547	0.634
Number of regions	5	5	5	5	5	5

Stars represent significant level (*** = 1 percent, ** = 5 percent, * = 10 percent); All results based on fixed-effects model with robust standard errors). a - R-squared statistic calculated using Stata's areg regression command. All production values are estimated in '000s of metric tonnes.

Collectively, the regression results confirm the link between observed NDVI outcomes and millet production levels. NDVI anomalies from June and August appear to be some of the best predictors of good millet production years, while positive NDVI anomalies from September may be indication of a later than normal growing season which is correlated with a lower millet production. Table 16, below, summarizes the results from alternative NDVI specifications using the cumulative variables discussed above. The results are generally consistent with the previous ones.

Table 16. Estimates for millet production and alternative NDVI variables

	Major Production Zones				
Dependent variable	Prod.	Prod.	Prod.	Prod.	Prod.
Top 3 months NDVI					1.91***
					0.58
Cumulative NDVI (Aug-Oct)				1.74***	
				0.461	
Cumulative NDVI (Jul-Oct)			1.44***		
			0.368		
Cumulative NDVI (Jul-Sep)		1.67***			
		0.481			
Lagged top 3 months NDVI	-10.51***	-9.86***	-9.61***	-10.03***	-9.60***
	1.661	1.668	1.541	1.386	1.648
NDVI off season	1.88**	1.73**	1.52**	1.32*	1.58**
	0.794	0.679	0.677	0.719	0.695
Year	32.5	24.29	24.77	25.96	15.43
	43.295	36.104	34.252	34.455	37.185
Constant	-63,076	-46,771	-47,807	-50,156	-29,561
	86,763	72,413	68,671	69,054	74,483
Observations	70	70	70	70	70
R-squared[a]	0.35	0.462	0.497	0.499	0.457
Number of regions	5	5	5	5	5

Stars represent significance level (*** = 1 percent, ** = 5 percent, * = 10 percent); All results based on fixed-effects model with robust standard errors); a - R-squared statistic calculated using Stata's areg regression command. All production values are estimated in ‘000s of metric tonnes.

For completeness, we also present results for the above analysis conducted with yields instead of production volume. The results are largely consistent with our findings above.

Table 17. Estimates for millet yield differences and monthly NDVI outcomes

	Major Production Zones					
Dependent Variable	Yield	Yield	Yield	Yield	Yield	Yield
October NDVI						0.53***
						0.157
September NDVI					-0.05	-0.64**
					0.147	0.24
August NDVI				0.37**	0.42**	0.45**
				0.147	0.2	0.198
July NDVI			0.13	-0.16	-0.17	-0.05
			0.122	0.183	0.177	0.15
June NDVI		0.30	0.18	0.25	0.25	-0.01
		0.303	0.348	0.335	0.338	0.293
May NDVI	0.06	-0.01	-0.11	0.1	0.1	-0.1
	0.151	0.16	0.168	0.183	0.181	0.161
Lagged top 3 months NDVI	-0.29***	-0.31***	-0.29***	-0.31***	-0.32***	-0.26***
	0.057	0.063	0.072	0.078	0.079	0.073
NDVI off season	0.12**	0.12**	0.14**	0.07	0.07	0.09
	0.05	0.054	0.054	0.06	0.063	0.059
Year	0.77	2.18	0.52	2.98	3.19	1.88
	3.366	3.48	3.55	3.73	3.89	3.74
Constant	-1,469.54	-4,269.98	-944.38	-5,869.94	-6,296.32	-3,696.45
	6,746.36	6,968.01	7,113.02	7,467.13	7,773.04	7,479.26
Observations	70	70	70	70	70	70
R-squared	0.288	0.302	0.314	0.389	0.39	0.482
Number of regions	5	5	5	5	5	5

Stars represent significance level (*** = 1 percent, ** = 5 percent, * = 10 percent); All results based on fixed-effects model with robust standard errors reported below the coefficient estimate. a - R-squared statistic calculated using Stata's areg regression command.

Chapter 7: NDVI Shocks and Market Performance

The analysis of millet prices and NDVI above suggested two theories worthy of further investigation. Firstly, millet prices exhibit tremendous intra and inter-annual variation, large price increases are frequently observed during the summer months, and by marketing-year prices appear to conform to different distributional shapes. Secondly, the analysis of NDVI revealed substantial departures from normal vegetation production conditions across multiple periods of time. Given that we have established a close relationship between NDVI anomalies and millet production, and millet production and millet prices are inversely related (ceteris paribus), a natural question is to ask is if there is an impact from abnormal NDVI outcomes on market performance throughout Niger.

O Grada (2007) notes that, based on the Law of One Price (LOP), we should expect variations in food prices to decline during famines, as long as transport costs remain constant. While we cannot ensure that transportation costs remain fixed during NDVI shocks, we can investigate this claim by analyzing if and how NDVI shocks influence price spreads among market dyads in Niger. We start by reviewing three hypotheses of how markets may function during times of extreme food production shortfalls. We then turn to a discussion of the potential effects of negative and positive NDVI shocks, with a special discussion of the 2005 growing year. The second half of the chapter outlines our estimation strategy for analyzing market performance and discusses our estimation results.

Markets and Production Shocks

Ó Gráda (1997) attests that the LOP dictates that in a well-integrated market, price differences that remain persistent over a geographic space are largely due to transportation costs. Thus, the LOP implies that variation (standard deviation) in prices will reflect the transportation costs. In periods of excessive production shortfalls (famine like conditions), if transactions costs remain fixed, the observed price variation across space will tend to be equal to or smaller than price variations in periods of normal production. However, if transportation costs vary with production outcomes, as may be the case when there is excessive rainfall or drought, then it is less clear on how we may expect price variation to compare across situations.

Historically, the interactions between markets and famines are varied and can be divided into three camps (Ó Gráda, 2005). A first theory posits that during times of harvest failures markets can minimize damage through spatial and inter-temporal arbitrage. Clear lines of communication, well developed infrastructure systems, and frictionless trade can ensure that food supplies are traded until margins equalize and no further gains can be realized through spatial arbitrage. This should ensure that food insecure areas have access to food. However, a well-integrated market will have little power over whether or not households are in possession of the appropriate endowments to command food. In this situation, the same well-functioning market could exacerbate bouts of food insecurity by removing food from locations with insufficient purchasing power to areas where households are better off. Under these conditions, well-integrated markets would harm those in need of food the most.

The third line of thought posits that during food production shocks, myriad factors affect the functioning of markets resulting in fragmented trading patterns. Producers and traders can misestimate the volume of food needed by cereal markets or households and create inefficiencies in the way food is allocated across time and space. Combined with rumors of shortages and hopes of cashing in when prices are high, these actions can create pricing bubbles or herding behavior. Alternatively, the breakdown in communication channels either due to weather, government policies, inadequate infrastructure, or even conflict, can lead to balkanized markets in which price signals do not reflect market fundamentals (Ó Gráda, 2005).

With limited information on these dynamic factors it is difficult to know what theory will characterize market behavior. Without additional information on transactions costs, trade volumes, and household demographics and income profiles, we cannot precisely describe the exact type of market we are likely to encounter. However, we can gain useful insight into how spatial price spreads have reacted to abnormal vegetation production conditions as measured by NDVI.

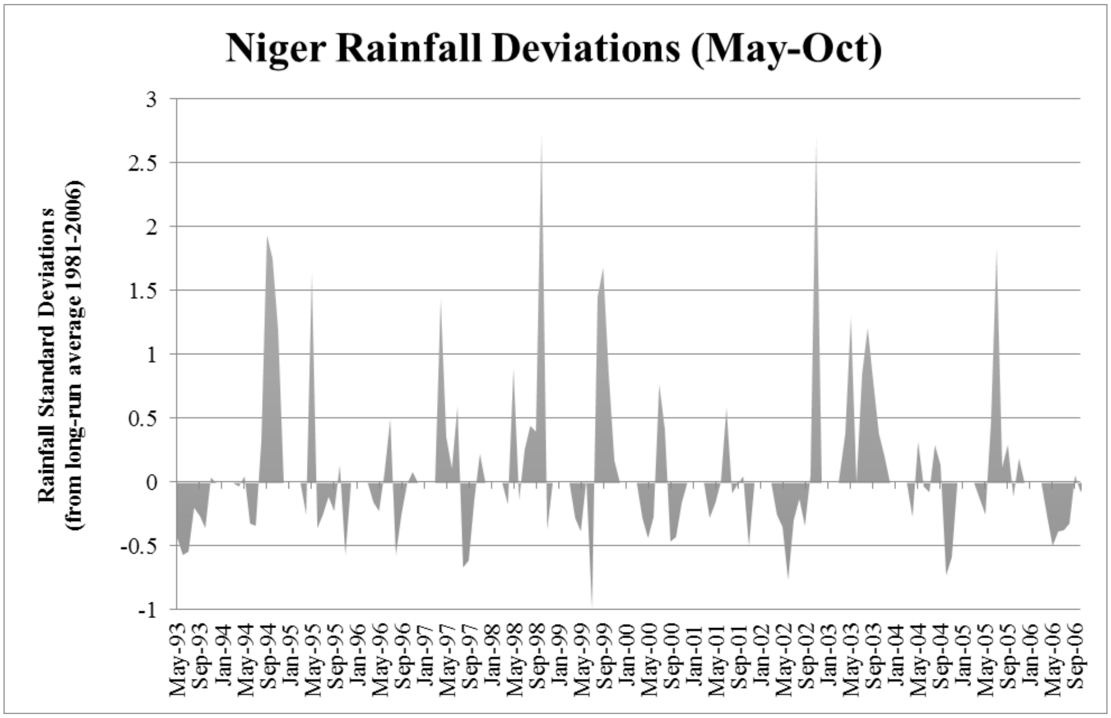
Potential Effects of Negative NDVI Shocks

A natural starting point when considering the impact of NDVI shocks on market performance is to consider the potential effects of extremely low vegetation production conditions (which may be correlated with production shocks) on price dispersion. Aker (2010b) concludes that drought has a heterogeneous impact on grain price dispersion, namely reducing price dispersion between two markets that are affected by drought at the same time. However, as pointed out above, the drought variables used in her study only span the months of July-September. Our analysis of

NDVI data reveals that phenological events associated with the growing season are not static and measures of vegetation production conditions fluctuate greatly from year to year. Thus, the point at which traders form expectations about local millet supplies may fluctuate from month-to-month within the growing season and across marketing years. To capture better the vegetation production conditions that are available to the market in a given month, we consider the impact of negative NDVI shocks throughout the growing season (defined as May-October). While it is plausible that negative shocks in July, August and September may strongly affect local millet supplies, we cannot rule out the scenario in which an early growing season changes the market's interpretation of a prolonged dry spell occurring in late in the growing season.

Recalling the theoretical trade model discussed in Chapter 4, and assuming constant transactions costs, we interpret negative NDVI shocks to be associated with a potential reduction in the local supply of millet. If both markets experience a negative supply shock that increases local prices at different rates, we may see a decrease in equilibrium price dispersion (a convergence in prices). However, if the NDVI shock also affects transactions costs, then a slightly different scenario is plausible. Because below average NDVI is strongly correlated with the lack of rainfall (see figure below), it is entirely reasonable that roads and bridges that are impassable during the rainy season may become traversable. This, in theory, could decrease the transactions costs between two markets. Instead of being washed away during the rainy season, infrastructure may remain intact or road conditions may simply improve due to the lack of rainfall. Depending on the magnitude of the supply shock and the transactions cost shock, we may witness improvements in grain market performance (convergence in prices) as profit margins (arbitrage opportunities) are widened by increasing prices and decreasing transactions costs.

Figure 26. Select historical rainfall anomalies 1993-2006



Source: Author's calculations based on Climate Research Unit Precipitation data (http://www.cru.uea.ac.uk/data)

Outside of the growing season in Niger the impact of negative NDVI shocks are likely to be less severe, but still may affect price dispersion. Normally, NDVI offers limited analytical value outside of the growing season in Niger but may be of value in assessing vegetation production conditions as we move further and further south where the growing season is longer. Where the shocks may be important is through secondary channels such as livestock production, off-farm income generating activities, or seasonal migration in search of work (the Exode). If NDVI is far below average (such as in January and February of 2005), this would likely decrease the overall food sources and inputs that are available for animal grazing rural, non-farm income generating activities, and demand for labor. As the cost of animal production grows, it is plausible that pressure may be exerted on millet prices at a local level (if millet grains are a substitute for animal products). A large enough effect may induce a response from the other node of the market pair where traders may find arbitrage opportunities in selling grain or millet-based goods to the stressed market. For these reasons it may be important to track NDVI outcomes outside of the growing season. However, in doing this we must be careful not to confuse excessively low NDVI outcomes with errors in the NDVI signal. Studies have shown surface bareness may be linked to dust emissions (Kim et al., 2013) rather than lack of vegetative cover.

Potential Effects of Positive NDVI Shocks

Positive NDVI shocks occurring during the growing season may have a different effect than outlined above. Two markets that simultaneously receive a positive shock may experience an apparent increase in price differences (or divergence in prices), given the positive shock affects the clearing price in each market at different rates. Trade may even stop between two markets if the local supply shocks are large enough to eliminate any gains from trade. Under these conditions we would expect market performance to degrade in the sense that price spreads may diverge between market-pairs (markets fragment). These shocks may also be associated with abundant rainfall which could increase transactions costs. Markets that are not connected to main roads may find themselves more isolated as trade routes become impassable due to poor or environmentally sensitive infrastructure (roads, bridges). If the production lag from the NDVI shock is significant and the immediate transactions cost effect large, this type of shock could actually increase local prices in the short-term because of the additional pressure on local supplies of cereal. However, in the longer-term we would expect that positive NDVI outcomes would decrease local millet prices by boosting local cereal production and supplies. Eventually, these lower prices would affect the spatial trade between markets and may even lead to little to no trade as arbitrage opportunities disappear or prices approach a floor across the entire region.

A special case, caused by a positive NDVI shock, may have unfolded during the peak of the growing season in 2005. According to satellite data, July 2005 NDVI levels were far above normal levels for the month, yet local millet prices continued to rise, likely due to the production shortfall from the previous harvest and offseason NDVI shocks at the start of the year. Some blamed the rapid rise in millet prices on the sensational media reports being broadcast to the world in July of 2005. However, other print news reports suggested that villagers remained hungry, despite the fact that their fields were green, because the elevated levels of rainfall had washed away many of the roads or made them difficult to transverse.[28] Thus, under certain conditions it is plausible that the immediate economic effects that correlate with positive NDVI shocks may increase price dispersion due to temporary transactions costs increases. If these effects occur at the earlier stages of the growing season, before the millet grains have set, the implications can be profound as benefits from the NDVI shock will be experienced with a lag, while the transactions cost effect is immediate. Should this occur at the peak of the hungry season, when local millet supplies do not keep pace with demand, prices are likely to increase due to reduced trade volumes caused by rising transactions costs. The irony is that even though

[28] "Rain threatens delivery of food aid in Niger", The Toronto Star August 2, 2005.

greening millet fields may foreshadow an impending bumper harvest, the local population may actually experience greater disutility due to the immediate effects of the transactions price shock.

Outside the growing season, a positive NDVI shock will likely have a similar effect, but again through secondary food source channels and increased income generating opportunities. Elevated NDVI levels may be associated with a longer than expected growing season resulting in decreases in grazing costs and increases in the supply of healthy animals, animal-based food products, and off-farm income generating activities. If the effect is large enough, local millet prices may also decline, but at different rates, as caloric substitutes fall in price. From a general environmental perspective, multiple positive NDVI shocks outside the growing season should improve general plant and tree quality thus increasing the availability of secondary food sources. This would tend to put downward pressure on millet prices, potentially at different rates, and likely reduce the incentives for trade depending on how localized the shock is.

A Review of Observed NDVI Shocks

To review the various shocks that have played out in Niger since 1993, we create a variable which captures major departures in NDVI from normal levels. We calculate a rolling mean of a 50 kilometer NDVI buffer for each market, as well as the rolling standard deviation using an 11-year, moving window. An 11-year window is selected so that we can align our NDVI anomalies with our price variables. We define an NDVI shock as a significant departure from the average NDVI value observed for a given window. Specifically, we tag a value as a shock if the observed rolling anomaly for a given market is two standard deviations above or below the rolling average at that point in time.

Table 18, below, summarizes the calculated NDVI shocks by marketing season alongside average NDVI anomalies combined from Burkina Faso, Mali, and Nigeria as well as price summary statistics. First, focusing on the marketing seasons 1992-93 through 2002-2003, the majority of shocks recorded were positive with the maximum number of positive shocks occurring in the growing season of 1993-94. In fact, this year was remarkably good for Niger as over 60 percent of markets in our sample experienced a positive NDVI shock in October and November of 1994. This run of exceptionally high NDVI outcomes continued through May of 1995 where over 20 percent of markets had positive shocks.

Table 18. Summary of NDVI shocks

Marketing Season	Negative NDVI Shocks (2 std. dev) Growing Season (May-Oct)	Positive NDVI Shocks (2 std. dev) Growing Season (May-Oct)	Average NDVI Deviation from Neighboring Countries (Growing Season)	Average Millet Price (real)	Average Standard Deviation
1992-93	0	3	91	142	30
1993-94	2	27	425	123	29
1994-95	0	70	-134	106	27
1995-96	1	27	-96	142	40
1996-97	3	2	-213	188	47
1997-98	5	0	17	238	53
1998-99	0	14	60	136	32
1999-00	2	9	-39	146	28
2000-01	0	1	-20	210	49
2001-02	19	0	-237	218	47
2002-03	3	59	175	176	37
2003-04	57	0	31	159	31
2004-05	8	11	120	230	62
2005-06	18	0	119	190	32
2006-07	6	3	24	170	31
2007-08	0	2	132	181	40
2008-09	75	0	-127	197	39
2009-10	63	9	18	210	33
2010-11	4	24	-11	173	32
2011-12	-	-	-	212	36
Total/Average	266	261	-	177	52

Source: Author’s calculations

Neighboring countries also experienced high NDVI outcomes as the average deviations from the growing and non-growing seasons were above 400 and 300, respectively. The effects of these positive outcomes appear to be borne out in millet prices as average, real millet prices were below their long-term average. Throughout the rest of the 1990s the number of NDVI shocks from the growing season was minimal, with 1998 being the best year with 14 shocks. From 1999 through 2002 the majority of positive shocks occurred during the non-growing season.

One interesting data point is the substantial increase in average millet prices and standard deviations in 1997-98. Prices, on average, were about 60 CFA higher than normal. While few NDVI shocks were recorded leading up to this time, many of the NDVI outcomes from Niger were well below average, as were the values for surrounding countries. NDVI levels in the major millet producing zones of Burkina Faso and Mali, on average, were below average for 11 consecutive months and nearly the entire 1997 growing season. This widespread occurrence of below average NDVI across the entire region likely resulted in decreased cereal production and stressed millet markets. This point is important as it demonstrates the importance of blending NDVI shock data and NDVI anomaly data to understand potential production shortages across the entire region.

Moving into the 2000s, a different picture emerges regarding the frequency and direction of extreme NDVI outcomes. In 2001-02, average NDVI levels from the surrounding countries were far below their expected value and there were 19 negative shocks recording during the 2002 growing season. Moving to 2002-03 marketing year, we see that NDVI outcomes in May of 2003 were far above normal as nearly 60 percent of markets recorded a positive shock in that month. Overall, the 2003 growing season produced 59 total positive shocks rivaling the 1994 growing season. Moreover, of the markets that had above average NDVI, 22 were in situated in the rainfed agricultural zones and 14 in the southern irrigated cash crop zones, the major production centers of millet in Niger.

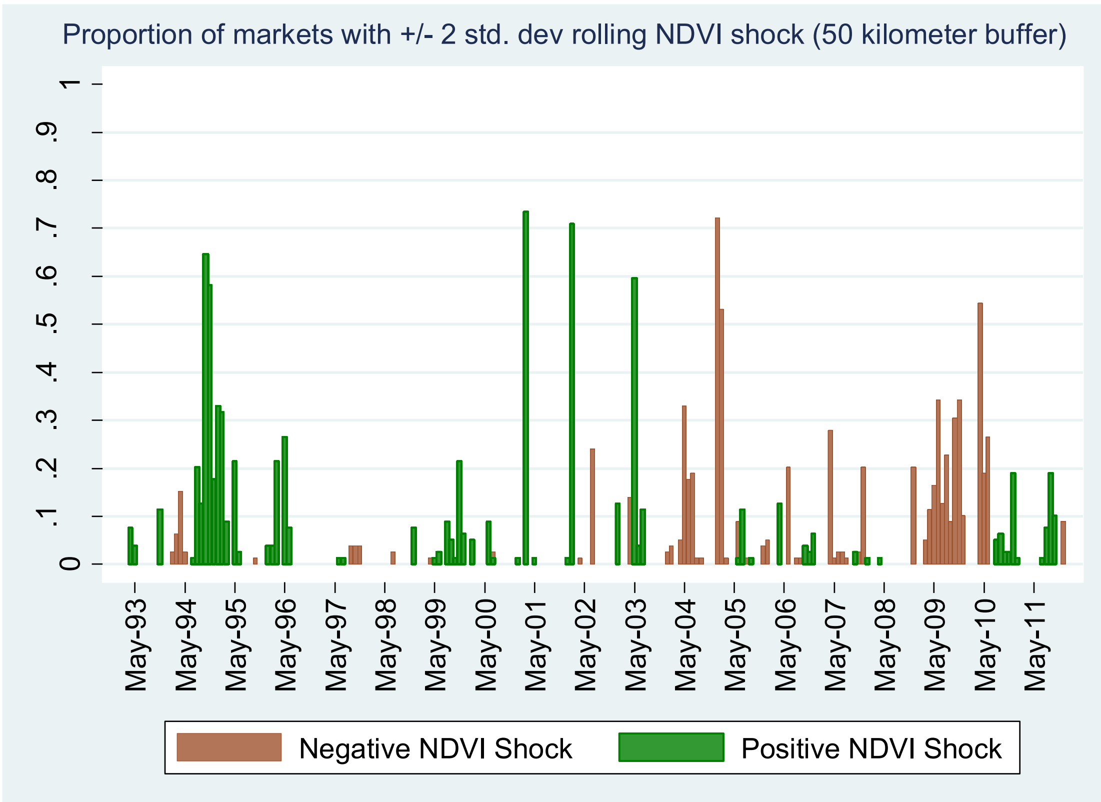
Moving to the 2003-04 growing season NDVI outcomes reverse direction. During the 2004 growing season 57 negative shocks are observed with nearly 33 percent of markets affected in May, and nearly 18 percent of markets affected in June and July.[29] The 2005 growing season brought a return to normalcy and a few positive NDVI shocks to markets in the rainfed agricultural zone and the southern irrigated cash crop zone. One average, 2005 NDVI levels were greater than expected across most of the markets, agro-ecological zones, and also in neighboring countries.

Surpassing 2003-04, the 2008-09 and 2009-10 growing seasons were some of the worst on record in terms of the number of extreme negative NDVI outcomes. Over 104 shocks are observed in 2008-09, the majority occurring during the growing season, and over 140 in 2009-10. NDVI in neighboring countries was, for the most part, below average, yet when we look at average millet prices they deviated little from their average value. Because Nigeria imported massive volumes of cereal into Niger, and the Nigerien government responded to the production shortfall with a multipronged approach, millet prices remained at near normal levels (Cornea, Deotti, and Sassi, 2012). This result is important as it demonstrates that increased trade and

[29] NDVI levels remained below normal and the extent of poor NDVI outcomes resulted nearly 100 shocks clustered in January and February of 2005. In January alone, over 70 percent of markets experienced a negative NDVI shock, and in February 53 percent of markets experienced a negative shock. However, it is unclear if these shocks have any meaning due to their occurrence during the dry season.

spatial arbitrage opportunities coupled with proper government response can smooth out domestic production shocks.

Figure 27. Graphical summary of NDVI shocks and proportion of markets affected



Source: Author's calculations

Figure 27, above, repackages the shock information from Table 18 as a graphic depicting the overall share of markets with NDVI shocks month-by-month. What is clear from the graphic is the unequal temporal distribution of shocks. From May 1993 through May of 2003 there were numerous positive NDVI shocks and few negative ones. The trend reverses from May 2004 through May 2011.

NDVI Shocks and Market Performance

To assess the impact of NDVI shocks on market performance we follow the lead of Aker (2010b) and estimate a difference-in-difference model, where NDVI shocks are represented by binary variables. As NDVI is an exogenous measurement reflecting the vegetation production conditions surrounding a market at a given point in time, it can plausibly be used to identify the effects of local production shocks on millet market performance. We interpret shocks occurring during the growing season to be production shocks and shocks occurring during the non-growing season to be indirect shocks, which may affect millet price dispersion through secondary sources (as discussed above). In order to estimate empirically the impact of a shock on market performance we consider the effect of NDVI on absolute price differences. That is, we exploit the temporal and cross-sectional variation in price spreads to identify the effects of exogenous NDVI shocks. We have little reason to believe that causality may run in the opposite direction given the nature of crop production in Niger and the ability of farmers to respond to sudden price spread changes by increasing vegetation production conditions.

Our basic model for analyzing NDVI shocks on market performance takes the form of:

$$Y_{ij,t} = \alpha + \beta_1 NDVI\_Shock_{ij,t} + \varphi X'_{ij,t} + \delta_{ij} + \theta_t + \varepsilon_{ij,t} \qquad (15)$$

where $Y_{ij,t} = |p_{it} - p_{jt}|$, the absolute value of the price difference between market *i* and market *j* at time *t*, $NDVI\_Shock$ is an indicator variable reflecting whether or an NDVI shock is present (defined as NDVI anomalies that are two standard deviations above or below the rolling average), $X_{ij,t}$ is a vector of exogenous variables including transportation costs measured by the IMF price of oil multiplied by the distance between two markets, δ_{ij} captures all time-invariant fixed-effects common to both markets, θ_t is a general time trend which captures unobserved temporal changes that may affect price dispersion among the markets, and finally $\varepsilon_{ij,t}$ is a market-pair disturbance term.

In order to assess the effect of shocks on price dispersion the model is estimated first with only negative NDVI shocks and then with both positive and negative shocks. We do this to determine if the effects of positive NDVI shocks mirror those of negative ones or if markets interpret extreme positive NDVI outcomes different than extreme negative outcomes. We consider the timing of the exogenous variation, looking at extreme outcomes that occur during the growing season (May-October) and across the entire year. To look at the heterogeneity of NDVI shocks on market performance we consider two additional variables. One captures whether or not a shock occurs in either of the markets at a given point in time, and the second variable is a ratio capturing the total share of markets experiencing an NDVI shock at a given point in time. The former variable allows us to analyze how market performance may be affected by localized shocks (increase/decrease in local millet supplies), while the latter captures how the extent of shocks affect market performance.

In addition to a base model, we also consider a dynamic panel data model where the dependent variable is lagged by a period to account for the fact that the current price spreads may be affected by unobserved or latent influences not captured by our exogenous covariates. With a small time-series (small T) and large number of cross-sectional observation (large N), one would normally account for endogeneity (see Nerlove, 1967; Nerlove 1971; and Nickell, 1981) that may be introduced by including a lagged dependent variable in a fixed-effects model through the use of an

Arellano-Bond Generalized Method of Moments (GMM) type estimator (Arellano and Bond, 1991).[30] However, Attanansio, Picci and Scoru (2000) contend that when the length of time (T) is greater than 30, then the bias that may be introduced by the lagged dependent variable with the fixed-effect estimator can be more than offset by its precision compared to instrumental variable and GMM estimators. Beck and Katz (2009) advocate a similar position in the context of time-series cross-section models (TSCEs) arguing that many of the proposed fixes are not worth their empirical costs. Because our time dimension is large (well over 200 periods) we do not explicitly employ an instrumental variables approach. We estimate a dynamic panel data model with a fixed-effects estimator using one lag in absolute price differences.

Regarding our standard error estimates, one of the standard assumptions of the fixed-effects model is that the error terms are independent across cross-sections. Given the nature our data, it is likely that the estimated error terms are correlated both temporally and spatially (cross-sectionally). Failure to correct for these two types of correlation will impart a downward bias on our estimated standard errors (Peterson, 2008). Thus, our confidence intervals will likely be too small and we may risk committing a Type I error. With our fixed-effects models, we can account for within market-pair temporal correlations by clustering at the market-pair level (Bertrand, Duflo & Mullainathan, 2004). This clustering should also help account for the dyadic nature of our data.

Cross-sectional dependence, however, will likely remain in the estimated residuals because of the spatial nature of the data. In order to check for spatial

[30] Beck and Katz (2009) note that the Nickell's derivation of the asymptotic bias is of order T^{-1}. Thus the bias should get smaller as T increases or one moves from the typical panel world to a time-series cross-section world. For most of our modeling, $T = 225$ and $T^{-1} = 0.004$ or $T=131$ and $T^{-1} = 0.008$.

dependence we conduct a cross-sectional dependence test following the methods show in Pesaran (2004). Pesaran's test is appropriate for our data as it is suitable for panels where N and T tend to infinity in any order (Hoechle, 2007). The null hypothesis for the test is that the estimated residuals are cross-sectionally uncorrelated.[31] Hoechle (2007) suggests that if one finds cross-sectional dependence, then the Driscoll and Kraay (1998) standard errors are more appropriate as they are robust to general forms of cross-sectional and temporal dependence. Using Stata's xtscc program, we correct for potential correlation of the disturbances. Driscoll and Kraay-based standard errors can be thought of as a cluster on time periods across cross-sections. We compare the Driscoll-Kraay standard errors to those generated by a fixed-effect estimator with robust (clustered at the market-pair level) standard errors, and an OLS model estimated with a large set of dummy variables as fixed-effects.

<u>NDVI Shocks and Market Performance Estimation Results</u>

Results from the estimation approach are presented below in the tables below. We start with a discussion of the results from the first table (Table 19), which reports the effect of all NDVI shocks, from both growing and non-growing season months, on price dispersion. Focusing on the first specification in the table, we see that across both models (partial and full) a negative NDVI shock in both markets, of a market pair, decreases price spreads between markets by nearly 3 CFA. However, when the standard errors are adjusted to account for general forms of cross-sectional

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[31] The formal test statistic is: $CD = \sqrt{\frac{2}{N(n-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\hat{\rho}_{it}\right)$ where T_{ij} is the number of common time-series observations and $\hat{\rho}_{it}$ is the sample estimate of the pairwise correlation of the residuals for the common time-series observations.

dependence, the estimated coefficient is not statistically different than zero. This pattern is mirrored in the second specification (third column). Including a metric (Table 20 specification 3) which captures the extent of an NDVI shock (percent of markets with a NDVI shock), yields a stronger affect. As the share of markets with negative NDVI shocks increase, price spreads between markets declines by over 4 CFA. Positive shocks appear to have a weaker effect in the opposite direction, suggesting that the market response is not symmetric. However, after we account for spatial dependence in the errors, the Driscoll-Kraay results suggest that the finding is not statistically different than zero.

The fourth specification introduces a dynamic factor (lagged price dispersion) and we see again that as the extent of an NDVI shock increases, price spreads on average appear to decline suggesting enhanced market performance. Moreover, if we look at the fourth specification and focus on the full model we see that as the extent of positive NDVI shocks grow (percent of markets with positive shocks), price spreads increase as indicated by the positive coefficient (1.64 CFA) on the variable. Thus, in periods of widespread negative NDVI shocks, markets appear to behave differently in that price spreads tend to converge, or overall market performance improves. In periods of positive NDVI shocks, the divergence of price spreads points toward a market segmentation but at a slower rate.[32]

Table 21 reports the results from the price dispersion analysis for all shocks that occur during the growing season. Reviewing the results from specification 1 and 2, we see that the impact of a negative shock in both markets appears to increase price

[32] These results should be caveated, however, by noting that the errors from fixed-effects models appear to be cross-sectionally dependent as shown by the Pesaran test statistic. When standard errors are adjusted to account for this, the estimated coefficients are not statistically different from zero.

dispersion, whereas the impact of a positive shock in both markets actually decreases price spreads. However, as we found in the previous estimation, when we control for cross-sectional dependence the coefficients are not statistically different than zero. Only in the third and fourth specification (Table 22), for both the partial and full model, do we find significant coefficients. As the extent of a negative NDVI shock grows, average price dispersion declines by nearly 6 CFA. This result is robust at the 5 percent level.

We interpret this as evidence that NDVI shocks experienced during the growing season months actually improve overall market performance by lowering the price spreads between markets. As discussed earlier, this may be due to declining, unobserved transactions costs and/or additional arbitrage opportunities across markets. The clear policy relevance to food aid officials is that if one observes a widespread negative NDVI shock during the growing season, the best policy may be to rely on markets to move food and smooth prices, given that food is available somewhere in the market (as was apparently done in 2009-10) and that transactions costs are not adversely affected by the shock. On the other hand, if one observes widespread positive NDVI shocks, food security analysts would be wise to pay close attention to isolated markets with below average NDVI outcomes. Our results suggest that increased price dispersion may be a signal that markets are unable to move food as effectively during these times. Thus, food aid may need to be targeted to underperforming markets in good years, particularly if a market is isolated and/or only connected through weather-prone infrastructure.

Table 19. Price dispersion analysis for all shocks specifications 1 and 2

	Specification 1			Specification 2		
Estimator:	Linear F.E.	F.E.	F.E. D-K	Linear F.E.	F.E.	F.E. D-K
Dependent variable: |Pit-Pij|						
Negative Shocks Only (partial model)						
Negative shock both markets	-2.78***	-2.78***	-2.78	-1.91**	-1.91**	-1.91
	0.778	0.819	2.729	0.829	0.891	2.284
Negative shock one market				-1.06***	-1.06***	-1.06
				0.346	0.344	1.124
Transportation costs	2.69***	2.69***	2.69	2.75***	2.75***	2.75
	0.702	0.598	3.324	0.702	0.598	3.325
All Shocks (full model)						
Negative shock both markets	-2.78***	-2.78***	-2.78	-1.90**	-1.90**	-1.9
	0.778	0.819	2.731	0.829	0.891	2.287
Negative shock one market				-1.07***	-1.07***	-1.07
				0.346	0.345	1.126
Positive shock 50 KM both markets	-0.84	-0.84	-0.84	-0.17	-0.17	-0.17
	0.714	0.553	2.176	0.776	0.638	2.474
Positive shock one market				-0.75**	-0.75**	-0.75
				0.341	0.364	0.957
Transportation costs	2.69***	2.69***	2.69	2.78***	2.78***	2.78
	0.702	0.598	3.321	0.702	0.598	3.321
Marking season effects	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects	Yes	Yes	Yes	Yes	Yes	Yes
Time	1993-2011	1993-2011	1993-2011	1993-2011	1993-2011	1993-2011
Observations	91,365	91,365	91,365	91,365	91,365	91,365
R-squared (full model)	0.361	0.061	-	0.361	0.061	-
Pesaran test of cross-sectional depend	-	Reject	-	-	Reject	-
Average absolute value of correlation	-	0.134	-	-	0.134	-
Number of market pairs	406	406	406	406	406	406

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1. Standard errors below coefficient estimates. All estimates include monthly and marketing-year fixed-effects. Linear FE indicates a linear regression model with large dummy variable set. F.E. indicates standard errors were based on clustering at the market-pair level. F.E. D-K indicates Driscoll-Kraay standard errors using Stata's xtscc, fe procedure.
*Footnote applies throughout tables presented immediately below.

Table 20. Price dispersion analysis for all shocks specifications 3 and 4

	Specification 3			Specification 4		
Estimator:	Linear F.E.	F.E.	F.E. D-K	Linear F.E.	F.E.	F.E. D-K
Dependent variable: |Pit-Pij|						
Negative Shocks Only (partial model)						
Lagged price difference				0.55***	0.55***	0.55***
				0.003	0.008	0.026
Negative shock both markets	-0.94	-0.94	-0.94	0.12	0.12	0.12
	0.844	0.898	2.237	0.704	0.705	1.106
Negative shock one market	0.13	0.13	0.13	0.13	0.13	0.13
	0.399	0.408	1.057	0.333	0.277	0.598
Percent of markets with negative shocks	-4.46***	-4.46***	-4.46	-2.66***	-2.66***	-2.66
	0.743	0.686	2.783	0.62	0.515	2.243
Transportation costs	2.98***	2.98***	2.98	4.14***	4.14***	4.14
	0.703	0.597	3.357	0.587	0.595	3.581
All Shocks (full model)						
Lagged price difference				0.55***	0.55***	0.55***
				0.003	0.008	0.026
Negative shock both markets	-0.93	-0.93	-0.93	0.12	0.12	0.12
	0.844	0.898	2.238	0.704	0.706	1.107
Negative shock one market	0.13	0.13	0.13	0.13	0.13	0.13
	0.399	0.408	1.058	0.333	0.277	0.599
Percent of markets with negative shocks	-4.46***	-4.46***	-4.46	-2.61***	-2.61***	-2.61
	0.743	0.682	2.768	0.62	0.513	2.237
Positive shock 50 KM both markets	-0.5	-0.5	-0.5	-0.02	-0.02	-0.02
	0.81	0.687	2.491	0.676	0.553	1.537
Positive shock one market	-1.13***	-1.13***	-1.13	-0.82**	-0.82***	-0.82
	0.402	0.411	1.017	0.335	0.288	0.629
Percent of markets with positive shocks	1.08	1.08*	1.08	1.64***	1.64***	1.64
	0.703	0.632	1.808	0.587	0.487	1.269
Transportation costs	2.98***	2.98***	2.98	4.10***	4.10***	4.1
	0.704	0.595	3.352	0.588	0.597	3.581
Marking season effects	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects	Yes	Yes	Yes	Yes	Yes	Yes
Time	1993-2011	1993-2011	1993-2011	1993-2011	1993-2011	1993-2011
Observations	91,365	91,365	91,365	91,227	91,227	91,227
R-squared (full model)	0.361	0.062	-	0.556	0.347	0
Pesaran test of cross-sectional dependence	-	Reject	-	-	Reject	-
Average absolute value of correlation	-	0.134	-	-	0.117	-
Number of market pairs	406	406	406	406	406	406

Table 21. Price dispersion analysis for all growing season shocks (May-October) specifications 1 and 2

	Specification 1			Specification 2		
Estimator	Linear F.E.	F.E.	F.E. D-K	Linear F.E.	F.E.	F.E. D-K
Negative Shocks Growing Season (partial model)						
Negative shock 50 KM both markets	1.79*	1.79	1.79	2.19**	2.19*	2.19
	1.047	1.188	2.232	1.101	1.208	1.632
Negative shock one market				-0.49	-0.49	-0.49
				0.421	0.444	1.362
Transportation costs	2.59***	2.59***	2.59	2.62***	2.62***	2.62
	0.702	0.597	3.317	0.702	0.598	3.318
All Shocks Growing Season (full model)						
Negative shock both markets	1.78*	1.78	1.78	2.20**	2.20*	2.2
	1.047	1.188	2.233	1.101	1.209	1.634
Negative shock one market				-0.53	-0.53	-0.53
				0.421	0.446	1.363
Positive shock both markets	-3.29***	-3.29***	-3.29	-2.63**	-2.63***	-2.63
	1.125	0.852	3.422	1.199	0.967	2.937
Positive shock one market				-0.76	-0.76*	-0.76
				0.465	0.444	1.248
Transportation costs	2.64***	2.64***	2.64	2.69***	2.69***	2.69
	0.702	0.598	3.314	0.702	0.599	3.313
Marking season effects	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects	Yes	Yes	Yes	Yes	Yes	Yes
Time	1993-2011	1993-2012	1993-2013	1993-2014	1993-2015	1993-2016
Observations	91,365	91,365	91,365	91,365	91,365	91,365
R-squared (full model)	0.361	0.061	0.061	0.361	0.061	0.061
Pesaran test of cross-sectional dependence	-	Reject	-	-	Reject	-
Average absolute value of correlation	-	0.133	-	-	0.133	-
Number of market pairs	406	406	406	406	406	406

Table 22. Price dispersion analysis for all growing season shocks (May-October) specifications 3 and 4

	Specification 3			Specification 4		
Estimator	Linear F.E.	F.E.	F.E. D-K	Linear F.E.	F.E.	F.E. D-K
Negative Shocks Growing Season						
Lagged price difference				0.55***	0.55***	0.55***
				0.003	0.008	0.026
Negative shock 50 KM both markets	3.53***	3.53***	3.53**	1.89**	1.89**	1.89
	1.111	1.217	1.614	0.926	0.931	1.152
Negative shock one market	1.58***	1.58***	1.58	0.73*	0.73**	0.73
	0.479	0.495	0.991	0.399	0.341	0.586
Percent of markets with negative shocks	-8.59***	-8.59***	-8.59***	-6.00***	-6.00***	-6.00**
	0.946	0.851	3	0.789	0.603	2.578
Transportation costs	3.08***	3.08***	3.08	4.31***	4.31***	4.31
	0.704	0.598	3.249	0.588	0.598	3.517
All Shocks Growing Season (full model)						
Lagged price difference				0.55***	0.55***	0.55***
				0.003	0.008	0.026
Negative shock both markets	3.55***	3.55***	3.55**	1.88**	1.88**	1.88
	1.111	1.22	1.62	0.927	0.932	1.158
Negative shock one market	1.57***	1.57***	1.57	0.73*	0.73**	0.73
	0.479	0.495	0.991	0.399	0.341	0.588
Percent of markets with negative shocks	-8.62***	-8.62***	-8.62***	-5.97***	-5.97***	-5.97**
	0.95	0.852	2.973	0.793	0.602	2.551
Positive shock both markets	-3.20***	-3.20***	-3.2	-1.91*	-1.91**	-1.91
	1.242	1.039	2.364	1.036	0.795	1.408
Positive shock one market	-1.39***	-1.39***	-1.39	-0.38	-0.38	-0.38
	0.536	0.534	1.239	0.447	0.386	0.875
Percent of markets with positive shocks	1.62	1.62*	1.62	0.98	0.98	0.98
	0.993	0.864	2.924	0.829	0.666	2.465
Transportation costs	3.12***	3.12***	3.12	4.31***	4.31***	4.31
	0.704	0.601	3.241	0.588	0.601	3.523
Marking season effects	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects	Yes	Yes	Yes	Yes	Yes	Yes
Time	1993-2017	1993-2018	1993-2019	1993-2020	1993-2021	1993-2022
Observations	91,365	91,365	91,365	91,227	91,227	91,227
R-squared (full model)	0.361	0.062	0.062	0.556	0.347	0.347
Pesaran test of cross-sectional dependence	-	Reject	-	-	Reject	-
Average absolute value of correlation	-	0.134	-	-	0.117	-
Number of market pairs	406	406	406	406	406	406

Table 23. Price dispersion analysis for all growing season shocks (select years)

Dependent variable: |Pit-Pjt|	1996-2006 F.E.	1996-2006 F.E. D-K	1996-2006 F.E.	1996-2006 F.E. D-K	2000-2011 F.E.	2000-2011 F.E. D-K	2000-2011 F.E.	2000-2011 F.E. D-K
Lagged price difference			0.49***	0.49***			0.53***	0.53***
			0.008	0.031			0.008	0.031
Negative shock 50 KM both markets	1.54	1.54	3.37*	3.37	3.43***	3.43**	1.79*	1.79
	2.209	3.214	1.888	2.269	1.213	1.667	0.94	1.168
Negative shock one market	2.77***	2.77*	1.97***	1.97*	1.76***	1.76*	0.98***	0.98
	0.696	1.499	0.577	1.089	0.524	1.05	0.364	0.652
Percent of markets with negative shocks	0.79	0.79	2.66**	2.66	-8.85***	-8.85***	-6.56***	-6.56**
	1.456	4.518	1.192	4.869	0.822	3.252	0.615	2.7
Positive shock 50KM both markets	-0.17	-0.17	-0.98	-0.98	1.85	1.85	0.99	0.99
	1.359	1.277	1.039	1.581	1.662	1.571	1.107	1.867
Positive shock one market	-1.60**	-1.6	-0.49	-0.49	-0.64	-0.64	0.07	0.07
	0.775	1.967	0.605	1.573	0.729	1.417	0.546	1.039
Percent of markets with positive shocks	6.60***	6.60**	6.32***	6.32**	4.73***	4.73	3.74***	3.74
	1.071	2.723	0.926	3.153	1.3	3.903	1.055	4.195
Transportation costs	6.74***	6.74*	7.68***	7.68*	2.64***	2.64	4.17***	4.17
	0.808	3.527	0.912	4.328	0.688	3.463	0.651	3.99
Constant	14.80***	14.80***	8.50***	8.50***	17.50***	17.50***	8.46***	8.46**
	1.933	2.745	1.157	2.271	2.09	4.938	1.233	3.516
Marketing season effects	yes	yes	yes	yes	yes	yes	yes	yes
Monthly effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	53,285	53,285	53,175	53,175	58,241	58,241	58,159	58,159
R-squared	0.33	0.33	0.49	0.49	0.39	0.39	0.56	0.56
Number of market pairs	406	406	406	406	406	406	406	406

While our results thus far have focused on 1993-2011, the analysis of shocks showed an unequal temporal distribution of good and bad outcomes. Positive shocks appear to cluster in periods up to 2000 and it is plausible that this clustering effect may influence our overall estimate. In order to understand the stability of our estimates over time, we also consider how price dispersion varies over 1996-2006 and 2000-2011. We focus on NDVI outcomes occurring during the growing season as these appear to be most policy relevant. The tables below present the results from our analysis.

Focusing on the middle part of the table above we see that a negative outcome in one market of the market pair appears to increase price dispersion by nearly 2 CFA over the period 1996-2006. As the extent of markets with NDVI shocks grows, there does not appear to be a discernible effect on price spreads. However, as the percent of markets with positive NDVI shocks increases, average price dispersion grows by between 6 to 7 CFA. The results are robust even after adjusting standard errors for cross-sectional dependence. This result is likely driven by the large number of positive NDVI shocks that occurred over 1996-2006, and the changing incentives for spatial arbitrage. As we move to 2000-2011, we see the opposite effect play out. Extensive negative NDVI shocks decrease price dispersion between 6 to 8 CFA, with the result likely driven by the large number of negative outcomes from 2000-2011. When we combine the data for the entire period, the effect of the extent of negative NDVI shocks is greater than all other coefficient estimates (shown above in Table 23). We interpret this result as evidence that negative production outcomes tend to affect market behavior to a greater degree than positive ones.

Collectively, our empirical results suggest that food security analysts should consider in detail the relative nature and extent of extreme NDVI outcomes. If one observes a larger than average NDVI outcomes in either direction, it may be prudent to calculate how many markets have deviations that fall outside of a two standard deviation bound. If the extent of markets with positive or negative NDVI shocks is large, this is a good indication that market performance will be different than one would normally expect, with different food aid policy implications. At the same time, food security analysts and policy makers should keep in mind that while decreased price spreads may indicate a well-functioning market system, higher than average price levels may mean that households still cannot afford to purchase food given their asset base and income level. If an intervention is required, this outcome may require a blend of food aid and cash transfers.

With our models above we have documented a link between NDVI shocks and market performance in Niger. Historically, NDVI shocks have not been equally distributed in a temporal sense. The past 10 years have produced some of the worst NDVI outcomes observed in our dataset, yet only during the 2004/05 marketing seasons did prices reach extreme levels. That 2008/09 and 2009/10 extensive NDVI shocks did not result in millet price spikes may be a testament to the improving nature of government response and spatial arbitrage. Our analysis above has only focused on the immediate impact of shocks on price dispersion. In the next section we consider how market performance and market integration interact, looking at whether or not market connectedness is empirically different in good, average and bad marketing years. To expand on this latter point, we also attempt to predict the type of price regime we are likely to encounter post-harvest using pre-harvest NDVI data.

Chapter 8: Using NDVI to Predict Price Regimes

In the previous chapter, our price dispersion model results suggest that NDVI shocks affect price convergence and overall market performance. As the share of market-pairs affected by NDVI shocks grows, prices converge faster, suggesting that markets perform better in the short-run. In order to investigate how market integration may change across entire marketing years, we consider how market connectedness varies by price regimes. Specifically, we construct a metric to measure the influence of neighboring millet prices on a central market in the form of a spatial price buffer. We then test whether or not the coefficient estimates are statistically different across price regimes, or that market connectedness differs by marketing year. In the second half of the chapter we build a prediction model to assess the ability of NDVI data to predict future marketing-year price regimes. We then incorporate the predicted regime values into our market connectedness model to determine how well NDVI-based forecasts can predict market connectedness. The goal of this chapter is to develop a methodology for predicting the type of marketing year encountered and the likely form of market connectedness using NDVI as our primary input.

Price Regimes and Market Integration

Our spatial price analysis, reviewed in Chapter 5, suggests that millet markets function in different manners depending on the nature of millet production in the region. In years with abundant production, we noted that price correlations were lower, suggesting fewer arbitrage opportunities, less connected markets, and thus likely lower levels of market integration. On the other hand, in years with negative production shocks, we observe the opposite effects. Price correlations were higher suggesting that the lack of local food availability stimulated arbitrage opportunities resulting in better integrated markets. In the last chapter, we empirically demonstrated that prices converge faster during extensive negative NDVI shocks.

Combining these two insights, we focus our attention on empirically estimating the relationship between market connectedness in surplus (good) and shortage (bad) years. The null hypothesis that we test is that spatial price buffers, measured by the degree of price influence from neighboring markets, have the same influence on central market prices across marketing years. We also seek to determine whether or not empirical specifications that explicitly account price regimes fit millet price data better than models estimated without regime variables. In some ways, our model may be thought of as a primitive switching model, where the switch is the type of price regime and the level of market connectedness associated with that regime type is measured as the interaction of the switch and the influence of prices from neighboring markets. While we could, in theory, estimate VAR to capture better the dynamic interactions of the market system, the sheer number of coefficients that would need to be estimated and interpreted may limit the utility of such an exercise.[33]

Formally, we test our null hypothesis using the following approach:

$$P_{i,t} = \alpha + \beta_1 P_{it-1} + \beta_2(\bar{P}_{j,t-1} * R_{it-1}) + B_3 R_{it} + B_4 \bar{P}_{j,t-1} + \varphi X'_{it} + \delta_i + \theta_t + \varepsilon_{it} \qquad (16)$$

where P_{it} is the price of millet in market i at time t, $\bar{P}_{jt-1}$ is the lagged average millet price from the market-level price buffer, and R_{it} is the price regime observed in the data. We consider both binary and tertiary regime specifications. If markets are less connected in good years, compared to other years, then we expect B_2 (lagged

[33] An alternative approach may also consider a VAR with lagged prices only for markets falling within the 50 kilometer price buffer for each market, across each equation.

interaction term) to be negative and statistically different than zero. To control for time-invariant heterogeneities, we include included market (δ_i) and time (θ_t) fixed effects. A vector of temporal control variables (X_{it}) is included to account for other time varying factors that may influence price levels. The error term (ε_{it}) is the market-level disturbance term.

We control for unobserved, potentially time-varying effects by including lagged prices ($P_{i,t-1}$) on the right hand side of our model. Not including the lagged dependent variable would likely result in a serious omitted variable bias. Because our time dimension is large (229), we expect that the potential bias introduced by the lagged dependent variable with the fixed-effect estimator to be offset by its precision when compared to other estimators (as discussed in Chapter 7; see also Beck and Katz, 2009).

Because we have a relatively small cross-sectional dimension ($N < T$), a more appropriate estimator that we plan to consider in future research is a Zellner's (1962) seemingly unrelated regression (SUR) approach. The SUR model treats each market as having its own equation to explain the evolution of millet prices. In fact, if each equation contains the same set of regressors the model is equivalent to OLS on each equation alone. If the equations do differ, the estimator can yield more efficient estimates by exploiting the correlation in the error terms across equations through feasible generalized least squares (FGLS). As a robustness check on our current model, we re-estimate the current model specifications using the dependent variable lagged two periods (as well as the market connectedness variable) as an instrumental variable. Our results are robust with the instruments and are available upon request.

To correct for cross-sectional (spatial) correlation in the errors we again estimate Driscoll-Kraay adjusted standard errors.

In order to assess the fit of our regime specification models versus a nested model that does not contain a switching variable, we calculate and compare the Akaike Information criterion (AIC) and the Bayesian Information criterion (BIC) for each model specification. The former measure is defined as:

$$AIC = 2k - 2\ln(L) \tag{17}$$

where k is the number of parameters in the model and L is the maximized value of the likelihood function for the estimated model. The latter criterion is calculated as:

$$-2 * \ln p(x|k) \approx BIC = -2 * lnL + k\ln(n) \tag{18}$$

where $p(x|k)$ is the likelihood of the parameters given the dataset, x is the observed data, k is the number of parameters estimated, n is the number of observations, and L is as follows above. The results of the modeling exercise are presented below in Table 24 and the model fit results are shown in Table 25.

We first consider results from a regime variable that collapses average and bad years into a single value. As shown in the table below, we consider various specifications in order to assess the robustness of our estimates. The first point to note is that, as expected, average price levels in good price regimes are anywhere between 8 to 10 CFA lower than other types of marketing years. This should come as no surprise given the construction of the regime variable. Transitioning to the coefficient on the lagged spatial price buffer, we see even that after for controlling of the influence of own price lags (columns 2-3, 5-6, 8-9), the influence of the spatial price buffer, on average, is anywhere between 0.07 – 0.11. However, when we interact the spatial price buffer with our regime variable we see that the coefficient is negative and statistically different than zero. Moreover, in some specifications (5-6, and 8-9) the size of the coefficient from the interacted term is greater than the coefficient on the lagged price buffer term alone. Together, these results suggest segmentation in markets at moderate distances (50 kilometer spatial price buffer) in good years. The results are robust across several specifications which account for varying price buffers and lagged prices. As the spatial price buffer increases in distance, the effect diminishes as reflected by the positive, but insignificant coefficient estimates for the 200km and 400km lagged interaction terms.[34] Overall, we interpret the results to mean that, on average in good marketing years, the influence of neighboring market prices on central markets weakens or markets become more fragmented compared to the base case. This is likely correlated with the increased supplies of local cereal and relatively more expensive transactions costs, both which reduce the incentives of spatial arbitrage.

[34] We also estimated the model using a 100 kilometer (instead of 50 kilometer) price buffer and find similar results.

Table 24. Market integration and price regime analysis results

	I	II	III	IV	V	VI	VII	VIII	IX
Dependent variable:	Millet price	Millet price	Millet price	Millet price	Millet price	Millet price	Millet price	Millet price	Millet price
Millet price one lag		0.55***	0.58***		0.54***	0.58***		0.53***	0.58***
		0.04	0.04		0.04	0.04		0.04	0.04
Millet price two lags			-0.12***			-0.13***			-0.13***
			0.03			0.03			0.03
Millet price three lags			0.08***			0.08***			0.07***
			0.02			0.02			0.02
Good regime*	-9.75***	-8.70***	-8.16***	-10.94***	-9.59***	-9.08***	-11.69***	-10.30***	-9.77***
	2.44	2.43	2.25	2.55	2.5	2.31	2.53	2.48	2.3
Lagged good regime	11.56**	9.66**	9.52**	8.52*	7.8	7.64*	6.66	5.7	5.79
	4.96	4.7	4.44	4.97	4.94	4.53	5.99	5.85	5.34
Lagged 50KM price buffer	0.63***	0.10***	0.11***	0.58***	0.06**	0.06*	0.58***	0.07**	0.07**
	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03
Lagged good regime X lagged 50KM price buffer	-0.08***	-0.06***	-0.06***	-0.12***	-0.08**	-0.08**	-0.12***	-0.09**	-0.08**
	0.03	0.02	0.02	0.05	0.04	0.04	0.05	0.04	0.04
Lagged 200KM price buffer				0.09**	0.07*	0.08**	-0.07	-0.07*	-0.06*
				0.04	0.04	0.04	0.04	0.04	0.04
Lagged good X lagged 200km price buffer				0.07	0.04	0.04	0.05	0.01	0.01
				0.04	0.04	0.04	0.06	0.05	0.05
Lagged 400KM price buffer							0.18***	0.16***	0.17***
							0.06	0.06	0.05
Lagged good X lagged 400km price buffer							0.04	0.05	0.04
							0.07	0.07	0.06
Time effect (period variable)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Marketing season effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Monthly effects (January base)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Estimator	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K
Observations	6,592	6,591	6,527	6,592	6,591	6,527	6,592	6,591	6,527
R-squared*	0.854	0.863	0.864	0.855	0.863	0.864	0.855	0.863	0.865
Number of markets	29	29	29	29	29	29	29	29	29

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1. All estimates include monthly and marketing-year fixed-effects. F.E. D-K indicates Driscoll-Kraay standard errors using Stata's xtscc, fe procedure with four lags. Standard errors below coefficient estimates.

In order to evaluate how our primitive switching model compares to a base model that does not explicitly account for price regimes, we compare the model criterion for a subset of models, using similar specifications. Because the base model is nested within the switching model, we can use the Akaike Information Criterion (AIC) and the Bayesian Information Criteria (BIC) to compare the two. Table 25 and Figure 28, both below, summarize the results of this exercise.

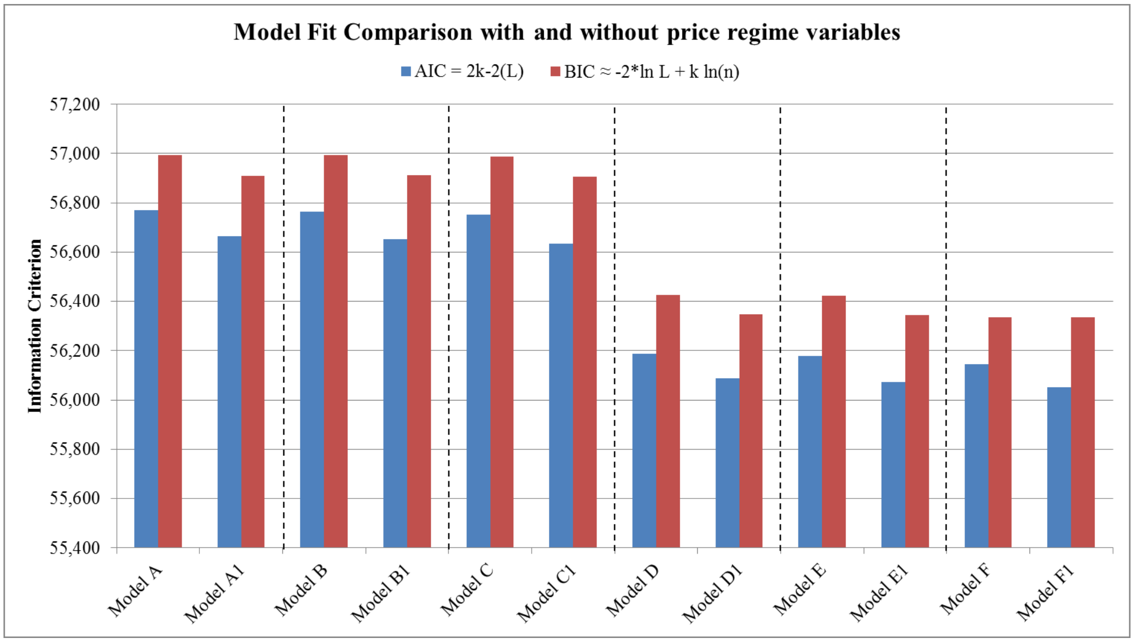
Table 25. Comparison of regime model fit to base models

Model Description	Description Short	Obs	Ll (null)	Ll (model)	df	AIC = 2k-2(L)	BIC ≈ -2*ln L + k ln(n)
One price lag, one price buffer (base)	Model A	6591	-34,839	-28,352	33	56,771	56,995
One price lag, one price buffer, regime variables	Model A1	6591	-34,839	-28,296	36	56,665	56,910
One price lag, two price buffers (base)	Model B	6591	-34,839	-28,348	34	56,764	56,995
One price lag, two price buffers, regime variable	Model B1	6591	-34,839	-28,289	38	56,654	56,912
One price lag, one price buffer (base)	Model C	6591	-34,839	-28,341	35	56,752	56,989
One price lag, three price buffers, regime variables	Model C1	6591	-34,839	-28,277	40	56,635	56,906
Three price lags, one price buffer (base)	Model D	6527	-34,507	-28,059	35	56,188	56,426
Three price lags, one price buffer, regime variables	Model D1	6527	-34,507	-28,006	38	56,088	56,346
Three price lags, two price buffers (base)	Model E	6527	-34,507	-28,053	36	56,178	56,422
Three price lags, two price buffers, regime variable	Model E1	6527	-34,507	-27,996	40	56,073	56,344
Three price lags, one price buffer (base)	Model F	6527	-34,507	-28,045	28	56,146	56,336
Three price lags, three price buffers, regime variables	Model F1	6527	-34,507	-27,984	42	56,051	56,336

Source: Author's calculations

From the table above, we can see that in nearly every specification the inclusion of the regime variable improves the overall fit of our model. This result is intuitive as the regime variable allows for an intercept switch across marketing years, or is simply a more flexible way of modeling the starkly different price outcomes. The figure below provides a visual summary of the results. Only in the final specifications (Models F and F1) does the BIC not improve with the inclusion of the regime variables. However, the AIC does improve slightly in the same specification. Overall, the largest gains in the model fit appear to come from the inclusion of the lagged dependent variables which is not surprising.

Figure 28. Observed binary price regime model fit comparison



Source: Author's calculations

While a simple two-regime switching model demonstrates the need to account for marketing-year classes, a more appropriate model may be one that permits prices to fall in bad, average, and good marketing years. Our price regime analysis in Chapter 5 showed that after controlling for predictable market fundamentals, prices across Niger tended to cluster within three types of regimes. Table 26, below, estimates a tertiary regime model in which we are able to compare how market connectedness varies by regimes. Bad regimes are the base case, so all coefficient estimates should be interpreted with this in mind.

Table 26. Market integration and price regime analysis results (specification 2)

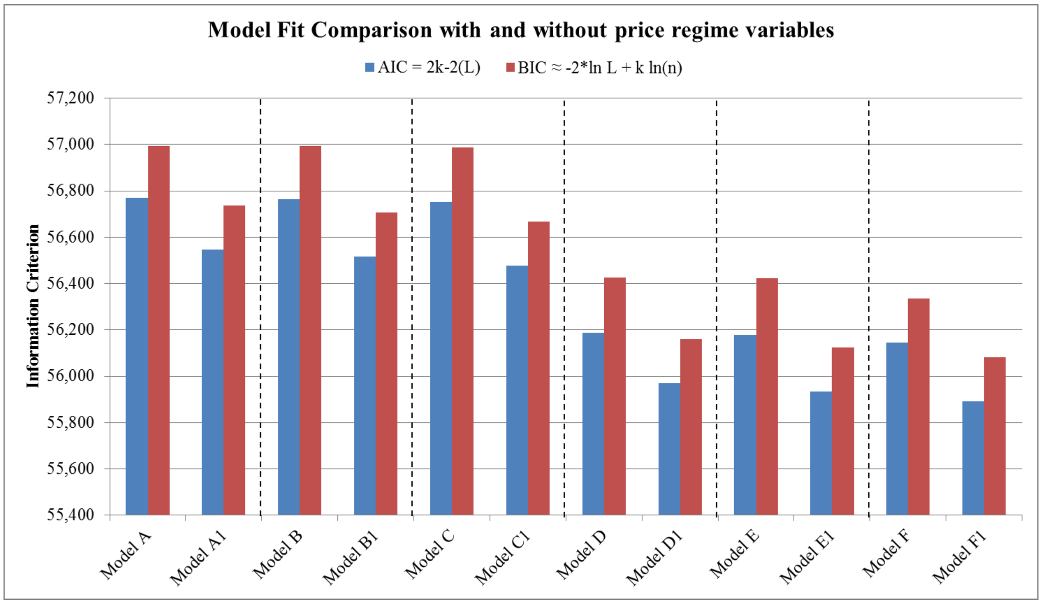
	I	II	III	IV	V	VI	VII	VIII	IX
Dependent variable:	Millet price (I)	Millet price (II)	Millet price	Millet price	Millet price	Millet price	Millet price	Millet price	Millet price
Millet price one lag		0.52***	0.56***		0.51***	0.56***		0.51***	0.56***
		0.034	0.036		0.034	0.036		0.034	0.036
Millet price two lags			-0.12***			-0.13***			-0.13***
			0.03			0.03			0.03
Millet price three lags			0.08***			0.07***			0.07***
			0.019			0.018			0.018
Average	-13.92***	-13.23***	-11.33***	-16.66***	-15.45***	-13.51***	-18.81***	-17.51***	-15.49***
	2.905	2.735	2.402	2.914	2.694	2.436	3.087	2.83	2.538
Lagged average	4.94	5.56	3.54	3.35	3.37	1.03	-0.1	-0.13	-2.53
	6.096	5.839	6.233	6.59	6.224	6.542	7.911	7.486	7.856
Good	-23.33***	-21.44***	-19.20***	-27.42***	-24.83***	-22.61***	-30.63***	-27.95***	-25.62***
	3.402	3.309	3.03	3.532	3.361	3.166	3.675	3.447	3.23
Lagged Good	13.74**	12.98**	10.91*	10.75	10.38	7.93	6.38	5.7	3.45
	6.437	6.172	6.548	6.789	6.562	6.764	8.545	8.139	8.268
Lagged 50 km price buffer	0.62***	0.12***	0.12***	0.54***	0.07*	0.06*	0.54***	0.07**	0.07*
	0.041	0.039	0.039	0.036	0.035	0.037	0.039	0.037	0.039
Lagged ave regime X lagged 50 km buffer	-0.03	-0.03	-0.03	-0.02	-0.04	-0.04	-0.03	-0.05	-0.04
	0.029	0.028	0.028	0.032	0.031	0.033	0.035	0.034	0.036
Lagged good regime X lagged 50 km buffer	-0.10***	-0.08**	-0.08***	-0.11**	-0.08**	-0.08*	-0.11**	-0.09**	-0.09*
	0.032	0.03	0.03	0.047	0.042	0.044	0.049	0.043	0.045
Lagged 200 km price buffer				0.12***	0.09**	0.10**	-0.06	-0.08	-0.07
				0.045	0.042	0.04	0.053	0.05	0.049
Lagged ave regime X lagged 50 km buffer				0.01	0.03	0.03	-0.01	0.01	0.01
				0.036	0.032	0.032	0.069	0.067	0.064
Lagged good regime X lagged 50 km buffer				0.04	0.03	0.03	0	-0.02	-0.01
				0.047	0.042	0.042	0.079	0.073	0.071
Lagged 400 km price buffer							0.20***	0.18***	0.19***
							0.071	0.069	0.067
Lagged ave regime X lagged 50 km buffer							0.05	0.06	0.05
							0.079	0.075	0.072
Lagged good regime X lagged 50 km buffer							0.08	0.09	0.08
							0.093	0.088	0.082
Time effect (period variable)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Marketing season effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Monthly effects (January base)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Estimator	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K	F.E. D-K
Observations	6592	6591	6527	6592	6591	6527	6592	6591	6527
R-squared*	0.857	0.865	0.866	0.858	0.865	0.866	0.859	0.866	0.867
Number of markets	29	29	29	29	29	29	29	29	29

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1. All estimates include monthly and marketing-year fixed-effects. F.E. D-K indicates Driscoll-Kraay standard errors using Stata's xtscc, fe procedure with four lags. All binary variables are relative to the bad regime base. Standard errors below coefficient estimates.

Similar to our first model, we estimate a variety of specifications in order to assess robustness. The first estimates of interest are those for the average and good regime variables which demonstrate the base difference in price levels for average years (13-18 CFA lower) and good years (23 – 30 CFA lower). Moving to the spatial price buffer and the regime interaction variable, we see that market connectedness in average years is negative in sign, but not statistically different than zero in any of the specifications. This suggests the ways in which markets interact is not fundamentally different across average and bad regimes. However, estimates for good regimes largely support the results from above, showing that market connectedness is negative and statistically different from zero when compared to bad price regimes. Again, in some specification (5-6, and 8-9) the magnitude of coefficient is greater than that of the standalone lagged spatial price buffer

Figure 29, below, depicts the comparison of model fit criteria from the base (Models A-F) and a subset of tertiary (Models A1-F1) regime model. Similar to above, in all cases the regime-based model fits the data better than the base model.

Figure 29. Observed tertiary price regime model fit comparison



Source: Author's calculations

The modeling exercise above provides support to our existing hypothesis governing price regimes and market integration: market behavior changes in a statistically meaningful manner across marketing-year regimes in that good marketing years are characterized from bad years by apparent market segmentation. We have also shown that by explicitly modeling price regimes, we can improve the overall fit of a base millet price model. While these findings are beneficial in improving our understanding market performance and how to specify price forecasting models for Niger, they are based on outcomes that have already occurred and statistical properties of the price data. To be policy relevant and useful to food security analysts, we need to leverage information contained within our NDVI data into a forecasting framework that can inform analysts of the type of price regime likely to be encountered and the expected degree of market connectedness. Previous research (Brown, Hinterman & Higgins, 2010) has focused on market price level forecasts through the explicit inclusion of various NDVI variables into a fixed-effect, autoregressive forecasting model. We opt for a two-stage approach in which we first attempt to predict the type of marketing-year price regime using only NDVI and past price information. We then use predictions from our probability model in our regime-augmented price model (from above) to assess the accuracy of our predictions in assessing market connectedness. The purpose of this exercise is to determine how well we can forecast price regimes and to assess how well the predicted regimes can capture market connectedness as estimated above.

Using NDVI to Predict Price Regimes

In order to examine the usefulness of NDVI in predicting price regimes, we estimate a probability model where regimes are categorized as binary outcomes. We collapse our good and average regime variables into a single value which allows us to use NDVI to predict whether or not we are likely to encounter a bad marketing-year price regime.[35] First, we assess how far in advance we can accurately predict the type of regime that will unfold in the months following the growing season (October-September of the following year). Second, we then take our predicted regime value and use it in our model of market integration to assess how well our NDVI-based regimes can predict market connectedness for a given year.

To generate price regime predictions at the market-level we estimate a probit model.[36] Our set of exogenous explanatory variables include NDVI anomalies for May through October, calculated at the market level using a 50 kilometer buffer, as

[35] We considered using an ordered logistic model to predict good, bad and average outcomes, however we were not able to obtain estimates that satisfied the proportional odds assumption and produced reasonable forecasts.
[36] Because of the temporal ordering of our regime data we conducted a Hausman test to determine if we should pool the data or estimate panel-based probability model. The results pointed towards pooling the data. Results are available upon request.

well as average, rescaled NDVI anomalies for the major millet producing zones of Burkina Faso, Mali and Nigeria. To control for localized NDVI shocks encountered during the growing season we include two variables reflecting the number of markets with shocks aggregated to the region-level.[37] Market-level explanatory variables include a market's proximity to the nearest major road, maximum price from the previous year, region-level population, a time variable to capture macro-level changes among millet markets, and aggregated local and national-level NDVI anomalies for non-growing months. Because our primary focus is on generating accurate forecasts of impending price regimes, we estimate four specifications of our model. We also combine each prediction and generate an average, overall prediction for each market. In order to assess the relative fit of each model we compute a pseudo R-squared, we plot the receiver operating characteristics and finally, we generate graphs of our predictions (shown in the appendix) for visual review.[38]

Model Results for Price Regime Predictions

The full set of probit model results are display below in Table 27 - Table 30. All coefficients reported are marginal effects which reflect the change in probability for an infinitesimal change in exogenous, continuous variables. P-values are reported below the coefficient estimates. For each model, we also estimate (but do not report) a base model excluding all NDVI variables. In all cases, models that included NDVI covariates outperformed the base models in terms of receiver operating characteristics

[37] All variables were created as temporal steps, so all variables only include information that was available at a given point in time.
[38] We also calculated link tests (available upon request) to determine how well specified our models were. In some cases, the link test suggested that our dependent variable did not adequately link to our exogenous variables. With time, we plan to do additional research to resolve this model inefficiency.

and pseudo R-squared estimates.

Starting with the first specification we note a few points of interest. First, our coefficient estimates for May, June and July NDVI deviations are positive and generally not statistically different than zero. As we incorporate additional months of NDVI, the coefficient estimates take on the expected sign for the months of August, September and October. The sign on the coefficient estimates for maximum prices from the previous months, population and distance to roads take the expected direction. The negative coefficient on the year variable suggests that with time, the probability of encountering a bad marketing year is declining. This is a positive sign overall as it suggest that markets are improving overtime and not clustering into certain types of regimes.

It is also worth noting that we see the largest drop in the log likelihood (from -231.1 to -151.1) between the specifications including August and September NDVI. In terms of a best fit, the specification that includes the full set of NDVI variables has the lowest log likelihood. This is not surprising as the complete signal representing millet production potential has been fully accounted for in this model. The model diagnostics, presented in Figure 36, depict the story in a visual manner.

Moving to the second specification, which takes into account NDVI from surrounding countries along with additional NDVI covariates reflecting the number of positive and negative shocks at the region level, we see a similar story unfold. NDVI values for May through September are not statistically different than zero. October NDVI takes on the expected sign and is significant. The positive and significance of July NDVI is somewhat puzzling as we would expect positive anomalies to be associated with better than expected millet production. For NDVI shock variable estimates, an increase in the number of positive shocks reduces the probability of entering into a bad marketing-year regime. NDVI anomalies from Nigeria and Mali are inversely related as we would expect. However, NDVI anomalies from Burkina Faso are positively associated with negative regimes.

Table 27. Probability models results for regime predictions (1)

Regime Type	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad
Best NDVI							-0.00007*
							0.062
October						-0.00003	
						0.782	
September					-0.00012	-0.00006	
					0.263	0.642	
August				-0.00016	-0.00001	0.00006	
				0.155	0.957	0.665	
July			0.0001	0.00011	0.00015*	0.00012	
			0.235	0.231	0.085	0.168	
June		0.00061***	0.00054***	0.00038**	0.00024*	0.00030***	
		0.000	0.001	0.016	0.071	0.008	
May	0.00024*	0.00011	0.00014	0.00016	0.00040***	0.00040***	
	0.072	0.433	0.281	0.24	0.001	0	
Dry season NDVI	-0.00010***	-0.00013***	-0.00014***	-0.00008**	-0.00006	-0.00007**	0.00001
	0.001	0.000	0.000	0.031	0.103	0.044	0.546
Year	-0.00108	-0.00114	-0.00153*	-0.00257***	-0.00281***	-0.00108	-0.00114
	0.230	0.205	0.083	0.001	0.000	0.230	0.205
Maximum price previous year	0.00173***	0.00178***	0.00213***	0.00311***	0.00563***	0.00577***	0.00646***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Distance to nearest road	-0.03185	-0.01681	-0.01606	-0.00249	0.08341***	0.08445***	0.05262**
	0.294	0.596	0.608	0.935	0.003	0.001	0.036
Population (logged)	-0.00010***	-0.00013***	-0.00014***	-0.00008**	-0.00006	-0.00007**	0.00001
	0.001	0.000	0.000	0.031	0.103	0.044	0.546
Observations	493	493	493	493	493	493	493
Psuedo-R2	0.083	0.132	0.152	0.217	0.488	0.604	0.555
Log Likelihood	-270.6	-256	-250.2	-231.1	-151.1	-116.8	-131.3

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1. Reporting results are marginal effects reported at the mean value of the corresponding independent variable. P-value reported below coefficient estimate. NDVI variables for neighboring countries have been rescaled.

Regarding the comparison of model fit for Specification 2, the model that includes only May and June NDVI produces a log likelihood of -140.6, which is lower than models that include only May or May-July NDVI. As was the case with the first specification, as we include additional NDVI information into the model, we see a reduction in the computed pseudo R-squared for nearly every specification. The largest jump occurs between July and August. This should come as no surprise as we find a similar result in Chapter 6.

Table 28. Probability models results for regime predictions (2)

Regime Type	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad
Best NDVI							-0.00009**
							0.012
October						-0.00013**	
						0.035	
September					0.00011	0.00009	
					0.274	0.311	
August				-0.00003	-0.00017	-0.00001	
				0.557	0.124	0.94	
July			0	0.00007***	0.00019**	0.00015**	
			0.969	0.007	0.03	0.036	
June		0.00023*	0.0002	-0.00002	-0.00019**	0.00009	
		0.096	0.188	0.740	0.038	0.140	
May	-0.00027	-0.00052***	-0.00013	-0.00009	0.00011	0.00009	
	0.21	0.003	0.501	0.197	0.482	0.429	
Burkina Faso NDVI	0.07227***	0.03395***	0.01561	0.03895***	0.04596***	0.00493	0.01697***
	0.000	0.000	0.194	0.000	0.009	0.257	0.002
Mali NDVI	-0.04948***	-0.02645***	-0.00701	-0.02624***	0.00287	-0.00827**	-0.00891**
	0.000	0.003	0.594	0.000	0.687	0.014	0.05
Nigeria NDVI	-0.05094***	-0.12907***	-0.02459**	-0.00568**	0.00033	-0.00357	-0.00131
	0.000	0.000	0.031	0.020	0.972	0.543	0.89
Region negative shocks	0.06157***	0.01492**	0.01066	-0.00328	-0.00699	-0.0027	-0.00518
	0.000	0.019	0.110	0.111	0.200	0.238	0.145
Regions positive shocks	-0.02317**	-0.02103**	-0.01278	-0.00538***	-0.01610**	-0.01086***	-0.01179**
	0.018	0.015	0.116	0.009	0.017	0.003	0.048
Dry season NDVI	-0.00001	0.00001	-0.00010***	0.00001	-0.00003	-0.00002	0.00001
	0.782	0.668	0.003	0.325	0.243	0.212	0.477
Year	-0.04372***	0.00326	-0.03073***	-0.01363***	-0.00278	-0.01983***	-0.03151***
	0.000	0.633	0.000	0.000	0.761	0.000	0.000
Maximum price previous year	0.00228***	0.00083**	0.00210***	0.00089***	0.00321***	0.00319***	0.00448***
	0.000	0.019	0.000	0.000	0.000	0.000	0.000
Distance to nearest road	-0.00186**	-0.00118*	-0.00158*	-0.00088***	-0.00202***	-0.00188***	-0.00280***
	0.048	0.099	0.058	0.000	0.000	0.000	0.000
Population (logged)	0.02292	0.00805	0.02523	0.02312***	0.06986***	0.06102***	0.08831***
	0.488	0.794	0.472	0.001	0.002	0.000	0.000
Observations	493	493	493	493	493	493	493
Psuedo-R2	0.308	0.523	0.259	0.733	0.708	0.772	0.764
Log Likelihood	-204	-140.6	-218.6	-78.92	-86.02	-67.26	-69.62

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1. Reporting results are marginal effects reported at the mean value of the corresponding independent variable. P-value reported below coefficient estimate. NDVI variables for neighboring countries have been rescaled.

Table 29. Probability models results for regime predictions (3)

Regime Type	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad
Best NDVI							-0.00005*
							0.055
October						-0.00012**	
						0.013	
September					0.00009	0.00006	
					0.322	0.326	
August				0.00001	-0.00015	0.000	
				0.641	0.147	0.98	
July			0.00005	0.00006***	0.00021**	0.00010**	
			0.644	0.007	0.012	0.035	
June		0.00032**	0.00008	0.00001	-0.00018**	0.00007	
		0.02	0.485	0.712	0.03	0.103	
May	0.00006	-0.00043***	-0.00009	-0.00005	0.00008	-0.00002	
	0.731	0.009	0.562	0.243	0.542	0.776	
Country NDVI offseason	-0.00000***	-0.00000*	-0.00001***	0.0000	-0.00000**	-0.00000***	0.000
	0.000	0.094	0.000	0.266	0.045	0.001	0.127
Year	-0.04550***	-0.03932***	0	-0.02315***	0.000	-0.00568*	-0.01
	0.000	0.000	0.73	0.000	0.64	0.07	0.22
Distance to nearest road	-0.00147*	-0.00117	-0.00133*	-0.00075***	-0.00191***	-0.00169***	-0.00259***
	0.071	0.157	0.097	0.000	0.001	0.001	0.000
Population (logged)	0.0055	-0.00218	0.0193	0.01960***	0.07058***	0.05936***	0.08669***
	0.86	0.947	0.562	0.003	0.002	0.000	0.000
Burkina Faso NDVI	0.07786***	0.03498***	-0.00926	0.03456***	0.04934**	0.00661*	0.01366**
	0.001	0.000	0.477	0.000	0.024	0.066	0.015
Mali NDVI	-0.04550***	-0.03932***	0.00499	-0.02315***	0.00399	-0.00568*	-0.00588
	0.000	0.000	0.729	0.000	0.636	0.066	0.221
Nigeria NDVI	-0.03889***	-0.11875***	-0.02661**	-0.00446*	0.00253	-0.00803	-0.00505
	0.000	0.000	0.03	0.051	0.786	0.18	0.62
Region negative shocks	0.02390**	0.00719	-0.01562**	-0.00214	-0.01634**	-0.00517**	-0.00778**
	0.018	0.309	0.015	0.304	0.029	0.043	0.033
Region positive shocks	-0.00853	-0.01203	0.00065	-0.00508***	-0.01377**	-0.01007***	-0.00919
	0.339	0.116	0.917	0.008	0.038	0.006	0.101
Maximum price previous year	0.00141***	0.00056	0.00152***	0.00088***	0.00297***	0.00282***	0.00422***
	0.0000	0.2390	0.0010	0.0000	0.0000	0.0000	0.0000
Observations	493	493	493	493	493	493	493
Psuedo-R2	0.363	0.522	0.362	0.731	0.718	0.786	0.766
Log Likelihood	-187.9	-141.1	-188.1	-79.43	-83.32	-63.15	-69.01

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1. Reporting results are marginal effects reported at the mean value of the corresponding independent variable. P-value reported below coefficient estimate.

Table 30. Probability models results for regime predictions (4)

Regime Type	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad	Good/Bad
Best NDVI							-0.00005
							0.134
October						-0.00013***	
						0.01	
September					0.00005	0.00005	
					0.474	0.423	
August				0.00001	-0.00014	0.000	
				0.63	0.13	0.98	
July			0.00004	0.00006**	0.00020***	0.00011**	
			0.679	0.012	0.002	0.023	
June		0.00024*	0.00008	0.00001	-0.00015**	0.00007	
		0.073	0.487	0.708	0.025	0.102	
May	0.00005	-0.00047***	-0.0001	-0.00005	0.00007	-0.00002	
	0.77	0.008	0.549	0.243	0.484	0.745	
Off season NDVI shock	0.00820*	0.02188***	0.00638	0.00016	-0.01249***	-0.00287	-0.00054
	0.093	0.000	0.214	0.957	0.005	0.143	0.847
Country NDVI offseason	-0.00000***	0.000	-0.00001***	0.000	-0.00000**	-0.00000***	0
	0.006	0.353	0.000	0.317	0.019	0.001	0.126
Year	-0.05134***	-0.00864	-0.04219***	-0.01221***	0.00793	-0.02121***	-0.02990***
	0.000	0.136	0.000	0.000	0.377	0.000	0.000
Distance to nearest road	-0.00161**	-0.00149*	-0.00140*	-0.00074***	-0.00153***	-0.00166***	-0.00260***
	0.049	0.052	0.085	0.000	0.001	0.001	0.000
Population (logged)	-0.005	-0.004	0.014	0.01987***	0.06142***	0.04675***	0.04643***
	0.745	0.788	0.166	0.000	0.003	0.001	0.001
Burkina Faso NDVI	0.07714***	0.03128***	-0.00701	0.03439***	0.05116***	0.00572	0.01354**
	0.000	0.000	0.609	0.000	0.002	0.11	0.015
Mali NDVI	-0.04637***	-0.03724***	0.00309	-0.02302***	0.00435	-0.00515*	-0.00572
	0.000	0.000	0.835	0.000	0.514	0.092	0.238
Nigeria NDVI	-0.04284***	-0.12704***	-0.02470*	-0.00439*	-0.00233	-0.00502	-0.00448
	0.000	0.000	0.054	0.056	0.756	0.402	0.673
Region negative shocks	0.01931*	-0.00948	-0.02035***	-0.00227	-0.0019	-0.00363*	-0.00752**
	0.067	0.216	0.002	0.55	0.719	0.094	0.031
Region positive shocks	-0.00873	-0.00947	0.00136	-0.00507***	-0.01227**	-0.01017***	-0.0092
	0.328	0.194	0.833	0.007	0.04	0.006	0.1
Maximum price previous year	0.00169***	0.00124**	0.00164***	0.00088***	0.00253***	0.00283***	0.00423***
	0.0000	0.0130	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	493	493	493	493	493	493	493
Psuedo-R2	0.368	0.55	0.364	0.731	0.729	0.788	0.766
Log Likelihood	-186.5	-132.7	-187.5	-79.43	-80.03	-62.67	-69

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1. Reporting results are marginal effects reported at the mean value of the corresponding independent variable. P-value reported below coefficient estimate.

Table 29 and Table 30 report two additional specifications with similar results. We see the largest gains, in terms of how well we fit the data, between models that include May-July NDVI and models that include May-August NDVI. In most cases, average NDVI anomalies from surrounding countries are inversely related to bad regime outcomes (the better the production potential the less likely we are to be a bad regime). Also, NDVI shocks, measured at the region-level, appear to have an effect on the type of regime we are likely to encounter. For nearly every specification, as the proportion of positive NDVI shocks increases a market is less likely to fall into a bad regime. Intuitively this makes sense, as more and more markets experience positive production shocks they are more likely to have greater local millet production and fall under a good or average price regime.

Figure 36-39, located in the appendix, summarize the receiver operating characteristics (ROC) for each model, the average, market-wide, year-by-year predictions generated for each model specification, and a summary graph of the combined, average predictions. The ROC graphs suggest that models including more NDVI covariates are better at predicting regime outcomes as indicated by the clustering of lines near the left, upper-axis of the graph. The graphs also demonstrate how incrementally adding NDVI outcomes observed during the growing improves the true positives predicted versus the false positives predicted. Turning to the regime predictions, we can see the general distribution of predictions for each year for each specification. Model 1 appears to have the largest clustering of predictions around 0.50, whereas the remaining models appear to have more clustering near the 0.10-0.00 range and the 0.80-1.00 range. It is somewhat surprising that models 2-4 do not offer variation in terms of predictions for 2006 through 2011. However, in recalling our distribution of regimes, there has not been a bad regime observed since 2004-05. As a note of closing, despite the poor fit of monthly NDVI covariates the general patterns in the model are consistent with what we may expect. Predictions based on May NDVI are generally not that useful, however, as we incorporate additional monthly NDVI into our model, predictions tend to move toward the correct regime quite consistently.

Assessing Market Connectedness using NDVI-based Regime Predictions

With the price regime predictions generated from our probability model above, we now examine how well the predicted regimes capture true levels of market connectedness. In order to conduct this assessment, we take our market integration model (described above in equation 16) and we insert our predicted regime variables for the actual observed regimes and then re-run the model. We then test the sign and significance on the predicted market connectedness coefficient. The null hypothesis is that our predicted regime variable (B_2) is not statistically different than zero, or that market connectedness does not vary by forecasted regime types. Formally, we estimate the following model:

$$P_{it} = \alpha + \beta_1 P_{it-1} + \beta_2 \bar{P}_{jt-1} * \hat{R}_{it-1} + B_3 \hat{R}_{it} + \varphi X'_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (19)$$

We apply similar corrections as above to our standard errors and we estimate dynamic panel models to account for potentially omitted variables. The results for all predictions generated by our probability models are presented below in Table 31-34. We report three types of estimators to determine the robustness of our results under different model assumptions.[39]

[39] We also estimate a linear regression with panel-corrected standard error for comparison. The model is estimated under the assumption of first-order autocorrelation within panels (see Beck & Katz, 2004).

Table 31. Market integration prediction results (1 & 2)

Rolling NDVI Deviations	Predictions from Probability Model 1 May	Jun	Jul	Aug	Sep	Oct	Best	Predictions from Probability Model 2 May	Jun	Jul	Aug	Sep	Oct	Best
Fixed-effects														
Lagged price band 50km	0.68***	0.61***	0.63***	0.65***	0.66***	0.65***	0.65***	0.61***	0.64***	0.62***	0.65***	0.65***	0.65***	0.65***
	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03
Good regime predicted	3.55	-3.62	-5.72	-12.46**	-9.90***	-16.51***	-21.00***	1.5	-3.02	-12.37**	-12.96**	-13.12***	-16.46***	-17.39***
	6.74	6.57	6.5	5.35	2.98	2.39	2.61	4.85	5	4.57	5.58	4.27	2.56	2.92
Lagged good regime predicted	-6.95	-22.11**	-17.10*	-7.52	10.26*	11.57**	12.72**	-19.03**	-7.09	-18.33**	6.48	8.91**	11.04**	9.88*
	10.98	9.39	8.73	7.16	5.7	5.22	5.55	6.94	5.29	7.46	4.12	4.2	5.16	5.14
Lagged good regime predicted X lagged 50km price buffer	-0.06	0.04	0.01	-0.04	-0.08**	-0.07**	-0.08***	0.05	0	0.02	-0.04*	-0.05**	-0.06**	-0.05**
	0.06	0.05	0.05	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.02	0.02	0.03	0.02
Fixed-effects (Driscoll-Kraay)														
Lagged good regime predicted X lagged 50km price buffer	-0.06	0.04	0.01	-0.04	-0.08*	-0.07	-0.08*	0.05	0	0.02	-0.04	-0.05	-0.06*	-0.05*
	0.08	0.07	0.07	0.07	0.05	0.04	0.05	0.06	0.04	0.07	0.03	0.04	0.03	0.03
PCSE with Fixed-effects														
Lagged price band 50km	0.58***	0.51***	0.53***	0.54***	0.53***	0.52***	0.51***	0.49***	0.52***	0.53***	0.52***	0.53***	0.52***	0.52***
	0.07	0.06	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.03	0.03	0.03
Good regime predicted	-0.24	-3.53	-5.92	-10.33	0.05	-8.82*	-14.38***	6.67	0.38	-11.97	-5.18	-3.8	-9.44**	-10.35**
	11.33	8.49	8.53	7.91	5.09	4.52	4.83	7.33	6.83	8.82	5.59	5.03	4.4	4.47
Lagged good regime predicted	-0.4	-18.06	-13.99	-8.08	1.27	1.75	1	-24.44*	-8.95	-13.97	-0.94	0.82	2.67	1.18
	21.46	16.78	16.35	14.54	9.92	9.51	9.92	13.03	10.75	14.36	9.3	9.04	8.56	8.747
Lagged good regime predicted X lagged 50km price buffer	-0.08	0.01	-0.01	-0.06	-0.09**	-0.07*	-0.07*	0.04	-0.02	-0.02	-0.06	-0.07*	-0.07*	-0.06
	0.09	0.07	0.07	0.06	0.04	0.04	0.04	0.05	0.05	0.06	0.04	0.04	0.04	0.04
Lagged dependent variable	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Time effect (period variable)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marketing season effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects (January base)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876
Periods	202	202	202	202	202	202	202	202	202	202	202	202	202	202
Number of markets	29	29	29	29	29	29	29	29	29	29	29	29	29	29

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1; Estimates based on regime predictions from rolling NDVI anomalies created using 50 kilometer buffer. Standard errors below coefficient estimates.

Table 32. Market integration prediction results (3 & 4)

	Predictions from Probability Model 3							Predictions from Probability Model 4						
Rolling NDVI Deviations	May	Jun	Jul	Aug	Sep	Oct	Best	May	Jun	Jul	Aug	Sep	Oct	Best
Fixed-effects														
Lagged price band 50km	0.61***	0.63***	0.62***	0.65***	0.65***	0.65***	0.65***	0.61***	0.64***	0.62***	0.65***	0.65***	0.65***	0.65***
	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03
Good regime predicted	-4.49	0.94	-18.29**	-11.88**	-12.73***	-16.35***	-17.89***	-3.1	2.63	-16.55**	-11.87**	-11.01**	-15.77***	-16.03***
	6.42	5.13	6.85	5.63	4.25	2.19	3.07	5.41	3.55	6.32	5.61	4.79	2.34	2.31
Lagged good regime predicted	-19.78***	-8.27	-16.20***	6.14	7.25*	9.93*	8.99*	-16.80***	-3.54	-15.06**	6.15	6.04	10.13**	9.84*
	6.16	5.26	5.67	4.08	4.02	4.85	5.19	5.67	4.9	5.49	4.08	3.71	4.79	4.82
Lagged good regime predicted X lagged 50km price buffer	0.05	0.01	0.04	-0.04*	-0.04**	-0.05**	-0.05*	0.04	-0.01	0.04	-0.04*	-0.04*	-0.06**	-0.06**
	0.03	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
Fixed-effects (Driscoll-Kraay)														
Lagged good regime predicted X lagged 50km price buffer	0.05	0.01	0.04	-0.04	-0.04	-0.05*	-0.05	0.04	-0.01	0.04	-0.04	-0.04	-0.06*	-0.06*
	0.06	0.05	0.07	0.03	0.04	0.03	0.03	0.06	0.05	0.07	0.03	0.04	0.03	0.03
PCSE with Fixed-effects														
Lagged price band 50km	0.49***	0.52***	0.52***	0.52***	0.53***	0.52***	0.52***	0.50***	0.52***	0.52***	0.52***	0.52***	0.52***	0.52***
	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.03	0.03	0.03
Good regime predicted	2.3	5.17	-12.78	-3.89	-3.25	-9.57**	-10.78**	3.6	8.27	-11.07	-3.87	-1.42	-8.88**	-9.26**
	8.81	7.66	8.82	5.61	5.13	4.36	4.62	8.03	6.34	8.79	5.6	4.98	4.39	4.42
Lagged good regime predicted	-21.90*	-9.66	-14.29	-1.11	-0.47	1.71	0.39	-20.04	-6.2	-13.65	-1.09	-1.39	1.99	1.66
	13.09	10.79	12.65	9.28	9.05	8.54	8.78	12.74	10.26	12.58	9.27	8.92	8.54	8.571
Lagged good regime predicted X lagged 50km price buffer	0.02	-0.02	-0.01	-0.06	-0.06	-0.07*	-0.06	0.02	-0.03	-0.01	-0.06	-0.06	-0.07*	-0.07*
	0.06	0.05	0.06	0.04	0.04	0.04	0.04	0.06	0.05	0.06	0.04	0.04	0.04	0.04
Lagged dependent variable	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Time effect (period variable)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marketing season effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects (January base)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876	5,876
Period	202	202	202	202	202	202	202	202	202	202	202	202	202	202
Number of markets	29	29	29	29	29	29	29	29	29	29	29	29	29	29

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1; Estimates based on regime predictions from rolling NDVI anomalies created using 50 kilometer buffer. Standard errors below coefficient estimates.

Table 33. Market integration prediction results (1A and 2A)

	Predictions from Probability Model 1							Predictions from Probability Model 2						
Rolling NDVI Deviations	May	Jun	Jul	Aug	Sep	Oct	Best	May	Jun	Jul	Aug	Sep	Oct	Best
Fixed-effects														
Lagged millet prices	0.58***	0.58***	0.57***	0.56***	0.56***	0.56***	0.56***	0.58***	0.58***	0.57***	0.58***	0.57***	0.57***	0.57***
	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.03	0.03
Lagged price band 50km	0.10**	0.05	0.06	0.09**	0.11***	0.11***	0.11***	0.06**	0.08***	0.07**	0.10***	0.10***	0.11***	0.11***
	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Good regime predicted	11.78**	2.12	0.63	-4.91	-7.02**	-15.03***	-18.72***	4.32	-2.87	-2.22	-11.28**	-10.67***	-15.42***	-15.56***
	5.46	5.05	4.88	3.89	2.69	2.06	2.62	4.32	3.49	3.48	4.55	3.46	2.27	2.53
Lagged good regime predicted	-15.68*	-25.13***	-21.81***	-13.81**	5.51	7.95**	8.56**	-15.25***	-5.36*	-19.51***	5.56**	7.76***	9.14**	8.44**
	8.41	6.51	6.5	5.72	3.37	3.4	3.67	5.06	2.78	5.2	2.61	2.8	3.44	3.55
Lagged good regime predicted X lagged 50km price buffer	-0.01	0.07*	0.05	0.01	-0.04*	-0.03	-0.03*	0.04	0.01	0.03	-0.02*	-0.03*	-0.03*	-0.02
	0.04	0.04	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.01	0.01	0.02	0.02
Fixed-effects (Driscoll-Kraay)														
Good regime predicted X lagged 50km price buffer	-0.01	0.07	0.05	0.01	-0.04	-0.03	-0.03	0.04	0.01	0.03	-0.02	-0.03	-0.03	-0.02
	0.07	0.06	0.06	0.07	0.05	0.04	0.05	0.06	0.04	0.06	0.03	0.04	0.03	0.03
PCSE with Fixed-effects														
Lagged millet prices	0.55***	0.54***	0.54***	0.53***	0.52***	0.53***	0.52***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Lagged price band 50km	0.12**	0.07	0.08*	0.11**	0.13***	0.12***	0.12***	0.08**	0.10***	0.09**	0.11***	0.12***	0.12***	0.12***
	0.06	0.05	0.05	0.04	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.03
Good regime predicted	9.81	1.36	-0.23	-5.35	-4.93	-13.49***	-17.30***	4.86	-2.08	-3.26	-9.77*	-8.95*	-14.04***	-14.24***
	11.88	8.9	8.9	8.2	5.27	4.7	4.97	7.47	6.53	8.94	5.45	5.03	4.52	4.56
Lagged good regime predicted	-13.02	-23.93	-20.57	-13.21	3.53	6	6.28	-16.35	-6.14	-18.39	3.87	6.01	7.49	6.74
	19.53	15.15	14.8	13.27	9.13	8.81	9.19	12.08	9.98	13.16	8.65	8.36	7.94	8.09
Good regime predicted X lagged 50km price buffer	-0.02	0.06	0.04	0.01	-0.04	-0.03	-0.03	0.04	0	0.03	-0.02	-0.03	-0.03	-0.03
	0.07	0.06	0.06	0.05	0.04	0.04	0.04	0.05	0.04	0.05	0.04	0.03	0.03	0.03
Lagged dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effect (period variable)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marketing season effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects (January base)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period (T)	202	202	202	202	202	202	202	202	202	202	202	202	202	202
Number of markets (N)	29	29	29	29	29	29	29	29	29	29	29	29	29	29

Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1; Estimates based on regime predictions from rolling NDVI anomalies created using 50 kilometer buffer. Standard errors below coefficient estimates.

Table 34. Market integration prediction results (3A and 4A)

	Predictions from Probability Model 3							Predictions from Probability Model 4						
Rolling NDVI Deviations	May	Jun	Jul	Aug	Sep	Oct	Best	May	Jun	Jul	Aug	Sep	Oct	Best
Fixed-effects														
Lagged millet prices	0.58***	0.58***	0.57***	0.58***	0.58***	0.57***	0.57***	0.58***	0.58***	0.58***	0.58***	0.58***	0.57***	0.57***
	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.03	0.03
Lagged price band 50km	0.06**	0.08***	0.07***	0.10***	0.10***	0.11***	0.11***	0.06**	0.08***	0.07***	0.10***	0.10***	0.11***	0.11***
	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03
Good regime predicted	1.76	0.67	-8.75*	-10.28**	-9.74***	-14.95***	-15.45***	1.62	1.87	-7.99*	-10.26**	-8.63**	-14.62***	-14.85***
	4.82	2.71	4.99	4.38	3.49	2.12	2.59	3.97	2.19	4.63	4.36	3.78	2.16	2.19
Lagged good regime predicted	-16.02***	-6.91**	-14.90***	5.39**	6.35**	8.21**	7.50*	-14.19***	-3.81	-14.13***	5.39**	5.40**	8.27**	8.12**
	4.27	2.76	3.96	2.6	2.7	3.27	3.68	4.11	2.73	3.87	2.6	2.54	3.22	3.24
Good regime predicted X lagged 50km price buffer	0.05**	0.02	0.04*	-0.02	-0.02*	-0.02*	-0.02	0.04*	0.01	0.04*	-0.02	-0.02	-0.03*	-0.03*
	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.01
Fixed-effects (Driscoll-Kraay)														
Good regime predicted X lagged 50km price buffer	0.05	0.02	0.04	-0.02	-0.02	-0.02	-0.02	0.04	0.01	0.04	-0.02	-0.02	-0.03	-0.03
	0.06	0.04	0.06	0.03	0.04	0.03	0.03	0.05	0.05	0.06	0.03	0.03	0.03	0.03
PCSE with Fixed-effects														
Lagged millet prices	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***	0.54***
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Lagged price band 50km	0.08**	0.10***	0.09**	0.11***	0.12***	0.12***	0.12***	0.08**	0.10***	0.09**	0.11***	0.11***	0.12***	0.12***
	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.03
Good regime predicted	2.39	1.66	-8.52	-8.75	-8.01	-13.64***	-14.16***	2.42	3.17	-7.65	-8.73	-6.83	-13.26***	-13.51***
	8.3	7.13	8.4	5.45	5.11	4.47	4.67	7.78	6.15	8.36	5.45	4.98	4.5	4.51
Lagged good regime predicted	-16.86	-7.63	-14.93	3.72	4.6	6.57	5.81	-15.17	-4.72	-14.24	3.73	3.66	6.64	6.49
	12.15	10.05	11.76	8.64	8.38	7.91	8.13	11.84	9.55	11.69	8.64	8.26	7.92	7.95
Good regime predicted X lagged 50km price buffer	0.04	0.01	0.04	-0.02	-0.03	-0.03	-0.02	0.04	0	0.04	-0.02	-0.02	-0.03	-0.03
	0.05	0.04	0.05	0.04	0.03	0.03	0.03	0.05	0.04	0.05	0.04	0.03	0.03	0.03
Lagged dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effect (period variable)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marketing season effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly effects (January base)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period (T)	202	202	202	202	202	202	202	202	202	202	202	202	202	202
Number of markets (N)	29	29	29	29	29	29	29	29	29	29	29	29	29	29

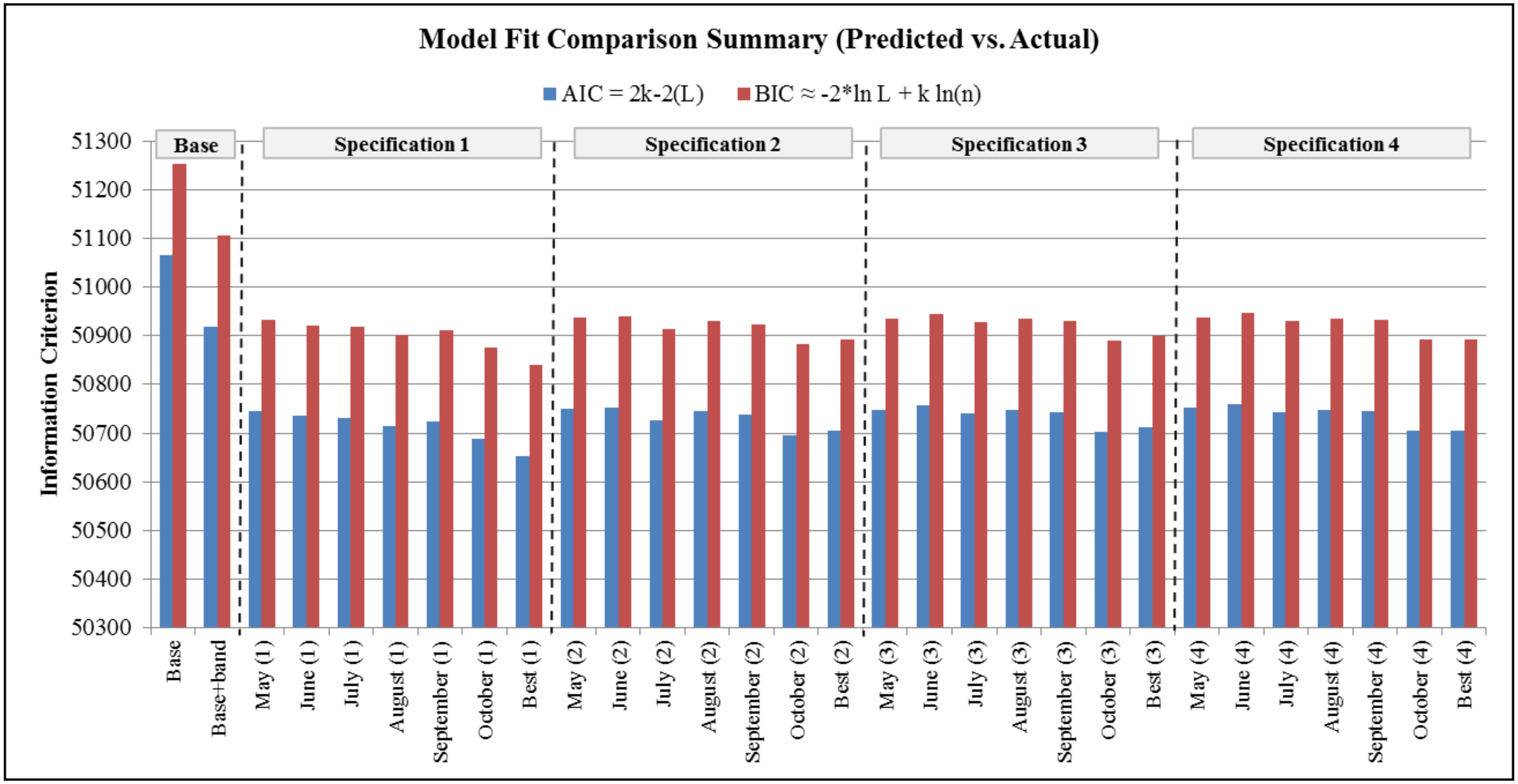
Stars indicate level of significance ***p<0.01, **p<0.05, *p<0.1; Estimates based on regime predictions from rolling NDVI anomalies created using 50 kilometer buffer. Standard errors below coefficient estimates.

We begin our discussion with the results from Table 31 which shows the second stage estimates using the predicted values from the first and second probability model specifications. Directing ones attention to the middle part of the table we first note that the coefficient on the predicted regime variable takes on values larger than our base model. In fact, using predictions from our Best NDVI specification for model 1, we see that our forecast for being in a good regime shifts the price level estimates down by nearly 21 CFA. This is encouraging as our base binary model only produced switch of about 10 CFA. More importantly, our predicted regime variable is able to forecast declining market connectedness as early as September, a result that is robust across all the estimators. Moving to the right hand side of the table, the results are similar. The fixed-effects estimator with robust standard errors does produce a significant result as early as August, but when we correct the standard errors for general forms of spatial dependence the estimated coefficient is not statistically different than zero. Table 32 summarizes the results for the third and fourth probability models for all estimated regimes. The predictions for market connectedness are similar in magnitude, but are only robust across all estimators in October.

Estimation results for our dynamic panel estimators are presented in Table 33 and 34. The predicted regimes, from nearly all probability model specifications, do a good job of capturing the price switch that is associated with good regimes and largely take on the expected sign. The fixed-effects estimator yields coefficient estimates that are significant at the 10 percent level, however, once we correct standard errors for potential spatial correlation the results are not statistically different than zero. Moreover, the magnitude of the coefficient estimates does not approach the magnitude estimated above, thought the sign taken by the coefficients is largely consistent with what expect from above. Overall, it appears the earliest that our NDVI-based prediction models can reasonably predict price regimes and market connectedness is the month of August. This result is consistent with what we found when we considered NDVI and millet production outcomes.

As a final exercise in model comparison, we plot the AIC and BIC for all models estimated above and compare them to our base regime model. Figure 30 depicts the results of this exercise and allows for easy comparison across models. From the figure above it is easy to see that regardless of the specification, our forecasted price regime variable leads to a better fitting model. Although we did not demonstrate it empirically, this fit is likely due to the continuous nature of our prediction variables which take on values bounded by zero and one, instead of simple zero or one. Also, surprisingly, the best fit appears to be the most parsimonious model (Best (1)) which only includes an NDVI variable that captures the best three months of NDVI. While using this composite metric may be one of the ways to generate regime forecasts that fit the data well, it may only be created at the end of the growing season by construction. Future research on the optimal NDVI metric may consider creating an optimal rolling NDVI variable that is updated each month to include only the top months of NDVI within a given window.

Figure 30. NDVI-based regime predictions model fit comparison summary



Source: Author's calcuations

Our analysis from this chapter provides insight in the nature of market connections across marketing-year price regimes. First, the model results indicate that the way in which markets interact in good and bad years is fundamentally different. On average, we found that in in good years market connectedness at local levels is weaker, as measured by the degree of price influence from neighboring markets, than in bad price regimes. This result is somewhat intuitive as good years are likely characterized by sufficient local supplies of millet and other cereals and likely thinner profit margins which reduce the incentives for inter-temporal spatial arbitrage. From a food security perspective, policies that enable households to better (more cheaply) store their excess production can help in smoothing consumption across different types of price regimes. Other policies that look into the international marketing and trading of excess production at the national level may also be beneficial if the policies can help put additional income in the pockets of rural households without affecting national cereal reserve levels. This may be a better alternative if storage facilities are scarce and storage costs expensive.

In the second half of this chapter, we tested whether or not NDVI could be used to forecast the type of price regime observed and how well the predicted regime values could forecast the expected levels of market connectedness. Our probability analysis demonstrated that the NDVI signal between July and August appears to add the most value to prediction models. Stated alternatively, the August NDVI signal appears to contain the most useful information for making forecasts (for production or price regimes) early in the growing season. May, June and July NDVI did not appear to add substantial value and in some cases only introduced additional noise.

Moreover, our NDVI-based regime predictions were able to predict the lower levels of market connectedness associated with good price regimes, on average, as early as August. The results were somewhat consistent across different specifications and estimator and suggest that NDVI-based regime predictions can add value to prediction models, and that the information may be useful in forecasting market behavior. Exploring alternative econometric methods for modeling this phenomenon would help to triangulate our results and may point out existing deficiencies in our current models.

Chapter 9: Discussion of Results, Policy Recommendations, Limitations, and a Future Research Agenda

This study attempts to provide an objective assessment of the utility of NDVI data in analyzing millet market behavior for food security monitoring purposes in Niger. We have considered numerous techniques for analyzing the linkages among NDVI data and millet price outcomes. Our analysis has demonstrated NDVI can add additional economic value to food security assessments when price and production data are incomplete, purposely inaccurate, or measured with noise due to market imperfections. While we may not be able to disentangle or control for all the factors that influence prices, we can disentangle what we observe in the NDVI data. Knowing in advance whether vegetation production conditions have departed from where we expect them to be, on average, can aid us in interpreting price data, forecasting market conditions, and providing policy makers an objective view of production conditions on the ground. This chapter reviews our major findings and offers analytical recommendations that we feel can enhance EWS analysis. This final part of the chapter discusses additional research topics that may be investigated using the satellite data from this study.

Conclusions

In the beginning of this dissertation we discussed some of the limitations of current EWS practices. Linking observed biophysical states to economic outcomes, in particular cereal prices, is not a simple task as it requires one to unpack the myriad factors that affect millet production, consumption and trade, as well as phonological events of the growing season. Moreover, our analysis has demonstrated that the links are likely not linear or static. Thus, conventional forecasting models that rely on fixed lag structures and linear specifications may be expected to underperform when compared to models that attempt to account for non-linearities and dynamic structures. Current, EWS appear to focus more on rainfall outcomes (Brown and Brickley, 2012) and price levels rather than on how far from historical averages these values have departed, and whether or not they are within the range of what may be considered normal. Our analysis of NDVI outcomes from 2003-2005 demonstrated that aggregate NDVI anomalies across all of Niger were far worse than what we would have expected across multiple years. Tracking NDVI shocks across markets may shed light on the extent of likely production shortfalls and may help analysts determine how far from normal current conditions are. Moreover, augmenting this type of analysis with varying NDVI buffer sizes may also help pinpoint the spatial extent of potential vegetation production shocks.

In Chapter 3, we document the numerous advantages that NDVI can bring to the table when food security analysis is conducted with prices, production and remote sensing data. Price and production data are superior to NDVI in the sense that they are observed outcomes and prices, at least, should reflect the current state of information available to the market as well as future expectations. However, as we noted, when markets are incomplete or missing, and institutions weak, the appropriate price signal may not be transmitted down the marketing chain. To help triangulate the signals emerging from these sources, NDVI can be used as tool to assess vegetation production conditions, which we show are correlated with production outcomes (as demonstrated in Chapter 6), it can be used to assess market performance by accounting for the extent and type of NDVI shocks observed in a period of time, and it can be used to generate predictions regarding the type price regime likely to unfold and nature of market connectedness that accompanies that regime. These are just a few ways in which NDVI data can be used and many others likely exist.

Chapter 5 reviews the spatial properties of millet prices and demonstrated that market linkages are dynamic in the sense that the observed patterns of Granger-causality appear to ebb and flow over time. Markets located in productive zones (as measured by the number of pixels falling in the Harvest Choice SPAM map) tended to be the origination of millet price signals. Food security policy makers should continue to monitor these markets and use real-time price dashboards to assess if and how observed Granger-causing relationships are evolving. If a central market is suddenly lagging behind, in terms of price signals, this is likely a sign of trade reversals or even a weakly integrated market. Knowing which outcome is actually occurring has different food security implications. Trade reversals made indicate insufficient purchasing power and the flow of food towards better off areas. Cash transfers may be a more appropriate response than food under these conditions because the transfers will alleviate cash constraints and allow households to command local food whereas food infusions may actually distort market incentives for sellers. On the other hand, balkanized markets will respond less kindly to market directed interventions because excessive spatial transactions costs may not permit the flow of food, regardless of the purchasing power of households. Instead, food infusion activities at the micro-level may be needed to smooth food shortages. Chapter 5 also demonstrated that millet marketing years can be categorized into different types of price regimes, in a distributional sense. Good years are not mirror reflections of bad years, in that prices hit a floor and remain there. On the other hand, bad years are generally characterized by large price anomalies as early as March or April. Prices also do not appear to hit a ceiling and often continue to rise throughout the hungry season when households are most vulnerable. While this outcome seems bleak, market performance, as measured by relative price spreads between markets, does appear to increase during times of excessive environmental shocks. Furthermore, market connectedness, captured by the degree of price influence from neighboring markets, appears to be better during bad years, on average, then during good years.

Chapter 6 explores the statistical and temporal properties of NDVI anomalies. We demonstrate that the peak NDVI signal from the growing season changes from year to year. In the 1990s, above average production outcomes tended to be correlated with NDVI anomalies peaking later in the growing season, with 1994 being the exception. However, from 2000 through 2005, we observed two years with early green-ups, 2003 and 2005. In terms of a forecasting model, the effect of these early and late green-ups is important as they determine when traders start off loading previous years' supplies of millet and forming expectations about the coming harvest. Furthermore, our within growing season NDVI ranking demonstrated that NDVI signals do not follow strict patterns over time. If anything, the trend has been for relative anomalies to reach peaks later and later in the growing season, thus complicating the ability to forecast production and price outcomes months in advance of the actual harvest. We concluded Chapter 6 with an empirical model and demonstrated that the NDVI signal from August appears to be the most important month for forecasting production outcomes. Somewhat surprisingly, NDVI anomalies from September had a negative relationship with production and NDVI from June had a positive effect. We recommend more research on this latter finding to determine if and how June NDVI can be exploited to make production forecasts ahead of time.

Chapters 7 and 8 focus on estimating the impact of extreme NDVI outcomes on market performance and on exploring how market connectedness varies with price regimes. Our analysis of market performance suggests that as the extent of a negative NDVI shock grows, market performance actually improves as reflected by declining price spreads among markets. Additionally, our market connectedness modeling efforts suggest that in years following production shocks, markets tends to be better connected than in than years of abundant production. These two outcomes have direct policy relevance for the food security community as they demonstrate that policies that are inflexible to market structures can produce unwanted results. For example, if millet production is abundant for most, but not all of Niger, policies that rely on the market to deliver food to deficit regions may be inappropriate. As we have shown with our model, market integration, on average, tends to become Balkanized in periods of excessive production and thus interventions that are solely market-based may not accomplish their desired task because the benefits from transporting food to deficit regions may not cover the costs. Direct intervention may be required, despite overall abundance in cereal production.

EWS Recommendations

In the following section, we propose some analytical recommendations for enhancing the use NDVI and millet prices to complement current food security assessment and analysis practices.

Expand the use of NDVI in conjunction with other data sources to contextualize price signals. Food security analysis conducted on markets in the Sahel should be done in conjunction with price, production, and NDVI data, particularly when other data streams are limited or non-existent, such as trade flows, transactions costs, and market barrier costs. Analysts may benefit from comparing current NDVI outcomes to similar historical outcomes to contextualize outcomes. NDVI outcomes may also be analyzed alongside current and historical cereal prices for a given market to determine if the price signal appears to be capturing all the relevant information that is available to the market. If NDVI outcomes have deviated substantially from historical levels, analysts should track the degree of the deviation, benchmarking it to similar deviations in the past, as well as the geospatial extent to determine if the shock is local, regional, or international.[40] This can be done by creating NDVI buffers around markets, testing how deviations vary across different buffer sizes, and comparing how current conditions compare to similar conditions from the past. Moreover, a millet marketing year NDVI balance sheet may help determine how aggregate NDVI measures up to what one would expect. This would enable an analyst to track back-to-back years of NDVI shocks, or consecutive years with below average outcomes that may not be categorized as shocks.

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[40] Sharing these analyses across country-level FEWSNET offices may also be fruitful as each country can compare and contrast their analyst to determine the likely effects in aggregate.

Explore the ranking of NDVI anomalies inter and intra-annually. In chapter 6 we demonstrated that the dynamics of the growing season can be largely summarized by ranking monthly NDVI against past years. From an operational perspective, a ranking system may be easily interpreted and used to triangulate results. Moreover, while NDVI anomalies can tell us how far off vegetation production conditions are from normal, ranking the anomalies against historical values can tell us exactly what the year looks like, or at the least, how the year compares relative to past ones. Ranking NDVI anomalies against each other within the growing season can reveal important information related to the month in which NDVI signal peaks. This information can be useful, particularly in confirming early starts or highlighting years with late green-ups. When these data are cross-referenced with prices, one can start to examine if and how traders and markets are reacting to the early/late green-ups.

Consider the calculation of NDVI shock counts to augment NDVI analysis and to track the number of markets with extreme outcomes. If multiple, extreme NDVI anomalies are recorded within the agricultural marketing year it may be beneficial to track the number of markets with one and/or two standard deviation departures from normal. Similar to the NDVI ranking variable, a shock variable can be easily communicated to policy makers and offers a relatively quick way to quantify geospatially the extent of significant departures from normal. Moreover, these variables can be calculated around key production markets for the entire the Sahel and can start to assess the extent of a potential production shortfall. Future research should consider historic geospatial patterns among NDVI shocks and look into testing whether or not particular patterns are associated with specific region-wide price regimes and/or price levels.

Explore the use of rolling Granger-causality tests to determine if market connections are normal or abnormal. While Granger-causality tests alone do not reveal the theory of change related to the causal nature of a relationship, they do highlight important statistical information contained in data that can help in isolating locations of price discovery or locations that are isolated and slow to react. A rolling-window approach to tracking these relationships can help determine if leading and lagging markets are following expected behavior. Trade flow maps appear to only exist for normal years. Augmenting these with dynamic Granger-causality analysis may aid in the development of maps for bad and good production years. Furthermore, when plotted against time, this type of analysis can reveal important insights as to the nature and degree of changes in the strength of market integration. Deviations from normal, in the sense that markets of price discovery no longer Granger-cause surrounding markets, may indicate reversals in trade flows or simply less integrated or less connected markets. Augmenting Granger-causality analysis with information on trade flows and prices from neighboring countries can help in making this distinction, but these data are difficult to collect in a timely manner, and even when collected they may not reflect the full volume of trade flows occurring in the informal market. Future research should consider exploring how the inclusion of NDVI variables in the estimating equation affects the results. This may reveal how sensitive trade relations are to localized and national production shocks.

Limitations

While this study has produced a reasonable amount of detail on the analytical usefulness of NDVI, it is also important to understand the potential limitations associated with the results. The study and all the results are limited by the spatial density of markets available for analysis as well as data quality and quantity. Important determinants of millet prices, such as trade volumes, transaction and transportation costs, locations and periods of distributional bottlenecks, agricultural policies, and the quality and quantity of land planted with millet do not exist or are only available for short periods of time and may be measured imprecisely. As a result of this, many of our models contain lagged dependent price variables as a way to account for these unobserved determinants of millet prices and price spreads. Not including these determinants would like lead to an omitted variable bias, as most of these factors are time varying. NDVI data also have limitations and the relationship between NDVI and yields (and thus millet availability) is not without error. These errors can be exacerbated if one has not carefully vetted the remotely sensed data and accounted for potentially distorting influences.

From an econometric perspective, lagged dependent variables in fixed-effect models can introduce a host of problems as the lagged term may be correlated with the error term thereby creating endogeneity and biased estimates. With the fixed effects estimator, the bias should become less significant as T increases. However, in our review of the literature we could not find a satisfactory answer for what critical value of T is needed for the bias to be "negligible" enough. Given we have over 200 time periods in our fixed-effect models we anticipate that any remaining bias will be relatively small. Bruno (2005) does provide a method for computing bias-corrected dynamic panel data models and a bootstrapped variance-covariance for small cross-sectional dimensions. We plan to consider these as an additional robustness check in future research.

The spatial nature of our data also means that outcomes are likely correlated across space and time which may also impart a bias on our standard errors through cross-sectionally dependent error terms. While we have attempted to test and correct for the potential bias introduced by lagged dependent variables and cross-sectionally, temporally dependent error terms, we realize that our methods may not be satisfactory to all. The one lesson we have learned from this study is that there is not one preferred method in the literature discussing practical empirical solutions for estimating dynamic panel, cereal price models where the time dimension largely dominates the cross-sectional dimension (T > N). Instrumental variables or generalized method of moments (GMM) methods are potential solutions for addressing the endogeneity introduced by the price lag, however, the literature suggests these may not be a satisfactory solution as it may decrease the efficiency of estimates as T increases (see Kivet, 1995; Judson and Owen, 1999; Beck and Katz, 2009). Explicit spatial panel data models are another way move forward, but the methods tend to be cumbersome and are heavily reliant upon a weighting matrix that is assumed to be fixed overtime and of which the true form is not known. Mutl (2006) provides some guidance on the topic. One could use try different types of weighting matrices and look for convergence in results, however our price regime and Granger-causality analysis suggests that market linkages are dynamic and thus separate weighting matrices may be needed for bad, average and good price regime. Future research may practically address these econometric issues by looking at a suite of estimators and comparing and contrasting the results in order to determine which method is "most" appropriate. However, this exercise would require substantial time and effort and is currently outside of the scope of the current study. We now conclude the dissertation with the presentation of a future research agenda.

Future Research Agenda

Explore the impact of NDVI shocks on regional millet markets. A simple extension of the work done in this study is an expansion of our market performance model to regional millet markets. NDVI data is readily available across the Sahel and a reasonable database of millet prices for Burkina Faso and Mali could be obtained from FEWSNET. Expanding the price dispersion model to a broader geographic area would allow one to estimate the regional impacts of spatially correlated NDVI shocks on market performance. The model would also enable one to determine the sensitivity our initial results to determine if they are limited to only markets in Niger, or if there is a larger, regional shift in overall market performance during times of abnormal NDVI outcomes.

Analyze the relationship between NDVI and other cereal and livestock markets. A natural extension of the work conducted above is to consider how NDVI outcomes commove with prices for other primary agricultural crops and livestock prices in Niger and the Sahel in general. Understanding additional patterns of market performance and connectedness across Niger and the region would afford food security analysts a more comprehensive picture into how future NDVI shocks may ripple throughout markets in the region. Harvest Choice's SPAM maps are available for a wide range of crops and are continually updated with improved data sources. Integrating these into similar models as the ones developed above would help in creating a dashboard of overall food market performance and connectedness across multiple dimensions. Moreover, incorporating an analysis on livestock prices and estimating the effects of changing vegetation production conditions on fodder shortages could deliver insights into how policies may smooth out market fluctuations, and reveal additional insight into historical and geospatial patterns not currently known.

Investigate the relationship between micro-level satellite data and households outcomes. Enhancements in satellite and sensor technology have increased the spatial resolution of available data.[41] An interesting research path forward is to consider the micro analysis of NDVI shocks on household well-being indicators (production, consumption, health, etc.). The World Bank Living Standards Measurement Survey of 2011 and the 2014 follow-up will enable panel analysis at the household level.[42] Moreover, because each household is georeferenced in the survey, outcomes could be matched to local NDVI outcomes. The panel nature of the dataset would help control for time invariant unobservable factors that could influence outcomes of interest. Using retrospective NDVI data would enable one to investigate into how numerous shocks in vegetation production conditions affect household outcomes and/or well-being at later points in time. This line of research has promise

[41] http://modis.gsfc.nasa.gov/data/

[42] http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,,contentMDK:23331219~menuPK:4196952~pagePK:64168445~piPK:64168309~theSitePK:3358997~isCURL:Y,00.html

along the health dimensions, particularly in looking at the impact of extensive and repeated environmental shocks on children's health outcomes. The 2005 food security crises in Niger resulted in many malnourished children, many of which were likely unobserved or uncounted due to isolation, poor infrastructure, or other limiting factors. Combining household level data with historical and current NDVI outcomes may help researchers better understand the long-term influence of such types of shocks.

Examine the impact of NDVI information on market performance. Our analysis of price volatility indicated that uncertainty in millet prices tended to be the greatest in August and September. While the introduction and rapid expansion in the use of cell phones has likely improved information flows during this period, uncertainty (excessive noise) may still remain regarding the quality and quantity of millet that is expected to arrive at market. If NDVI data does contain information that is not currently available to the market, it is plausible that one could test for this by introducing NDVI summaries to farmers, consumers, and traders in randomly selected markets. Each randomly selected market could be allocated a different packet of NDVI information or no information at all and then one could plausibly use the methods of experimental design to determine if the information packet had any effect on price spreads and/or price levels. Varying types of NDVI summaries from local, regional, and international zones could be introduced into the experiment to determine which information source has the largest effect, if any effect is detected.

Use NDVI to assess fundraising activities in the Sahel. A final line of research steps away from markets and production and into the realm of using NDVI to test the objectiveness of government and/or charity press releases. O Grada (2007 citing Iriye 2002) notes that independent monitoring of NGO activities is important because the increasing dependence of NGOs on public funding may tempt them into exaggerating the risks of a crisis. The same line of thinking may apply to official government press releases which may tend to downplay the risk of a crisis to avoid negative press. Building and analyzing a historical database of agricultural or environmental focused press releases alongside NDVI data could provide insights into whether or not the rhetoric of a document matches the remotely sensed vegetation production conditions recorded over a similar period of time. Historical millet prices could also be used to demonstrate which NGOs tend to exacerbate price outcomes by comparing them with prior years rather than years which look the same from a production perspective. To assess objectively whether or not NGOs or governments were exaggerating the risks or extent of a crisis, NDVI and price data could be analyzed alongside official releases to determine if language is justified or exaggerated. At the government level, these data sources could be used to determine how accurately (or inaccurately) official information reflects actual conditions on the ground.

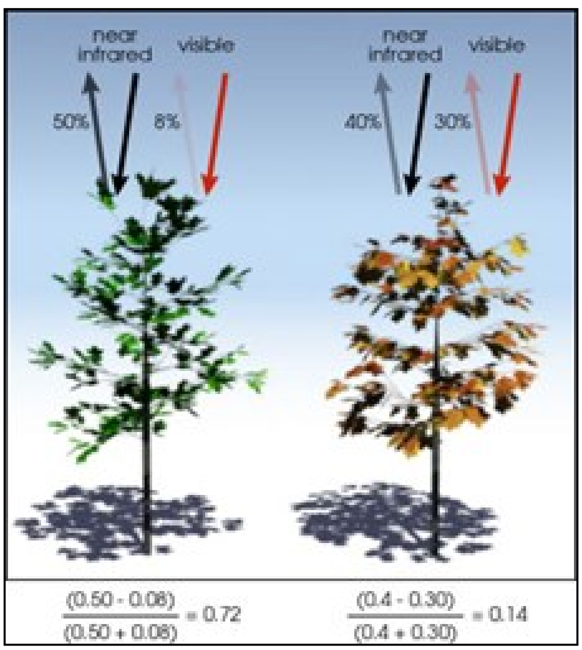
Appendices

The following pages contain additional figures and graphs on the data used in the analysis. Some of these figures and graphs are discussed in the main text, some are not. They are included to provide a complete picture into the nature of the data used in the analysis.

Normalized Difference Vegetation Index

According to NASA (2009), NDVI can be calculated by measuring the visible and near-infrared light reflected by vegetation. Healthy vegetation, shown on the left in the figure below, absorbs most of the visible light that it comes in contact with it. On the other hand, a large portion of the near-infrared light that reaches the plant is reflected. For unhealthy vegetation the process is reversed. Less visible light is absorbed, and more near-infrared light is reflected yielding a lower NDVI. Bare soil and rock will reflect about the same levels of near-infrared and red thus resulting in NDVI values near zero, whereas clouds, water and snow yield negative NDVI values.[43]

Figure 31: Visual Representation of NDVI



Source: NASA

NOAA's Advanced Very High Resolution Radiometer (AVHRR) has been measuring and mapping the density of green vegetation over the Earth. The actual

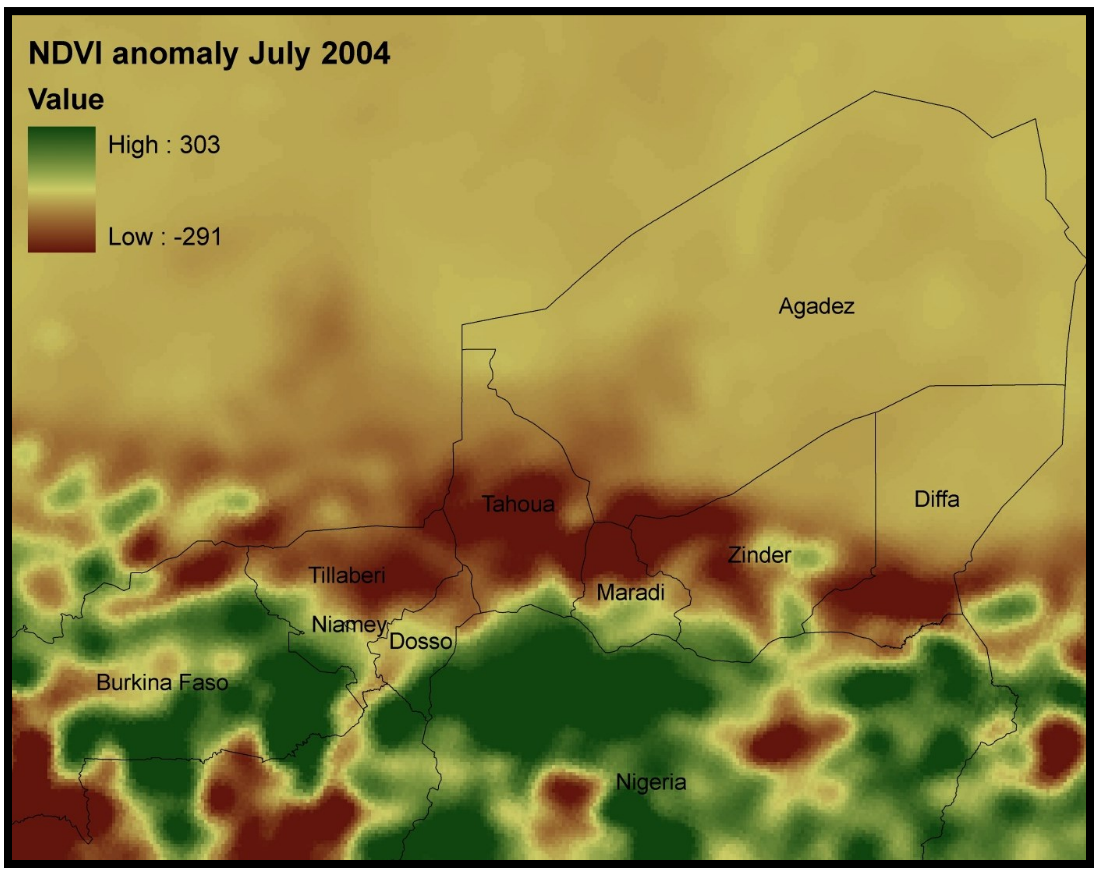
[43] http://adde.itc.nl/idv/documentation/docs/workshop/dsa/thematic/psn/veg_indices_ndvi.html

index part of NDVI is created by applying the following formula to process AVHRR data:

$$NDVI = \frac{Near\ infrared\ light - Visible\ light}{Near\ infrared\ light + Visible\ light}$$

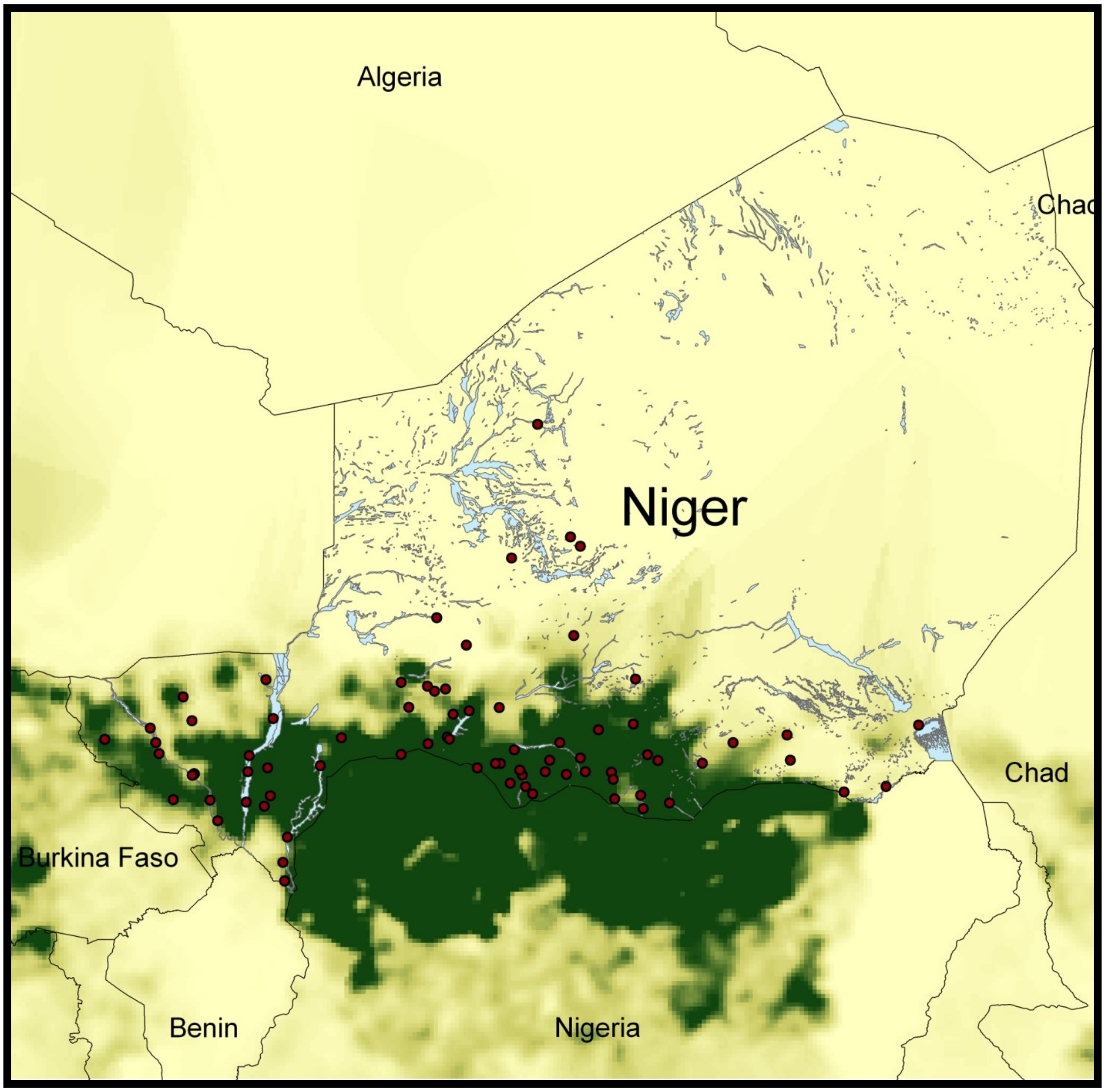
Calculations will always result in a number that ranges from minus (-1) to plus (+1). When the index is zero this indicates no vegetation. A reading near one indicates the highest possible density of green leaves.

Figure 32. Example of interpolated NDVI anomalies



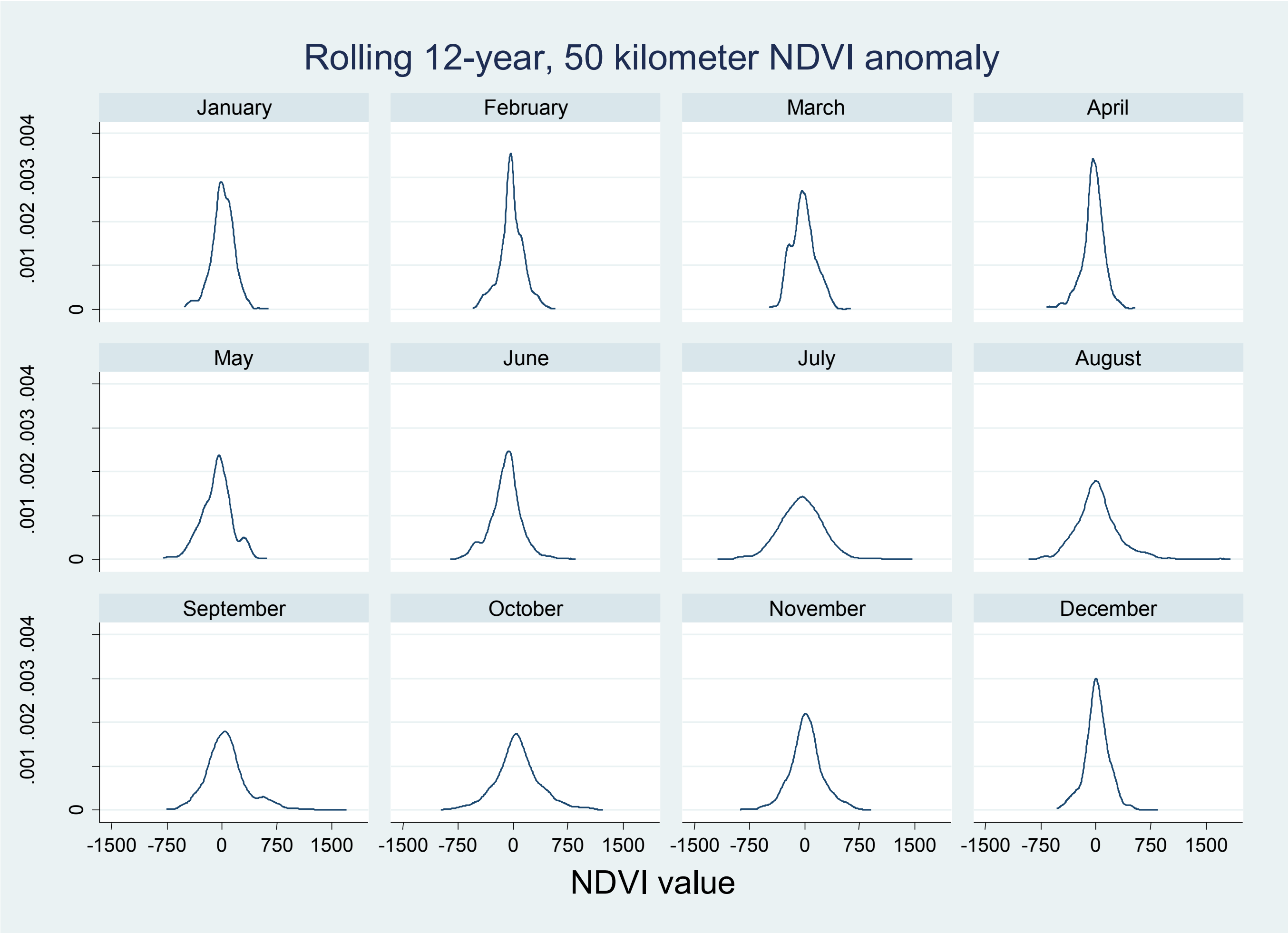
Source: Author's calculations

Figure 33. SPAM overlay of physical area planted



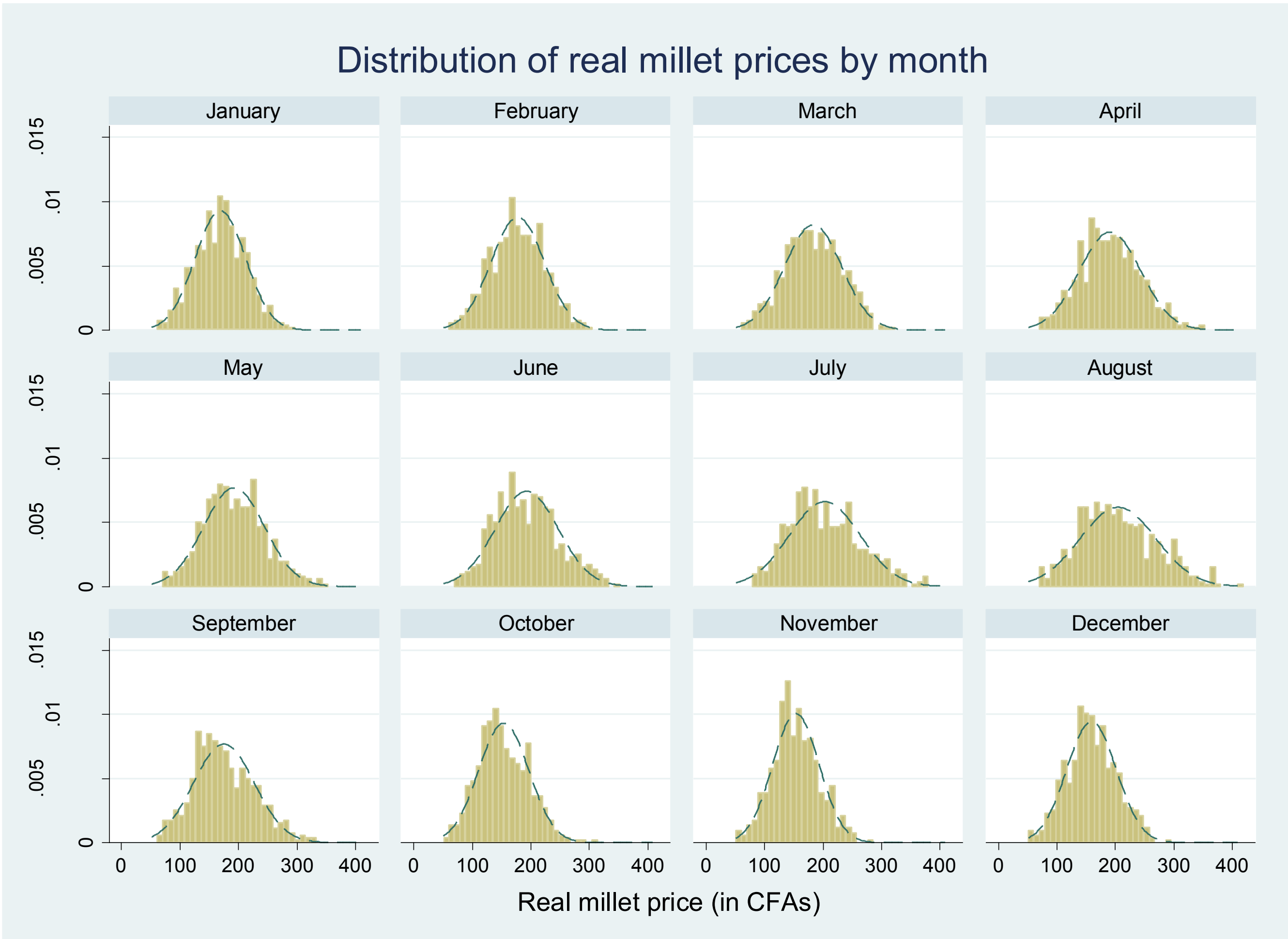
Source: Author's calculations

Figure 34. Distributions of NDVI anomalies



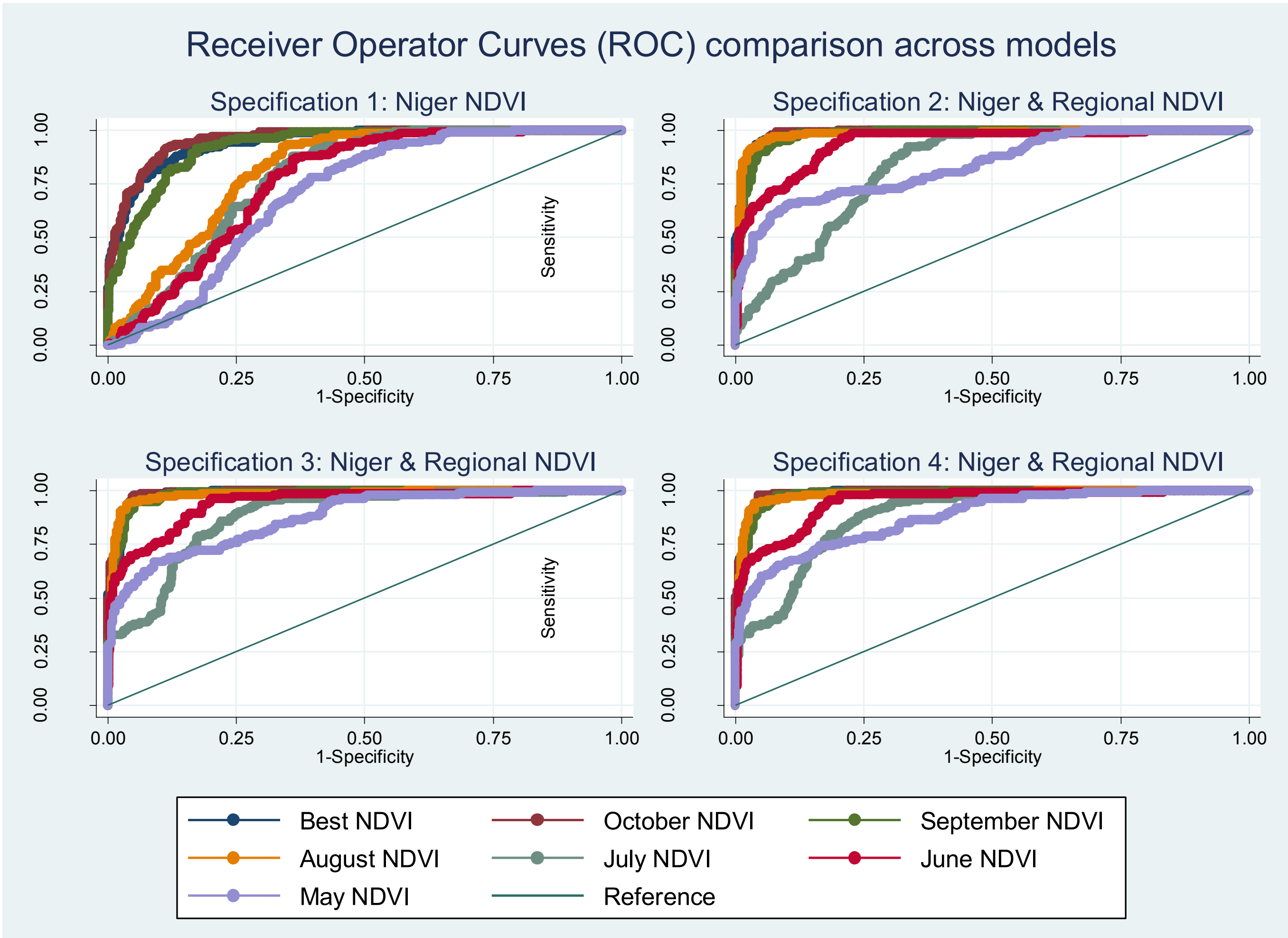
Source: Author's calculations.

Figure 35. Distributions of real millet prices



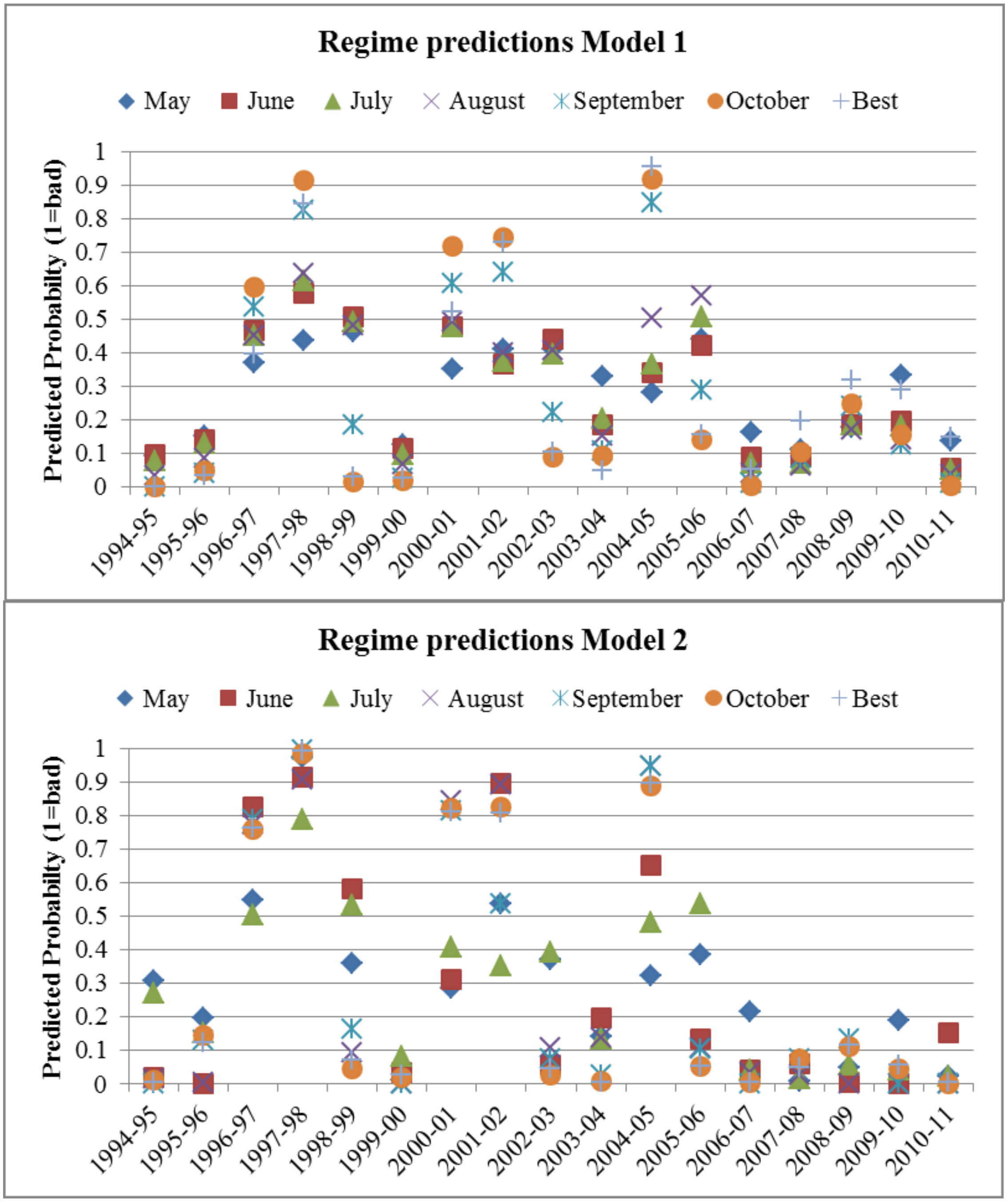
Source: Author's calculations.

Figure 36. Comparison of receiver operating curves for probit specifications 1-4



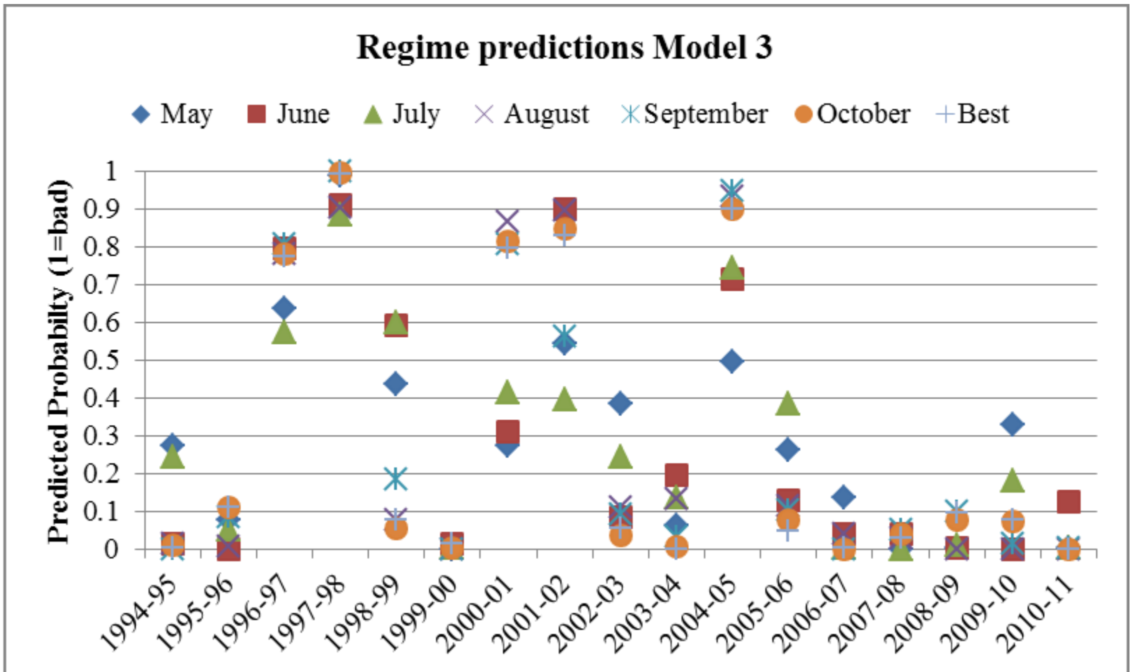
Source: Author's calculations

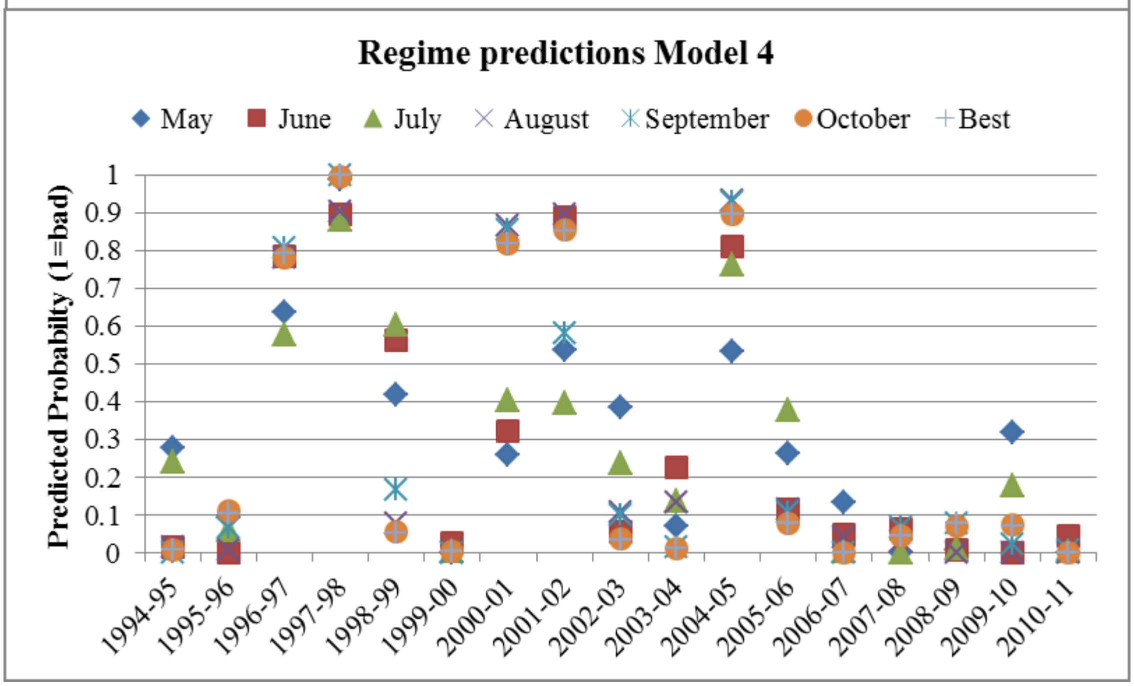
Figure 37. Probit specification 1-2 predictions



Source: Author’s calculations

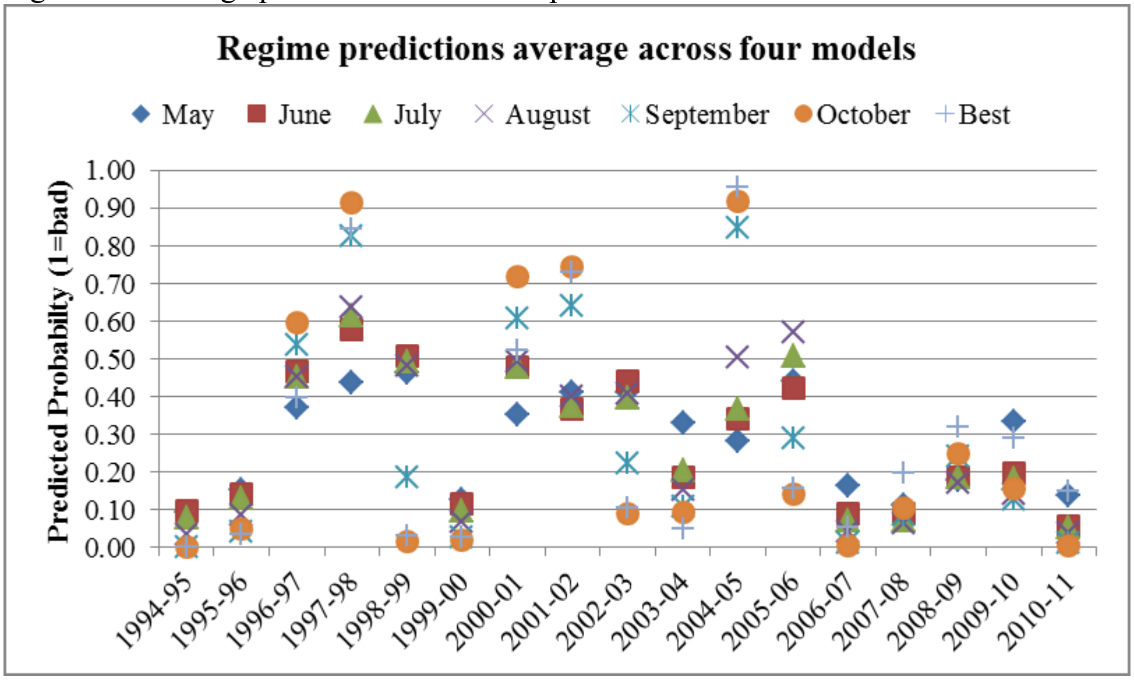
Figure 38. Probit specifications 3-4 predictions





Source: Author's calculations

Figure 39. Average predictions across all specifications



Source: Author's calculations

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EDUCATION

Ph.D. in Agricultural and Resource Economics, University of Maryland *2013*
Dissertation: *Analyzing Millet Price Regimes and Market Performance in Niger with Remote Sensing Data*
Fields: Development Economics, Resource Economics
Awards: 2007 Rhona Lantin Award for Best First Year Paper

Master of Science in Agricultural and Resource Economics, University of Maryland *2010*

Master of Arts in International Development, American University (*with Distinction*) *2006*
Thesis: PROCAMPO Impact Evaluation
Awards: Graduate Award for Combined Academic Excellence and Service
Presidential Management Fellow (PMF) Finalist 2005
Boren Graduate Fellowship 2005-2006

Bachelor of Science in International Business, University of Nebraska (*with Distinction*) *2000*
Bachelor of Arts in French, University of Nebraska
Minors: Math & Economics

PROFESSIONAL EXPERIENCE

USIAD Office of Science and Technology GeoCenter, *Washington, DC* *Present*
Senior GIS Analyst (Oakstream Systems, LLC)

- Build, manage, and publish geo-statistical databases and provide geo-statistical analysis and data visualization products to support agency-wide programs

Summit Consulting, LLC, *Washington, DC* *2011 – 2013*
Senior Consultant, Quantitative Program Evaluation Practice

- Engagement lead for US Department of Labor's (DOL) Office of Chief Evaluation portfolio, including evaluation and econometric review of Agency papers and reports, statistical review of Paperwork Reduction Act (PRA) information collection submissions, ad-hoc statistical analysis, and all business development related activities
- Developed three new business contract awards with DOL CEO worth over $1.4 million
- Managed day-to-day aspects of DOL Wage and Hour Division's National Evaluation, including technical guidance and briefings on the design, implementation, and statistical analysis of the study, and supervision of project staff
- Coordinated projects with teaming partners and academic consultants by organizing meetings, managing technical deliverables, and ensuring timely delivery of monthly reports, invoices and other project deliverables
- Developed data mining algorithm to evaluate the effectiveness of DOL computer targeting queries on pension data
- Created, edited and assisted in delivery of statistical sampling and power analysis training courses for DOL staff
- Produced detailed sampling maps from hotel database using ArcGIS for DOL senior officials

The World Bank, *Washington, DC* *2008 – 2011*
Economic Consultant to Climate Change Team

- Created, developed and designed e-learning module on the economics of adaptation to climate change for Bank staff
- Co-authored synthesis article for *Climate Policy* on the Economics of Adaptation to Climate Change (EACC) Study
- Analyzed Bank projects and refined existing methodology measuring mitigation and adaptation co-benefits
- Assisted in the development of economic models used to estimate adaptation costs for climate change study

- Analyzed existing adaptation and mitigation literature and authored background reports for consultation draft
- Created database of disaster expenditures for economics of adaptation to extreme weather events study

Inter-American Development Bank (IDB), *Washington, DC* *2009 – 2011*

Economic Consultant to Office of Strategic Planning and Development Effectiveness

- Co-authored technical report on indicators of effectiveness for evaluating mitigation and adaptation projects
- Authored technical papers on effectiveness of Bank interventions in climate change, energy, natural resource management, and transportation sectors for 2010 Development Effectiveness Overview
- Reviewed IDB project components for best-practices as highlighted by impact evaluation literature and provided suggestions to improve interventions or sectors lacking sufficient impact evaluation measures

Centre for Development and Population Activities (CEDPA), *Washington, DC* *2009*

Monitoring and Evaluation Consultant

- Authored monitoring and evaluation report for "The Global Women in Management Training" program
- Reviewed individual questionnaire responses and synthesized summaries from 6-month follow-on surveys to determine qualitative and quantitative impact of six training sessions

International Food Policy Research Institute (IFPRI), *Washington, DC* *2007*

Economic Consultant

- Co-authored manuscript analyzing the impact of Chilean water user associations on agricultural productivity for IFPRI's "Integrating Governance and Modeling" project
- Programmed Stata do files to conduct regression analysis on household data and output results to summary tables

Food and Agriculture Organization of the United Nations (FAO), *Washington, DC* *2006 – 2007*

Economic Consultant to Agricultural Development Economics Division

- Co-authored *Journal of Agricultural Economics* article analyzing the relationship between rural development patterns and income composition for FAO's "Incorporating Rural Nonfarm Activities into Rural Development Policy and Poverty Reduction Strategies"

ACADEMIC PAPERS

"Listening while Evaluating: Examining the Benefit of an NGO Program using Season Extenders (greenhouses) in Bosnia-Herzegovina," with K. Leonard and J. Hanson, *Journal of Development Effectiveness*, vol. 5(1):116-136, 2013

"Regional Price Indices for Improved Identification of Food Insecurity," with M.E. Brown, F. Tondel, J.A. Thorne, B.F. Mann, K. Leonard, B. Stabler and G. Eilerts, *Global Environmental Change*, vol. 22: 784-794, 2012

"Estimating Costs of Adaptation to Climate Change," with U. Narain and S. Margulis, *Climate Policy*, 11(3):1001-1019, 2011

"Impact of El Niño on Staple Food Prices in East and Southern Africa," with F. Tondel, Working Paper, Agricultural and Applied Economics Association (AAEA) 2011 Annual Meeting, July 2011

"Patterns of Rural Development: A Cross Country Comparison Using Microeconomic Data," with P. Winters, G. Carletto, B. Davis, K. Stamoulis and A. Zezza, *Journal of Agricultural Economics*, vol. 61(3): 628-651, 2010

"Idle Chatter or Learning? Evidence from Rural Tanzania of Social Learning about Clinicians and the Health System," with K. Leonard and S. Adleman, *Social Science & Medicine,* vol. 69(2): 183-190, 2009

"The Effect of Rainfall Variability on Large Ruminant Holdings in Rural India," AREC Working Paper, June 2009

BOOK CHAPTERS

Estimating costs of adaptation to climate change. In E. Haites (Ed.) International Climate Finance. Routledge, March 2013

Commentary on the Effect of Public and Private Quality Information on Consumer Choice in Health Care Markets (with K. Leonard). In L. Ramaman and M. K. Macauley (Eds.) The Value of Information: Methodological Frontiers and New Applications in Environment and Health. Springer, 2012

POLICY PAPERS & OTHER PUBLICATIONS

"Indicators to Assess the Effectiveness of Climate Change Projects," with A.M. Linares, N. McCarthy and P. Winters, Inter-American Development Bank, Office of Strategic Planning and Development Effectiveness (SPD) Working Paper 1202, May 2012

"Economics of Adaptation to Climate Change – Ecosystem Services," with G.M. Lange, S. Dasgupta, T. Thomas, S. Murray, B. Blankespoor and K. Sander, Discussion Paper Number 7, The World Bank, August 2010

"Impact of Water User Associations on Agricultural Production in Chile," with N. McCarthy, IFPRI Paper 892, August 2009

"A Profile of the Rural Poor," with A. Valdes, W. Foster, G. Anriquez, C. Azzarri, K. Covarrubias, B. Davis, S. DiGuiseppe, T. Hertz, A. Paula de la O., E. Quiñones, K. Stamoulis, P. Winters, A. and Zezza, Background Paper for International Fund for Agricultural Development Rural Poverty Report, 2009

PRESENTATIONS & INVITATIONS

"Using Satellite-Based Remote Sensing Data to Assess Millet Price Regimes and Market Performance in Niger," Selected Paper Session Presentation at AAEA Annual Meeting, Seattle, WA, August 2012

"Impact of El Niño on Staple Food Prices in East and Southern Africa," Selected Paper Session Presentation with F. Tondel at the AAEA Annual Meeting, Pittsburgh, PA, July 2011

"Cereal Price Forecasting in West Africa Using NASA Satellite Remote Sensing Data," Poster presentation at the University of Maryland, College of Agriculture and Natural Resources' Open House, Ellicott City, MD, October 2010

"Relationship between NDVI and Millet Prices in West Africa," Presentation at the USGS-FEWSNET Science Meeting, National Oceanic and Atmospheric Administration (NOAA) Earth System Research Laboratory, Boulder, CO, August 2010

Invitation to participate in review of Development Effectiveness Overview by the Inter-American Development Bank, March 2010

GRANTS & FELLOWSHIPS

NASA Grant (2009-2011), "Cereal Price Forecasting in West Africa using NASA Satellite Remote Sensing," College Park, MD ($30,000)

David L. Boren Graduate Fellowship: National Security Education Program, US Department of Defense (2005-2006)

"Youth Unemployment and Political Activism," Brčko, Bosnia and Herzegovina ($19,600)

OTHER SKILLS

Software: ArcInfo (ArcMap, ArcCatalog, AcrInfo), G*Power, MATLAB, Optimal Design**,** Python (basic), R, SPSS, Stata, StatTransfer
Languages: French, Bosnian-Croatian-Serbian (BCS)
Field Experience: Bosnia and Herzegovina, Burkina Faso, Croatia, India, Mali, Mauritania, Niger, Serbia