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Essays on Agricultural Trade in Sub-Saharan Africa

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Essays on Agricultural Trade in Sub-Saharan Africa

By

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Abstract

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This dissertation consists of two essays on agricultural trade in sub-Saharan Africa. The 42 countries of continental sub-Saharan Africa include 21 of the 24 poorest countries in the world. Unlike industrialized countries where structural transformation and income growth have led to declines in the share of agriculture in overall output and consumption, nearly two-thirds of the labor force in sub-Saharan Africa still works in agriculture and nearly half of consumer expenditure is on food. Agricultural products are produced by tens of millions of farmers and consumed by hundreds of millions of consumers across Africa. In this dissertation, I show that the costs of trade between producers and consumers in different locations are very high, I explore the consequences of these high trade costs, and I evaluate the effects of a type of trade policy that has been used to insulate markets in particular countries from high and volatile prices elsewhere. My findings can be used to improve the design and understand the impact of infrastructure investment, trade liberalization, agricultural technology adoption, and price stabilization initiatives in Africa and elsewhere in the developing world.

In the first chapter, I estimate and solve a dynamic model of agricultural storage and trade in sub-Saharan Africa using a new intra-national dataset of monthly prices and production of the 6 major staple grains from 2003 to 2013 and a new approach to identify cost parameters when trade and storage are unobserved. The model includes monthly storage in each of 230 large hub markets in all 42 countries of continental sub-Saharan Africa, monthly trade between them, as well as monthly trade with the world market through 30 ports. I find median intra-national trade costs over 5 times higher than elsewhere in the world along with significant extra costs for trade across borders and with the world market. I then simulate a counterfactual in which trade costs for staple grains are lowered to match an international benchmark. Lowering trade costs results in a 46% drop in the average food price index, a 42% loss of net agricultural revenues, and a welfare gain equivalent to 2.2% of GDP. I show that 86% of this welfare gain can be achieved by lowering trade costs through ports and along key links representing just 18% of the trade network, supporting a corridor-based approach for infrastructure investment and trade policy. In an extension, I find that the effects of

agricultural technology adoption depend crucially on trade costs, with technology adoption increasing farmer incomes only when trade costs are low. Compared to my dynamic monthly model with storage, a static annual model of agricultural trade underestimates trade costs by 23% and welfare effects by 33% by failing to correctly identify *when* trade occurs.

In the second chapter, I investigate the empirical effects of temporary export restrictions, which have been widely used by many countries in sub-Saharan Africa and elsewhere in recent years in an attempt to stabilize domestic prices of staple grains. I use monthly, market-level price data from a 10-year period during which 13 short-term export bans on maize were implemented by 5 countries in East and Southern Africa. I find no statistically significant effect of export bans on the price gaps between pairs of affected cross-border markets. My results for price gaps match those from a simulation of the model developed in the first chapter in which export bans are not implemented. However, prices and price volatility in the implementing country are significantly higher during export ban periods in the data than in the model simulation with no bans. Export bans in the region are imperfectly enforced, divert trade into the informal sector, and appear to destabilize domestic markets rather than stabilizing them.

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Chapter 1

High Trade Costs and Their Consequences: An Estimated Dynamic Model of African Agricultural Storage and Trade

1.1 Introduction

The 42 countries of continental sub-Saharan Africa have a combined population of 960 million people. Despite recent economic growth, these countries have a GDP per capita of just 3.71 USD per day and include 21 of the 24 countries worldwide with a GDP per capita less than 2 USD per day. Agriculture is the dominant sector in most African economies: 64% of the labor force in sub-Saharan Africa works in agriculture and 44% of consumer expenditure is on food, with even higher numbers for the poorest countries. Although there are large areas of land well-suited to agricultural production in sub-Saharan Africa, productivity in African agriculture is extremely low with output per hectare 5 times lower and output per worker 78 times lower than in North America, facts which (together with the large share of the labor force in agriculture) can explain most of the income differences between sub-Saharan Africa and the rest of the world (Caselli 2005, Restuccia et al 2008, Vollrath 2009).

One of the most striking facts that emerges from data on the African agricultural sector is that the prices of agricultural products vary tremendously across space. The left panel of figure 1.1 shows monthly maize prices from four large hub markets in East Africa on a 2000 kilometer south-north axis from Songea — a maize surplus area in southern Tanzania — to Mandera — a maize deficit area in northern Kenya. The right panel shows equivalent maize prices from three markets in the US on a 2000 kilometer north-south axis from inland surplus area Minneapolis to the major export ports near New Orleans. By December 2011, maize prices in Mandera had exceeded 0.85 USD/kg during the height of the Horn of Africa famine — the first UN-declared famine in 30 years. Meanwhile, maize prices in New Orleans were 0.25 USD/kg and maize prices in Songea were a mere 0.15 USD/kg.

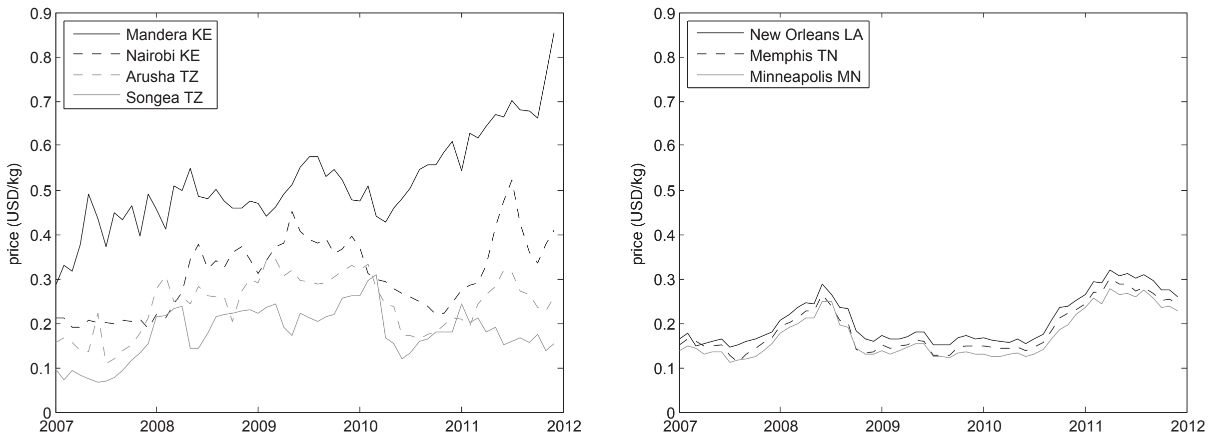

Figure 1.1: Monthly Maize Prices in East Africa (left) and the US (right), January 2007 – December 2011. Sources: WFP VAM, USAID FEWS NET, USDA Feed Grains Database.

Empirical evidence from African agricultural markets suggests that traders in large hub markets like those in figure 1.1 behave competitively, facing low four-firm concentration ratios and not deviating detectably from marginal cost pricing (Aker 2010, Osborne 2005). The large price gaps between markets within African countries, between African countries, and between Africa and the world market must therefore be reflective of large trade costs — the total costs involved in getting a product from a producer or trader in one location to a trader or consumer in another. There are several reasons why one might expect *ex ante* that trade costs in Africa are higher than elsewhere in the world, including poor infrastructure, lots of borders with formal and informal tariffs and delays, vast interior areas far from ports including 16 countries that are completely landlocked, high fuel costs, etc. Several recent studies have provided evidence that freight rates and the distance-dependent component of total trade costs are two to five times higher in particular African countries than elsewhere in the world (Taravaninthorn and Raballand 2009, Atkin and Donaldson 2015).

Given the importance of agricultural production and consumption in Africa, high trade costs and the large spatial price gaps they cause have significant consequences. In surplus regions like Songea, trade costs confine African farmers to local markets with low prices and inelastic demand, limiting their incentives for productivity-enhancing technology adoption. In deficit regions like Mandera, trade costs mean that African consumers face high food prices that fluctuate with volatile local harvests, leading to regular food security crises. How big are trade costs in the agricultural sector in Africa? What would be the gains from lowering them to match levels in other parts of the world? What is the most efficient way to achieve these gains? And how do trade costs alter the potential effects of productivity-enhancing technology adoption? This chapter addresses these questions by building and estimating a dynamic model of African agricultural storage and trade.

I start by assembling a new intra-national dataset including ten years of monthly price and production data for the 6 major staple cereal grains in 230 regional markets covering all 42 countries of continental sub-Saharan Africa. While many previous studies have made use of spatial data on grain prices from individual countries or regions within sub-Saharan Africa[1], I am the first to compile and use monthly intra-national grain price data from all countries in the entire sub-continent. I combine these price data with GIS grid cell level production data, which I allocate to individual markets using a market catchment methodology based on minimum travel time (Pozzi and Robinson 2008).

With data in hand, I proceed to write down, estimate, and solve a two-part model including (i) a model of consumer demand for staple grains and an outside numeraire good, from which I derive an expression for welfare; and (ii) a rational expectations model of monthly grain storage and trade under uncertainty (Williams and Wright 1991, chapter 9) including storage in each of the 230 markets, overland trade between them, and trade with the world market through 30 ports. Although the focus of this chapter is trade and the consequences of high trade costs, forward-looking storage is inextricably linked to trade in a sector where uncertain harvests occur once or twice a year, harvest periods vary by location, and both harvests and prices fluctuate dramatically (figure 1.2). Dimensionality problems have traditionally restricted the use of this class of dynamic models to contexts involving two markets and a single commodity (e.g. Gouel and Jean 2015, Steinwender 2015). I make use of an additional assumption about trader expectations that converts the intractable stochastic problem into a series of tractable deterministic problems, and I show that this assumption does not significantly affect my results.

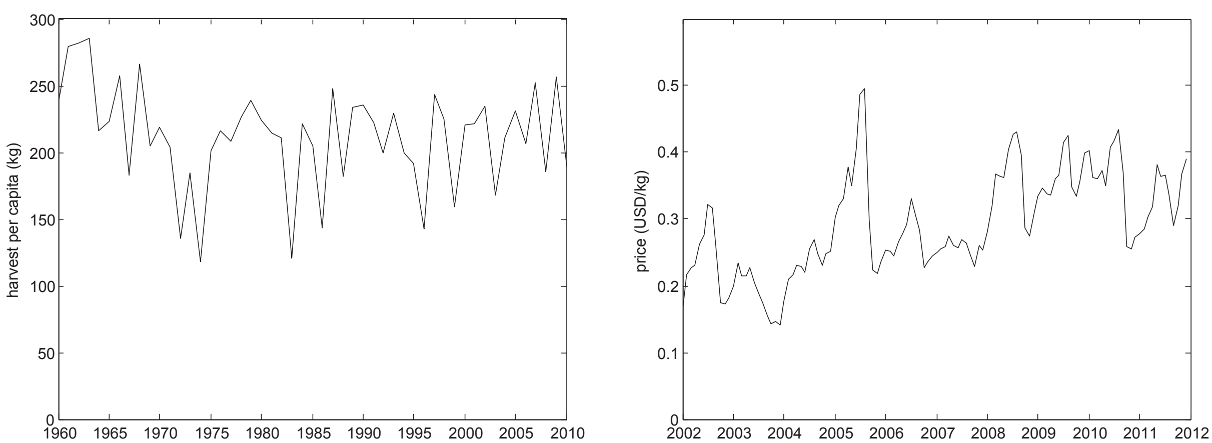

Figure 1.2: Annual Millet Harvest Per Capita (kg) in Niger, 1960 – 2010 (left) and Monthly Millet Prices (USD/kg) in Maradi, Niger, 2002 – 2011 (right). Sources: FAO-STAT, FAO GIEWS.

My estimation strategy includes a new, iterative approach to inferring trade costs from price differences when precise data on where trade occurs is not available (as it was for Donaldson 2012 and Atkin and Donaldson 2015). My median estimated intra-national trade

[1]Recent examples include Aker 2010, Brenton et al 2014, Dillon and Barrett 2015, and Myers 2013.

cost using this approach is over 5 times higher than benchmark freight rates elsewhere in the world. My estimates appear to be in line with the results of trucking surveys (Taravaninthorn and Raballand 2009) and studies of the distance-dependent component of trade costs (Atkin and Donaldson 2015), with larger magnitudes reflective of additional components of overall trade costs not previously captured. In reduced-form regressions, I find that higher trade costs are correlated with lower road quality, international borders, the absence of regional trade agreements, and lower scores on the Transparency International Corruption Perceptions Index and the World Bank Logistics Performance Index. My port-to-world trade cost estimates are also over five times higher than benchmark shipping rates.

After verifying the goodness of fit of my model-generated equilibrium, I begin my counterfactual analysis. In my main counterfactual, I lower trade costs in Africa to match benchmark freight rates in other parts of the world. Lowering trade costs leads to a 46.4% drop in the average price index for staple grains across all markets, a decrease in continent-wide agricultural revenues net of storage and trade costs of \$117.4 billion over ten years (–42.1%), and a welfare gain equivalent to 2.2% of GDP (a \$125 billion equivalent variation). The aggregate drop in prices and revenues is largely attributable to increased penetration of imports from the world market (the "missing food imports" of Tombe 2015), with the gains from lower food prices outweighing the lost income for farmers. However, there is significant heterogeneity in my results, with exporting regions experiencing increases in prices, revenues, and welfare and some regions experiencing welfare losses due to terms-of-trade effects. My results are robust to different demand specifications and allowing for a long-run reallocation of factors of production between sectors.

Reducing trade costs everywhere in Africa may be politically and financially infeasible in the near future. However, in additional counterfactuals, I show that 86% of the aggregate welfare gain from lower trade costs can be achieved by lowering trade costs through ports and along key links representing just 18% of the trade network. This suggests that a corridor-based approach of the kind advanced by multilateral donors may be effective (African Development Bank 2010).

In two additional counterfactuals I estimate the effects of widespread agricultural technology adoption under existing high trade costs and counterfactual low trade costs. In 2013, African cereal grain yields were half of South Asia's and a third of Latin America's due largely to the low use of inputs like fertilizer. Institutional donors and organizations like the Alliance for a Green Revolution in Africa (AGRA) are promoting widespread technology adoption to increase smallholder incomes and decrease food prices. While I find that doubling agricultural productivity under either existing high or counterfactual low trade costs does lower food prices, the effects on farmer incomes are dramatically different in the two cases, with net agricultural revenues actually falling by 71.4% under existing high trade costs and increasing by 12.4% under counterfactual low trade costs. These results underscore the importance of implementing policies to lower trade costs and improve market access in tandem with technology adoption initiatives.

This chapter is most closely related to a recent literature on trade costs along intranational spatial transportation networks that has expanded rapidly since the seminal work of Donaldson 2012. Atkin and Donaldson 2015 estimate the distance-dependent component of intra-national trade costs within two sub-Saharan African countries (Ethiopia and Nigeria) using price and origin data for specific, narrowly-defined manufactured goods. Sotelo 2015 uses a richer dataset from Peru to explore how intra-national trade costs lower agricultural productivity by preventing agricultural producers in particular locations from specializing in the crops in which they have a comparative advantage, a mechanism which is less important in the African context for the range of crops that I consider. This chapter goes beyond the existing literature in several important ways, including covering a larger network of African markets (including international trade between countries and with the world market) and using a dynamic monthly model with storage, which I show is important for identifying *when* trade occurs so as to avoid underestimating trade costs and welfare effects. In my case, using a static annual model underestimates trade costs by 23% and welfare effects by 33%.

The balance of this chapter proceeds as follows. In Section 2, I describe the context and data. In Section 3, I present my model. In Section 4, I detail my estimation strategy, present my estimates for the model parameters including trade costs, and examine the goodness of fit of my estimated model. In Section 5, I present the results of my counterfactual analysis and robustness checks. Section 6 concludes.

1.2 Context and Data

Agricultural products are consumed everywhere and produced nearly everywhere in sub-Saharan Africa. Due to data limitations and comparability issues, I restrict my attention in this chapter to the consumption and production of the six major staple cereal grains: maize, millet, rice, sorghum, teff, and wheat[2]. Table 1.1 shows the relative share of cereal grains and other categories of agricultural goods in production value, caloric intake, and gross value of international trade in sub-Saharan Africa. Although they make up only 17.2% of the total value of agricultural production in sub-Saharan Africa, cereal grains are by far the most important source of calories in African diets. Tubers like cassava and yams are another important source of staple carbohydrates, but their perishability and low value-to-weight ratios severely constrain their trade and storage. Cash crops like cocoa and tea make up the largest share of the value of African countries' international agricultural trade, but they differ from cereals in that their production is often localized near ports or in certain geographic niches and is nearly all exported to the world market.

Grain trade in sub-Saharan Africa can be roughly classified into two types: farm-to-market and market-to-market trade. Although farm-to-market trade may involve much higher trade costs than market-to-market trade due to extremely poor rural infrastructure, I will not be able to capture farm-to-market trade and trade costs in a continent-level model due to data limitations and will focus exclusively on market-to-market trade instead. One important difference between the two types of trade is the level of competition — while

[2]Cereal grains (cereals), legumes, and oilseeds are sometimes all considered to be grains. This chapter just focuses on the six major cereal grains.

Table 1.1: Relative Share of Categories of Agricultural Goods in Continental Sub-Saharan Africa

	Production Value	Caloric Intake	Gross Trade Value
Cereal Grains	17.2%	46.3%	22.1%
Tubers	30.2%	16.8%	0.2%
Legumes/Seeds/Nuts	6.8%	8.6%	6.3%
Fruits/Vegetables	12.0%	5.6%	5.1%
Animal Products	20.8%	7.3%	15.9%
Cash Crops	13.0%	15.4%[a]	50.4%

Note: Value of production in local prices and caloric intake are from FAO-STAT for 2010. Gross international trade value is value of imports plus value of exports from CEPII BACI (Gaulier and Zignago 2010) for 2003-2012. All countries with available data are included (30 for production, 37 for calories, 37 for trade).
[a]Includes vegetable oil, sugar, and beverages.

farm-to-market trade may be conducted by relatively few traders with significant market power, market-to-market trade at the level considered here tends to be highly competitive with many traders, low firm concentration ratios, homogeneous products, and few barriers to entry (Osborne 2005, Aker 2010). I will therefore assume that traders are competitive price-takers.

Grain is bought and sold in thousands of open-air markets across sub-Saharan Africa. I seek to identify and include in my model the larger, regionally important hub markets that collect grain from surrounding smaller markets for trade with other hub markets. I do so in three steps. First, I include the 178 towns and cities in my 42 countries of interest which have a population of at least 100,000 people and are at least 200 kilometers apart (if two towns with over 100,000 people are closer than 200 kilometers I include the larger one). Second, I add smaller towns that are located at important road junctions or ports. Third, I add additional major towns (some closer than 200 kilometers apart) in countries which still have high population-to-market ratios after my first two steps. Together these steps produce a list of 263 markets (cities/towns).

In order to be able to include a particular market in my model, I must have grain price data for it. Using my "ideal" list of 263 markets, I conducted an exhaustive search for monthly grain price series from these markets and obtained price series for 230 of them. I then used maps of road networks and navigable waterways to identify the pairs of these markets between which direct trade (trade that does not pass through another market in the network) is feasible. A map of my final network of 230 markets with the 413 direct links between them is shown in figure 1.3. A complete list of markets and further details on the market selection process are contained in the appendix.

The median market town has a population of 207,000, and the median transport distance between directly linked markets is 337 kilometers. Among the 230 markets, I identify 30 major ports that trade with the world market and include direct links between them and the most important world market for each crop (Bangkok, Thailand for rice and the US

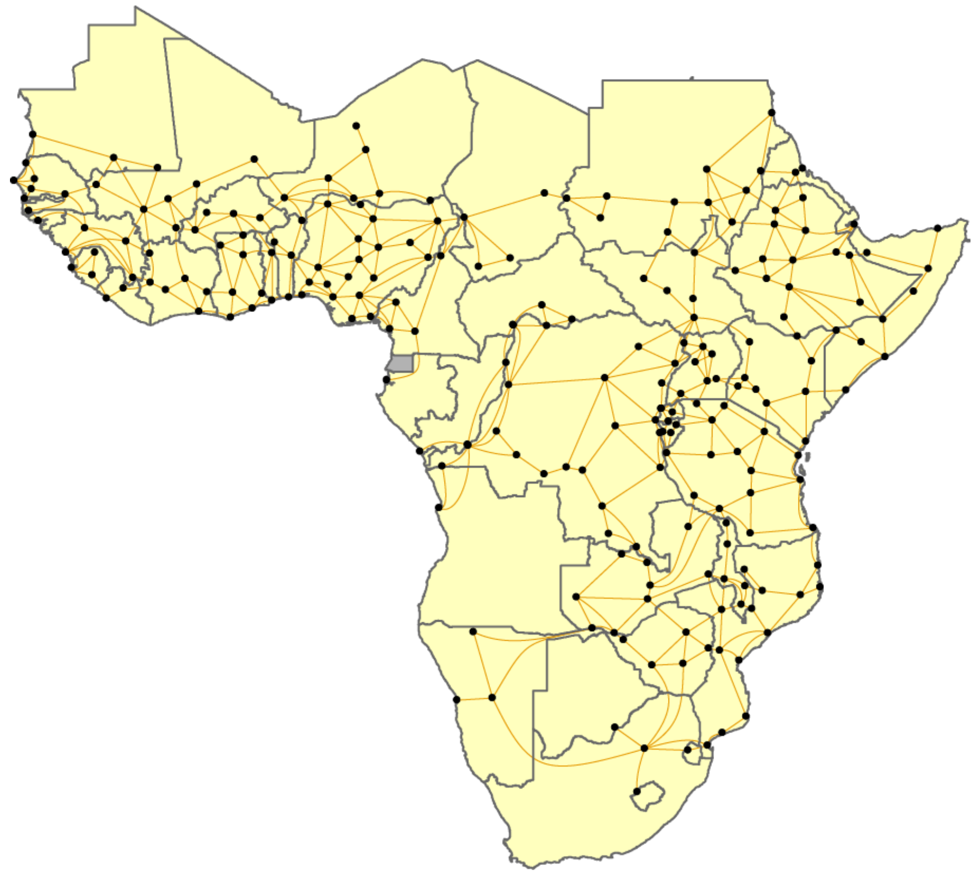

Figure 1.3: Map of 230 Markets and 413 Direct Links

Gulf for maize, sorghum, and wheat; millet and teff are generally not traded on the world market except for small shipments by specialized companies). I also treat Johannesburg, South Africa like the world market for maize in my model due to its special circumstances[3].

The monthly grain price series for the 230 markets cover a 10-year period from May 2003 to April 2013. The price series include series for the 6 cereal grains most produced and consumed in sub-Saharan Africa – maize (45.6% of total cereal grain production), sorghum (21.8%), millet (14.3%), rice (7.7%), wheat (5.3%), and teff (2.6%)[4]. In each market, only a subset of these major grains are sold – 54 markets have price series for 1 grain, 111 have series for 2 grains, 24 have series for 3 grains, and 41 have series for 4 grains. Maize is by far the most common grain with price series from 180 of the 230 markets, followed by rice (126), sorghum (110), millet (64), wheat (23), and teff (9).

[3]These include its functioning commodity exchange which is used as a reference point throughout Southern Africa, its close integration with the world market, South Africa's very large maize production relative to its neighbors, and South Africa's advanced internal market information systems. Johannesburg is the only market from South Africa included in my model for the same reasons.

[4]The remaining 2.7% of total cereal grain production consists of minor cereal grains (barley, oats, fonio, etc.).

Of the 512 total price series, 42% were obtained from the World Food Programme's VAM unit and 25% from FAO's GIEWS project, which both maintain online databases of staple food price series collected by themselves or by national government agencies. The remaining 33% were obtained directly from national ministries of agriculture and statistical offices or through USAID's FEWS NET project, non-governmental organizations, and other researchers. Each original source typically employs teams of surveyors who observe and record prices at multiple points of sale in each location on a weekly or monthly basis and then relay them to analytical teams in the capital city who compile and publish monthly and annual reports. The price series are not all complete — the average series has 72 observations (6 years) worth of data. The original price series are in local currency. Of the 512 series, 76% are identified as retail price series for quantities ranging from 0.5 to 3.5 kg, while the remaining 24% are identified as wholesale price series for quantities ranging from 50 to 100 kg. I convert all price series to USD/kg using monthly exchange rates and conduct a statistical analysis of 37 series for which I have both retail and wholesale prices that fails to reject a hypothesis of equality between retail and wholesale prices. This is consistent with interviews of market participants which suggest that separate retail and wholesale markets typically do not exist and that prices per kilogram often do not vary with quantity sold. Details on this statistical test as well as the grain types and data sources by market are contained in the appendix.

Across all time periods and all markets, average prices are \$0.41/kg for maize, \$0.44/kg for wheat, \$0.45/kg for both millet and sorghum, \$0.58/kg for teff, and \$0.84/kg for rice. Regressions with market fixed effects comparing price levels within particular markets show maize significantly cheaper than sorghum, which is significantly cheaper than millet and wheat, which are significantly cheaper than teff, which is significantly cheaper than rice (significance at the 5% level).

My next step is to acquire production and population data for sub-Saharan Africa and assign each of the 230 markets a monthly production and population to match its monthly prices. I start by obtaining annual national totals for production of all cereal grains from FAO and annual national totals for population from the UN Population Division. To allocate the production data by month, I use agricultural calendar data from FAO to divide the continent into three zones: a Northern Hemisphere zone with a single annual grain harvest in October (112 markets), an Equatorial zone with a larger grain harvest (two-thirds of the annual total) in July and a smaller grain harvest (one-third of the annual total) in December (70 markets), and a Southern Hemisphere zone with a single annual grain harvest in May (48 markets)[5].

Allocating the national-level data by market is more challenging. I first obtain GIS grid cell level data for population and production of each crop for the year 2000 at the 5 arc-minute (10 km by 10 km) level from the GAEZ project of FAO and IIASA and the HarvestChoice project of IFPRI and the University of Minnesota[6] and use it to derive the percentage of

[5]These divisions involve some simplification (e.g. some specific areas may have harvests a month earlier or later or not exactly a two-thirds / one-third breakdown), but for the purposes of my model they are enough to capture the seasonal variation at the continent level.

[6]You, L., S. Crespo, Z. Guo, J. Koo, K. Sebastian, M.T. Tenorio, S. Wood, U. Wood-Sichra. Spatial

national population and production of each crop belonging to each grid cell. Under the assumption that these percentages stay constant during my study period, I combine them with my monthly national production and population data to get monthly production and population series at the grid cell level.

The final step is to assign grid cells to particular markets. I do this by constructing market catchment areas following the methodology of Pozzi and Robinson 2008. The underlying assumption of this methodology is that if producers and consumers in a given grid cell have to choose one of the markets in the network at which to sell and buy their grain they will choose the market to which they can travel in the least time. To identify which of the 230 markets is the closest in terms of travel time for each of the 292,000 grid cells, I combine information from the following GIS datasets: the roads layer from the World Food Programme's SDI-T database[7], the FAO Land and Water Division's Rivers of Africa and Inland Water Bodies in Africa datasets, the USGS-EROS Global 30-Arc Second Elevation (GTOPO30) dataset, the European Commission Joint Research Centre's Global Land Cover 2000 dataset, and the US Department of State's Large Scale International Boundaries and Simplified Shoreline datasets. Following Pozzi and Robinson 2008, I assign different average travel speeds to different categories of road and different average walking speeds to different land cover classes, and I then adjust these speeds based on the degree of slope of the terrain. I assign inland water bodies and rivers with Strahler number of at least 4 a travel speed of zero (except when crossed by a bridge)[8]. I also assign a travel speed of zero to international borders so as to keep market catchment areas within countries to match my national production and population data. Combining all of this information, I assign each pixel a travel cost in minutes and then use a least-cost path algorithm to identify the minimum travel time from each grid cell to any market in the network. I then assign each grid cell to the market catchment area of its nearest market in terms of travel time. Figure 1.4 shows maps of estimated grid-cell level travel time to the nearest market in the network and the resulting market catchment areas.

Once each grid cell has been assigned to a market catchment area, it is straight-forward to add up the production and population data for all of the grid cells in a given market catchment area and assign the total production and population to that market and its price series. Although my 512 price series do not include a price for every grain in every market, 86.3% of total cereal grain production in my countries of interest is covered by a price series in its associated market.

To obtain an initial sense of the dispersion of agricultural production across market catchment areas, I use a comprehensive database of the caloric value of food crops in Africa (Leung 1968) to assign an approximate caloric level per unit weight to all staple carbohydrates (cereal grains as well as tubers and plantains) and convert production data into calories[9]. The

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Production Allocation Model (SPAM) 2000 Version 3 Release 6.

[7]Kindly provided by the UN World Food Programme Emergency Preparedness and Response Branch.

[8]Strahler numbers are measures of branching complexity that are used to classify rivers by size based on their tributaries. Rivers with Strahler number 1–3 are headwater streams that are unlikely to impede travel.

[9]I assign a value of 350 kcal/100 grams to all cereal grains. I assign the following values to non-grain

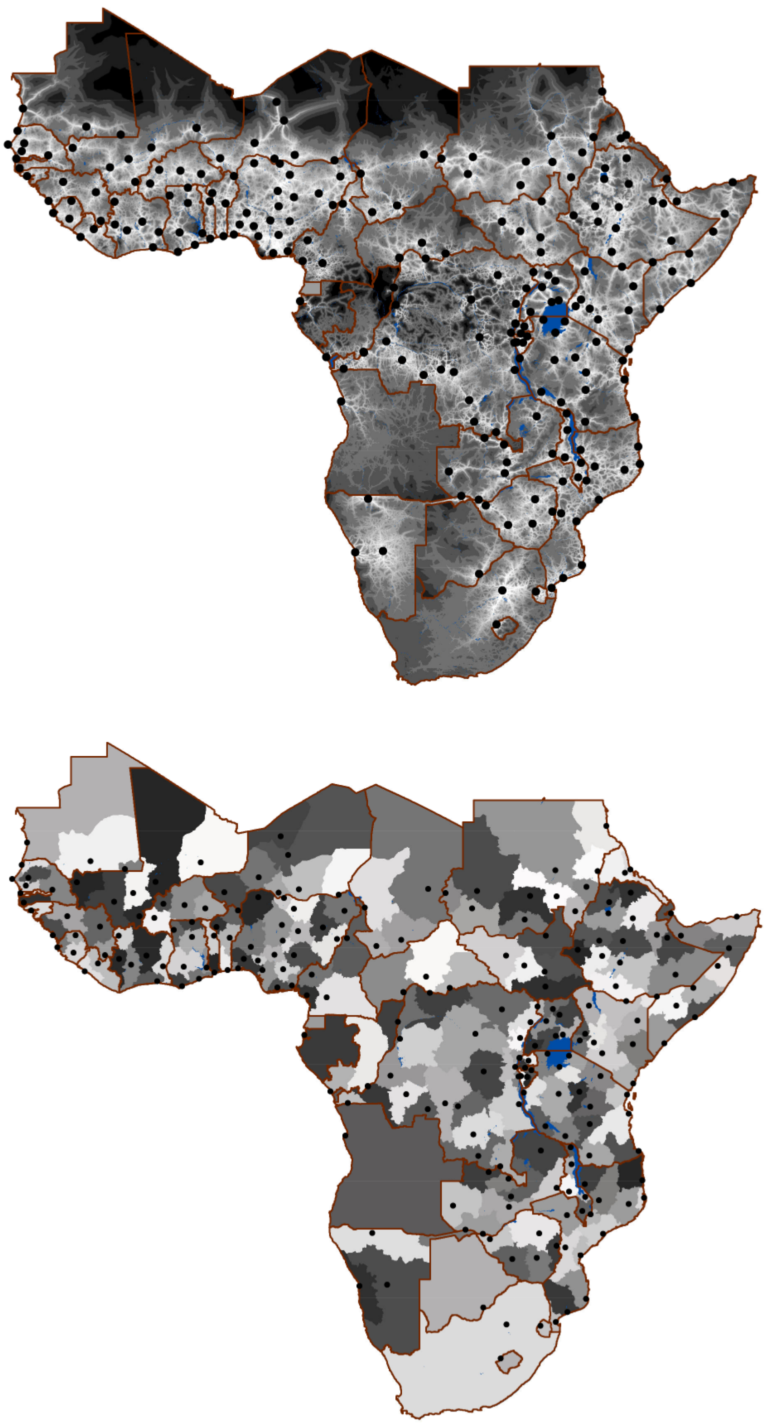

Figure 1.4: Estimated Travel Time from Grid Cells to Nearest Network Market (top, grid cells in lighter colors have smaller travel time) and 230 Market Catchment Areas (bottom)

median market catchment area had a 2010 population of 2.37 million and has an average production per capita of 1,863 kcal per day of staple carbohydrates during my study period. Average production ranges from 0 to 10,347 kcal per person per day with 63 markets (27.4%) producing less than 1,000 kcal per person per day and 54 markets (23.5%) producing more than 3,000 kcal per person per day, suggesting significant opportunities for net trade between markets.

Table 1.2: Regression of Price Levels on Market Characteristics

	(1)
Capital City	0.0248
	(0.0435)
Port	0.1110*
	(0.0618)
Town Population (thousands)	–0.000223
	0.0125
Per Capita Prod'n (thousand kcal)	–0.0184***
	(0.00588)
Constant	0.4331***
	(0.0268)
Fixed Effects	Crop
Observations	512
Clusters	230

Note: Robust standard errors in () clustered by market; *significant at 10%, ** at 5%, *** at 1%. Maize is the omitted crop.

Table 1.2 shows results from regressing the average price level for each of the 512 price series on market characteristics and crop fixed effects to reveal some basic correlations. Town population and whether or not the town is a capital city are not significantly correlated with higher or lower price levels. Ports appear to be weakly correlated with higher price levels, which is likely due to the geography of much of sub-Saharan Africa in which grain production is concentrated in inland non-port regions and port cities must import grains from either the inland regions or the world market. In contrast, per capita production (kcal/person/day) is significantly negatively correlated with price levels. The point estimates imply that price levels are on average 2 cents (5%) lower for each additional 1,000 kcal/person/day production of staple carbohydrates.

Having assembled a dataset of monthly prices, production, and population for a network of 230 market catchment areas covering all 42 countries of continental sub-Saharan Africa, I proceed in the next section to build a dynamic model of grain consumption, storage, and trade.

staples: cassava 150 kcal/100 grams, plantains 135 kcal/100 grams, sweet potatoes and yams 120 kcal/100 grams, and potatoes 80 kcal/100 grams.

1.3 Model

My model uses the notation and basic framework of the one-commodity, two-market rational expectations storage and trade model of Williams and Wright 1991, chapter 9, which I extend to include the storage and trade of 6 grains across the network of 230 African markets and the world market built in the previous section. I embed this storage and trade model within a simple general equilibrium setting by including a composite outside good. While the six grains are subject to trade costs between locations (which I estimate), the outside good has no trade costs so that its price is the same in all locations, and I choose units so as to normalize its price to 1[10]. Production of the outside good is used either for final consumption or for trade and storage services in the agricultural sector. In my simplest baseline case reflective of the short-term, I abstract away from production decisions by letting production of both the 6 grains and the outside good be an exogenous endowment that is unaffected by price changes. In an extension presented at the end of this section, I explicitly model production in each sector and allow for reallocation of factors of production between sectors in response to price changes.

In each location, a representative consumer chooses monthly consumption of each grain and the outside good to maximize utility and a representative competitive grain trader with rational expectations chooses monthly storage, trade, and local sales of each grain to maximize profits. I proceed by considering each of these agents in turn.

1.3.1 A Model of Consumer Demand and Welfare

Let m index the markets in the network, t the time periods in months, and i the six grains in my dataset, with I_m the set of grains sold in a particular market m. Let the representative consumer in market m have utility quasilinear in a grain composite Q_{mt} and the outside good X_{mt}:

$$U_{mt} = \theta_{mt} \frac{Q_{mt}^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} + X_{mt} \tag{1.1}$$

where θ_{mt} is a parameter and $\epsilon < 0$. Let preferences for individual grains be CES with elasticity of substitution σ and share parameters α_{im} (normalized such that $\sum_{i \in I_m} \alpha_{im} = 1$):

$$Q_{mt} = \left[\sum_{i \in I_m} \alpha_{im}^{1/\sigma} Q_{imt}^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)} \tag{1.2}$$

Let Y_{mt} represent total income, which is endogenous to the model but which the consumer takes as given. The consumer chooses consumption to maximize utility subject to a budget constraint:

[10] The use of an outside numeraire good with no trade costs has been a common device in the trade literature since Krugman 1980. Recent examples include Costinot et al 2014 and Sotelo 2015.

$$\max_{\{Q_{imt}\}_{i\in I_m}, X_{mt}} \frac{\theta_{mt}\left(\prod_{i\in I_m}\left[\sum_{i\in I_m}\alpha_{im}^{1/\sigma}Q_{imt}^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}\right)^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} + X_{mt} \text{ such that } \sum_{i\in I_m} P_{imt}Q_{imt} + X_{mt} \leq Y_{mt} \quad (1.3)$$

Let $\theta_{mt}^{-\epsilon} = A_m N_{mt}$ where A_m is a parameter and N_{mt} is the population of market catchment m in time t[11]. Taking first order conditions and solving for demand[12] gives:

$$Q_{mt} = A_m N_{mt} P_{mt}^{\epsilon} \quad (1.4)$$

where P_{mt} is the CES grain price index ($P_{mt} = \left[\sum_{i\in I_m}\alpha_{im}P_{imt}^{1-\sigma}\right]^{1/(1-\sigma)}$). This demand structure has three important and desirable features:

(1) *Demand is non-homothetic.* Demand for staple grains is independent of income and depends only on price. Demand for the composite numeraire good is the residual $X_{mt} = Y_{mt} - P_{imt}Q_{imt}$. In other words, consumers decide first how much grain to buy (based on grain prices) and then use all remaining income to buy the composite numeraire good[13].

(2) *Demand for staple grains has constant price elasticity* ϵ. This demand elasticity has been precisely estimated in the literature (Roberts and Schlenker 2013), an estimate which I will use in my baseline specification.

(3) *Demand for staple grains has constant population elasticity* 1. A doubling in population size will lead to a doubling in quantity demanded for staple grains at a given price.

For integration with the representative trader's side of the model I will use the inverse demand function for a particular grain i:

$$P_{imt} = \frac{\alpha_{im}^{1/\sigma}}{Q_{imt}^{1/\sigma}} * \frac{Q_{mt}^{1/\sigma+1/\epsilon}}{(A_m N_{mt})^{1/\epsilon}} \quad (1.5)$$

Equation 1.4 can be used to derive an expression for indirect utility V_{mt}:

$$V_{mt} = Y_{mt} - \frac{1}{\epsilon+1} A_m N_{mt} P_{mt}^{\epsilon+1} \quad (1.6)$$

The main counterfactual scenario in this chapter — lowering trade costs — acts through

[11] For notational simplicity, the representative consumer in each market is treated as a single aggregate consumer. The derived expressions for demand and welfare are equivalent to those for a population of N_{mt} individual consumers each with $\theta_{mt}^{-\epsilon} = A_m$ whose incomes sum to Y_{mt}.

[12] The full derivation for the demand and welfare expressions in this section is provided in the appendix.

[13] Related papers with demand functions for agricultural products and an outside good typically use either homothetic Cobb-Douglas preferences with income elasticity 1 (e.g. Sotelo 2015) or quasilinear preferences with income elasticity 0 as I have here (e.g. Costinot et al 2014). The quasilinear structure is helpful for model tractability and more realistic in my view than homothetic demand. Engel's law suggests an income elasticity between 0 and 1. Empirical estimates for the income elasticity of expenditure on the category "cereals" are available for 39 of the countries in my dataset and range from 0.363 to 0.685 (Muhammad et al 2011), but this includes expenditure on processed cereals (e.g. flour and bread). Income elasticity estimates for staple grains themselves in Africa are as low as 0.030 (maize, Nairobi, Gsaenger and Schmidt 1977). In my main counterfactual, 81% of markets experience an income change less than 5% and 96% less than 10%, so a positive income elasticity would not change my results substantially.

changes in grain prices, which affect both terms in this expression. A price increase, for instance, has a positive effect on welfare by increasing revenue from grain sales (which is part of income Y_{mt}) but has a negative effect on welfare by raising consumer prices (the second term).

For any counterfactual, the associated welfare change for market m for the entire period of interest expressed as a percentage of baseline GDP is given by:

$$\frac{\sum_{t=1}^{T} \Delta V_{mt}}{\sum_{t=1}^{T} Y_{mt}} = \frac{\sum_{t=1}^{T} (Y_{mt} - \frac{1}{\epsilon+1} A_m N_{mt} P_{mt}^{\epsilon+1})' - (Y_{mt} - \frac{1}{\epsilon+1} A_m N_{mt} P_{mt}^{\epsilon+1})}{\sum_{t=1}^{T} Y_{mt}} \tag{1.7}$$

where the prime symbol denotes counterfactual values. Given quasilinear preferences, the numerator of equation 1.7 is the equivalent variation of the counterfactual, since additional income is spent exclusively on the outside good, for which price and marginal utility are both equal to 1.

1.3.2 A Model of Grain Storage and Trade

Consider the problem of a representative competitive trader in market m in month t who takes prices as given. Without loss of generality, consider the trader's problem for a particular crop i. The trader enters the period with non-negative stocks of crop i from the previous period ($S_{im,t-1} \geq 0$). In addition, the trader buys up all local production of crop i (H_{imt}, with $H_{imt} = 0$ in all months except for market m's harvest months). The trader then must decide how much of this total available supply ($S_{im,t-1} + H_{imt}$) to sell for local consumption (Q_{imt}), how much to put into storage for the next period ($S_{imt} \geq 0$), and how much to trade with other markets indexed n (T_{imnt}, where $T_{imnt} > 0$ indicates exports from m to n, $T_{imnt} < 0$ indicates imports from n to m). The choice of any two of these three variables determines the value of the other: I focus on the choice of S_{imt} and T_{imnt} and solve for consumption in a later step using the market clearing condition:

$$Q_{imt} = S_{im,t-1} + H_{imt} - S_{imt} - \sum_{n \neq m} T_{imnt} \tag{1.8}$$

There are obviously many factors that our representative trader must take into account when making her decision. Storage and trade both entail some costs. I make the standard assumption that there are no costs to move grain into and out of storage, but that there is a per-unit monthly storage cost k_m and a monthly interest rate r_m in market m. Let τ_{mn} represent per-unit trade costs from market m to market n. I assume that trade costs are additive, symmetric ($\tau_{mn} = \tau_{nm}$), and cumulative ($\tau_{mo} = \tau_{mn} + \tau_{no}$ if trade from m to o must travel via n). Despite being unusual in the recent trade literature, additive trade costs are standard in models of agricultural storage and trade where additive freight rates tend to be much larger empirically than *ad valorem* costs like tariffs due to low value-to-weight ratios (see for instance Steinwender 2015). Letting trade costs be cumulative allows me to focus exclusively on the 413 direct links shown in figure 1.3 (plus 49 direct links with the world market) rather than the 26,335 possible combinations of 230 markets, since I can capture

100 units traded from m to o as 100 units traded from m to n and 100 units traded from n to o if trade from m to o must travel via n. Let $N_m \in M$ represent the subset of markets with which market m trades directly (excluding itself).

Our representative trader must also take prices into account, both in her own market and in the N_m markets with which she directly trades. Moreover, the possibility of storage means that expected future prices must also be considered. With this in mind, I write the trader's profit maximization problem in period t as:

$$\max_{S_{ims},T_{imns}} \mathbb{E}_t \left[\sum_{s=t}^{\infty} \frac{-P_{ims}H_{ims} + P_{ims}Q_{ims} - k_m S_{ims} + \sum_n (P_{ins}T_{imns} - \tau_{mn}|T_{imns}|)}{(1+r_m)^{s-t}} \right] \tag{1.9}$$

where $S_{ims} \geq 0$ and there is one T_{imns} for every n in N_m. Combining this with the market clearing condition (equation 1.8) I get:

$$\max_{S_{ims},T_{imns}} \mathbb{E}_t \left[\sum_{s=t}^{\infty} \frac{P_{ims}(S_{im,s-1} - S_{ims} - \sum_n T_{imns}) - k_m S_{ims} + \sum_n (P_{ins}T_{imns} - \tau_{mn}|T_{imns}|)}{(1+r_m)^{s-t}} \right] \tag{1.10}$$

Taking the first-order condition with respect to S_{imt} gives the temporal arbitrage condition:

$$P_{imt} + k_m - \frac{\mathbb{E}_t[P_{im,t+1}]}{1+r_m} \geq 0, \ = 0 \text{ if } S_{imt} > 0 \tag{1.11}$$

Taking the first-order condition with respect to T_{imnt} gives the spatial arbitrage conditions:

$$P_{imt} + \tau_{mn} - P_{int} \geq 0, \ = 0 \text{ if } T_{imnt} > 0 \quad \text{and} \quad P_{int} + \tau_{mn} - P_{imt} \geq 0, \ = 0 \text{ if } T_{imnt} < 0 \tag{1.12}$$

The world market enters the model through 49 direct links subject to the spatial arbitrage conditions in equation 1.12. As sub-Saharan Africa's cereal grain production makes up only 5% of world production, I assume that traders take the world market prices as given and can import or export unlimited quantities from the world market at these prices (plus trade costs), so I do not include storage, trade, and consumption outside of Africa in my model[14]. The model thus combines elements of a small open economy taking world prices as given and a closed economy with local prices determined endogenously, as in Sotelo 2015.

1.3.3 Competitive Equilibrium

In a competitive equilibrium, the representative consumer in each location maximizes utility, the representative trader in each location maximizes profits, and markets clear. Since grain demand is independent of income, the equilibrium in the grain market can be fully characterized before considering the numeraire good:

[14] I treat Johannesburg, South Africa in the same way as the world market for the reasons described previously, i.e. Johannesburg is treated as exogenous to the model with traders in connected markets in neighboring countries able to import or export unlimited quantities at the Johannesburg price (plus trade costs).

Definition 1. *A grain market equilibrium is a set of prices P_{imt}, consumption Q_{imt}, storage S_{imt}, and trade T_{imnt} such that the inverse consumption demand function (equation 1.5), temporal and spatial arbitrage conditions (equations 1.11 and 1.12), and market clearing condition (equation 1.8) hold for every grain i, market m, market pair mn, and time period t.*

The numeraire good can be traded but not stored and can be used either for final consumption or for trade and storage services in the agricultural sector. Therefore, local production of the numeraire good (Π_{mt}) must equal the sum of local final consumption (X_{mt}), net exports of the numeraire good $\sum_{n\in N_m} T_{Xmnt}$, and expenditure on local storage services and local trade services (half of trade costs for a market pair are allocated to each market), as summarized in the following accounting identity:

$$\Pi_{mt} = X_{mt} + \sum_{n\in N_m} T_{Xmnt} + \sum_{n\in N_m}\sum_{i\in I_m} 0.5\tau_{mn}|T_{imnt}| + \sum_{i\in I_m} r_m S_{im,t-1}(P_{im,t-1}+k_m) + \sum_{i\in I_m} k_m S_{imt} \quad (1.13)$$

Total income for a given market m and period t is the sum of revenue from selling the production of the numeraire good (Π_{mt}) at price 1 and from sales of grains net of storage and trade costs[15]:

$$Y_{mt} = \Pi_{mt} + \sum_{i\in I_m} P_{imt}(S_{im,t-1} + H_{imt} - S_{imt}) - \sum_{i\in I_m} r_m S_{im,t-1}(P_{im,t-1}+k_m) - \sum_{i\in I_m} k_m S_{imt} \quad (1.14)$$

Once the model has been solved for a grain market equilibrium, equation 1.14 and data on income Y_{mt} can be used to solve for Π_{mt}[16]. In my counterfactual scenarios, the endogenous variables change, meaning that overall income Y_{mt} changes according to equation 1.14. Income and prices under both baseline and counterfactual can then be plugged into equation 1.7 to obtain the change in welfare.

I define a full competitive equilibrium as follows:

Definition 2. *A competitive equilibrium consists of a grain market equilibrium together with consumption X_{mt} of the numeraire good such that equation 1.13 holds for every market m and time period t and trade for every market m is balanced in every period t:*

$$\sum_{n\in N_m} T_{Xmnt} = -\sum_{n\in N_m}\sum_{i\in I_m} P_{imt}T_{imnt} - \sum_{n\in N_m}\sum_{i\in I_m} 0.5\tau_{mn}|T_{imnt}| \quad (1.15)$$

A competitive equilibrium can clearly be found directly from a grain market equilibrium using equations 1.13 and 1.15. I therefore spend the rest of this section exploring the properties of a grain market equilibrium.

[15] Note that trade costs τ_{mn} do not appear explicitly here as they are accounted for by the use of the local price.

[16] Practically speaking, I multiply N_{mt} by national per capita GDP for the relevant year and country and divide by 12 to obtain Y_{mt} for each market m and month t. This implicitly assumes that GDP per capita is the same across regions of a country, a necessary assumption to obtain estimates of market-level income.

The model makes strong predictions about when and where grain storage and trade occur in equilibrium. Under identical or similar storage costs, traders will "store first and trade later" in equilibrium, with storage and imports never occurring simultaneously. This is a general result for this class of commodity storage and trade models first noted by Williams and Wright 1991, chapter 9. The intuition is that it is cheaper for storage to occur in the exporting market so as not to incur interest on the trade costs in the importing market. The following proposition and its corollaries summarize the relevant results:

Proposition 1. *Consider any two markets m and n. If m and n have identical storage costs then neither market stores and imports from the other simultaneously in equilibrium, i.e. for any month t and grain i:*

$$S_{int} > 0 \Rightarrow T_{imnt} \leq 0 \quad \text{and} \quad T_{imnt} > 0 \Rightarrow S_{int} = 0 \tag{1.16}$$

with a symmetric condition holding for S_{imt} and trade from n to m.

Corollary 1. *Consider a particular harvest year for two markets m and n with net trade of grain i from m to n in equilibrium. Let the harvest year months be indexed s with the last month before the next harvest $\bar{s}$. Let the first month with trade from m to n be designated s^*. Then the following must be true for any grain i:*
(i) If $r_m \leq r_n$ and $k_m - k_n < \frac{r_m \tau_{mn}}{1+r_m}$, then $S_{ins} > 0$ for $s < s^* - 1$, $S_{ins} \geq 0$ for $s = s^* - 1$, $S_{ins} = 0$ for $s \geq s^*$, $T_{imns} \leq 0$ for $s < s^*$, and $T_{imns} > 0$ for $s \geq s^*$. Traders store first and trade later.
(ii) If $r_m \geq r_n$ and $k_m - k_n > \frac{r_m \tau_{mn}}{1+r_m}$, then $S_{ins} > 0$ for $s < s^* - 1$, $S_{ins} \geq 0$ for $s = s^* - 1$, $S_{ins} > 0$ for $s^* \leq s < \bar{s}$, $T_{imns^*} > 0$, and $T_{imns} \leq 0$ for all $s \neq s^*$. Trade from m to n only occurs in s^*.
(iii) For any values of r_m, r_n, k_m, and k_n, the pattern of storage and trade will be the same as (i) if the following expression is negative and the same as (ii) if the following expression is positive:

$$(1 + r_m)k_m - (1 + r_n)k_n + (r_m - r_n)P_{ims^*} - r_n \tau_{mn} \tag{1.17}$$

Corollary 2. *Given a set of demand and cost parameters, there is a unique grain market equilibrium (competitive equilibrium).*

Proof. See appendix. □

Importantly, these results establish that storage and trade flows (not just prices and consumption) are unique, which means that the set of periods in which the spatial and temporal arbitrage conditions (equations 1.11 and 1.12) hold with equality is unique. Intuitively, equation 1.17 encapsulates the trade-off between storing in the exporting market (m) and storing in the importing market (n). Practically speaking, there is little reason why k and r would be significantly different between a particular market and its direct trading partners (particularly when they are within the same country), so equation 1.17 is likely to be negative (especially with high trade costs), implying that case (i) holds in most cases. This means that trade will generally only occur (and the spatial arbitrage conditions will generally only hold with equality) during the later months of the harvest year.

1.3.4 Extension: A Model of Production

In the baseline case, I assume for tractability and transparency that production of both grains and the outside good are exogenous endowments that do not change in my counterfactuals. This assumption is realistic in the short term when factors of production are immobile. In the longer term, factors of production would likely reallocate as a result of the relative price changes in my counterfactuals. Incorporating a supply response into a rational expectations model of commodity storage and trade and estimating supply parameters is a non-trivial task that is beyond the scope of this chapter, particularly given the fact that agricultural producers typically make planting decisions ahead of time based on expected future prices with supply realizations affected by subsequent stochastic shocks. In this section, I outline a simplified approach under the assumptions that the price elasticity of supply is a known constant, that supply decisions are made in the harvest month, and that these decisions do not affect expected future harvests, which are still exogenous. Importantly, while allowing for a supply response changes my counterfactual equilibria, it has no effect on my estimation of the demand and cost parameters and the baseline equilibrium, as these rely on actual production data.

For simplicity, assume that there is a single composite factor of production called labor (L). In each time period, the labor endowment in each market ($\bar{L}_{mt}$) is allocated between production of the numeraire good and each grain i:

$$L_{Xmt} + \sum_i L_{imt} = \bar{L}_{mt} \tag{1.18}$$

Let production of the numeraire good be linear in labor ($\Pi_{mt} = B_X L_{Xmt}$) and production of each grain be concave in labor[17]:

$$H_{imt} = B_{imt} L_{imt}^{\beta} \tag{1.19}$$

where B_{imt} is a crop-market-time specific productivity shock and $0 < \beta < 1$. Labor is perfectly mobile between sectors, and workers are paid a wage W equal to the value of their marginal product. Given that the freely-traded numeraire good is produced everywhere with the same technology, the wage W is equal across locations. Choose units of labor such that $W = 1$. Then for any grain i:

$$W = 1 = \beta B_{imt} L_{imt}^{\beta-1} P_{imt} \tag{1.20}$$

Combining equations 1.19 and 1.20 leads to the following supply function:

[17]This reflects the diminishing returns to labor for agricultural production on a fixed amount of land.

$$H_{imt} = \beta^{\frac{\beta}{1-\beta}} B_{imt}^{\frac{1}{1-\beta}} P_{imt}^{\frac{\beta}{1-\beta}} \tag{1.21}$$

The supply function in equation 1.21 has a constant price elasticity of supply $\eta = \frac{\beta}{1-\beta}$. For a given value of η, equation 1.21 can be used with data on H_{imt} and baseline equilibrium prices P_{imt} to back out the implied productivity shocks B_{imt}. These can then be used with equation 1.19 to obtain implied L_{imt}, which can then be used with equation 1.18 and equilibrium Π_{mt} (solved for in the previous section) to solve for labor endowments $\bar{L}_{mt}$ given that $L_{Xmt} = \frac{\Pi_{mt}}{B_X} = \frac{\Pi_{mt}}{W} = \Pi_{mt}$. In my counterfactual scenarios, I can then endogenize the harvests H_{imt} by incorporating equation 1.21 into the model and back out the new production of the numeraire good by subtracting the implied L_{imt} for the new harvests H_{imt} from the fixed labor endowments $\bar{L}_{mt}$. Proposition 1 and its corollaries are unaffected by the addition of a supply response, so the grain market equilibrium (competitive equilibrium) is still unique.

1.4 Estimation

In this section, I first outline how I solve the model from the previous section given a set of parameters. I then describe how I estimate both the demand parameters and the cost parameters using my price data and present the results from these estimates. Finally, I explore the goodness of fit of my estimated model.

1.4.1 Solution Algorithm for Given Parameters

Table 1.3 summarizes the parameters and variables in the core grain market model summarized by equations 1.5, 1.8, 1.11, and 1.12. My estimation of the demand parameters and cost parameters using price data is detailed in subsequent sections. In this section, I describe how I solve for the grain market equilibrium (endogenous S_{imt}, T_{imt}, Q_{imt}, and P_{imt}) given a set of demand and cost parameters and data on the exogenous variables (N_{mt}, H_{imt}, and world prices).

Table 1.3: Summary of Model Parameters and Variables

Demand Parameters	ϵ, σ, A_m, α_{im}
Cost Parameters	r_m, k_m, τ_{mn}
Exogenous Variables	N_{mt}, H_{imt}, world prices
Endogenous Variables	S_{imt}, T_{imnt}, Q_{imt}, P_{imt}

When a representative trader in market m in time t decides how much of grain i to store, trade, and sell locally, she must take into account both the current and expected future values of the exogenous variables for her market and all others. The complexity of the resulting problem has traditionally limited the application of rational expectations commodity storage and trade models to contexts involving two markets and a single commodity (e.g. Gouel and Jean 2015, Steinwender 2015)[18]. I make the following assumption to be able to apply the model to my network of 230 markets and 6 commodities:

Assumption. *When making storage decisions, traders assume (i) that all future harvests will equal a linear prediction of the subsequent harvest and (ii) that all future world prices will equal the current world price.*

This is a strong assumption that eliminates the effects of uncertainty on traders' storage decisions and could therefore lead to under-estimation of equilibrium storage[19] (Williams and Wright 1991, chapter 3). However, I show in later sections by estimating smaller scale models with full rational expectations using my parameter estimates from Africa that it does not significantly affect my results *in this context*, largely due to the high storage costs in Africa and its position as a net grain importer, which limit inter-annual storage of grains even under full rational expectations[20].

Practically speaking, this assumption converts the intractable stochastic problem into a series of tractable deterministic dynamic problems (one for each of the 120 months of interest), which I solve consecutively using the PATH solver in GAMS. For a given month t, traders are given: (1) initial stocks ($S_{im,t-1}$) from the previous month, (2) current harvests (H_{imt}), (3) expected harvests for the following year (calculated separately for each market each year based on regression results from harvests over the previous 10 years with a time trend), (4) current population and population for the following year (which I assume is known with perfect foresight), and (5) identical current and expected future world prices. For month t, I let traders plan for a sufficiently long time horizon (with repeated identical expected harvest, population, and world prices) such that initial shocks are smoothed out and storage decisions start repeating themselves with inter-annual storage falling to zero[21]. I then solve for all trader decisions for this time horizon, record the endogenous variables only for the first month (month t), and then move forward to the next month ($t+1$), repeating the same exercise with initial stocks S_{imt}. To obtain initial stocks for the very first month (May 2003), I start my month-by-month solution algorithm a full year earlier (May 2002) and assume zero inter-annual stocks from 2001 to 2002, which allows traders to have some

[18]The challenge is not unique to commodity storage and trade models. Desmet and Rossi-Hansberg 2014 note that "the dimensionality of the problem... typically make(s) spatial dynamic models intractable, both analytically and numerically. Thus, the only way forward is to simplify the problem." The potential solutions they describe limit either the spatial or the temporal effects on the current equilibrium. My approach (like theirs) falls in the latter category.

[19]Intra-annual storage to cover the periods between harvests and some inter-annual storage to smooth out positive harvest shocks still occur. The assumption removes the motive to store for low harvest or high world price events.

[20]Brennan et al 1997 use context specificities in a similar way to apply a rational expectations model of commodity storage and trade to 104 locations in the Western Australia wheat market, where inter-annual storage is insignificant.

[21]Given the range of storage costs in this context, this convergence occurs within 36 months of repeated identical expectations as described.

inter-annual stocks by the time they get to May 2003. Solving the model month by month for the 132 months from May 2002 to April 2003 takes several days of computer run-time.

1.4.2 Estimation of Demand Parameters

Given the solution algorithm for a given set of parameters, the only remaining task to be able to solve the model is to actually estimate the parameters. To estimate the demand parameters, the price data that I have must be combined with data on consumption. Unfortunately, analogous intra-national monthly consumption data for grains does not exist for Africa. Instead, I combine my production data with national annual data on imports and exports of each grain obtained from CEPII's BACI project (Gaulier and Zignago 2010) to back out national annual consumption of each grain as the sum of production and net imports[22]. I then proceed to estimate my demand parameters using these national annual data and average national annual prices for each grain across markets and months. I use these national parameters for all markets within a country under the assumption that the per capita grain demand function is identical in different markets within a single country[23].

The degree of averaging and aggregation necessary for this exercise makes the estimation of precise elasticities of substitution (σ) and demand (ϵ) difficult. Consequently, rather than using estimated elasticities, for my baseline case I let preferences among grains be Cobb-Douglas ($\sigma = 1$) and use a precise and well-identified estimate of the elasticity of demand for staple grains from Roberts and Schlenker 2013 ($\epsilon = -0.066$). To confirm that these values are realistic, I estimate the elasticities by running instrumental variables regressions on my annual national consumption and price data. As an instrument, I use the landed world price (the world price plus the average price difference between the world market and the country's largest city, which is a lower bound on trade costs). The identifying assumption is that the landed world price only affects the quantity consumed through its effect on the local price. The details of these regressions as well as their OLS equivalents are reported in the appendix and the results summarized in table 1.4. As expected, these estimates are imprecise, but it is reassuring to note that $\sigma = 1$ and $\epsilon = -0.066$ are both within the 95% confidence intervals of my instrumental variables estimates. Since the elasticities I use are on the low end of elasticity estimates in the literature (particularly for σ), I later report the results of robustness checks using higher elasticity values[24].

For a given σ and ϵ, it is straight-forward to estimate α_{im} and A_m for each country. In the Cobb-Douglas case ($\sigma = 1$), α_{im} is the expenditure share on grain i. Quantity and price indices can then be computed using σ and α_{im}, and A_m can then be solved for using

[22] This could be slightly different than actual consumption due to the possibility of inter-annual storage, but this is not a major concern given that I find extremely low inter-annual storage in equilibrium.

[23] Atkin 2013 uses evidence from India to show how this type of assumption could lead to over-estimation of gains from trade cost reduction if tastes for food are skewed towards crops well-suited to local agro-climatic conditions. This is less of a concern for most African countries, which are typically much smaller with relatively homogeneous agro-climatic conditions.

[24] Sotelo 2015, for instance, estimates $\sigma = 2.6$ for the primary 20 crops in Peru, which he describes as being "on the higher end of plausible values." I use a value of $\sigma = 3$ in my robustness checks.

Table 1.4: Elasticity Estimates

	OLS: σ	OLS: ϵ	IV: σ	IV: ϵ
Estimate	0.51**	–0.256***	0.90***	–0.136
	(0.21)	(0.071)	(0.18)	(0.116)
1st Stage F Stat			6.0	70.3
Observations	463	289	387[b]	289
Clustered Errors	country-crop	country	country-crop	country
Clusters	67	28	56	28

Note: Robust standard errors in () and F statistic clustered as indicated; * significant at 10%, ** at 5%, *** at 1%.
[b]Crops with no world price (millet, teff) excluded.

equation 1.4. Due to the small number of annual observations, I combine several neighboring countries with similar per capita grain consumption and estimate α_{im} and A_m for 28 countries or groups of countries[25]. Table 1.5 shows results for the demand parameters for the 6 most populous countries in my dataset (excluding South Africa) with full results presented in the appendix. Parameter estimates are obtained by averaging across years with standard errors calculated by bootstrapping (10,000 iterations). Different values of A_m (a per-capita variable) may reflect several factors including the relative importance of cereal grains in local diets vis-à-vis other foods like tubers.

1.4.3 Estimation of Cost Parameters

The storage cost parameters (r_m and k_m) and trade cost parameters (τ_{mn}) are more difficult to estimate, and my estimation strategy is more innovative. Let $\mathbb{C}$ be the set of unknown cost parameters to be estimated and $\mathbb{P}$ be the set of price data. The key challenge is to identify the sets of crop-market (pair)-months in which storage and trade occur in equilibrium ($\mathbb{S}$ and $\mathbb{T}$). Since the arbitrage conditions in equations 1.11 and 1.12 hold with equality in these periods, the price data in these periods can be used to estimate $\mathbb{C}$. However, $\mathbb{S}$ and $\mathbb{T}$ are not observed and in equilibrium are clearly a function of the set of cost parameters $\mathbb{C}$ itself.

My approach is to search for an internally consistent fixed point in which my cost parameters $\mathbb{C}$ exactly match the estimates I obtain from solving for equilibrium $\mathbb{S}$ and $\mathbb{T}$ with those cost parameters and re-estimating $\mathbb{C}$ with the price data only in crop-market (pair)-months $\mathbb{S}(\mathbb{C})$ and $\mathbb{T}(\mathbb{C})$. Mathematically, I find $\mathbb{C}$ such that:

$$\mathbb{C}(\mathbb{P}, \mathbb{S}(\mathbb{C}), \mathbb{T}(\mathbb{C})) = \mathbb{C} \tag{1.22}$$

Based on the spatial arbitrage conditions (equation 1.12), my estimation rules $\mathbb{C}(\mathbb{P}, \mathbb{S}, \mathbb{T})$

[25]Even with this aggregation, the number of annual observations per unit remains low as seen in Table 1.5. However, using multiple observations per country is an improvement over using a single year as in other recent papers in the trade literature (e.g. Costinot et al. 2014) and allows me to quantify the variation among observations.

Table 1.5: Demand Parameter Estimates for 6 Most Populous Countries

	Nigeria	Ethiopia	D.R. Congo	Tanzania	Kenya	Sudan
A	166.9***	143.0***	32.1***	98.1***	79.1***	212.7***
	(7.4)	(5.2)	(2.1)	(5.7)	(2.9)	(10.1)
α_{maize}	0.218***	0.210***	0.712***	0.561***	1***	0.018***
	(0.011)	(0.006)	(0.018)	(0.025)	(0)	(0.005)
α_{millet}	0.257***					0.089***
	(0.009)					(0.008)
α_{rice}	0.223***		0.288***	0.439***		
	(0.013)		(0.018)	(0.025)		
$\alpha_{sorghum}$	0.302***	0.176***				0.465***
	(0.015)	(0.010)				(0.026)
α_{teff}		0.308***				
		(0.015)				
α_{wheat}		0.306***				0.428***
		(0.011)				(0.033)
Observations	7	7	14[c]	7	9	5

Note: Standard errors in () are bootstrapped (10,000 iterations);
* significant at 10%, ** at 5%, *** at 1%.
[c]Joint estimation with Central African Republic.

identify trade costs (τ_{mn}) using price differences between markets during periods with trade. Letting $\mathbb{T}_{mn}$ denote the set of crop-months in which trade occurs between market pair mn in equilibrium and T_{mn} denote the total number of crop-month pairs in $\mathbb{T}_{mn}$, my estimation rule for each trade cost parameter τ_{mn} is:

$$\tau_{mn} = \frac{1}{T_{mn}} \sum_{it \in \mathbb{T}_{mn}} |P_{imt} - P_{int}| \tag{1.23}$$

Based on the temporal arbitrage conditions (equation 1.11), my estimation rules $\mathbb{C}(\mathbb{P}, \mathbb{S}, \mathbb{T})$ identify storage costs (r_m and k_m) using the rise in price in market m from the harvest month to the month following the final month with storage within each harvest year y. Let D_{imy} be the number of consecutive periods in harvest year y starting with the harvest month for which there is storage of grain i in market m in equilibrium. Let P^{min}_{imy} and P^{max}_{imy} be the minimum and maximum prices during these periods and the month immediately following. Rather than estimating storage costs at the individual market level, I estimate storage costs in 5 broad regions with similar institutions and climates (Southern Africa, East Africa including the Horn of Africa, Central Africa, the West Coast of Africa, and the Sahel). For each region, I run a non-linear regression to estimate r_m and k_m such that the following equation holds[26]:

$$P^{max}_{imy} = (1 + r_m)(P^{min}_{imy} + k_m) \text{ iterated } D_{imy} \text{ times} \tag{1.24}$$

[26]Note that D_{imy} is the number of times by which P^{min}_{imy} is increased by r_m and k_m in the regression expression, e.g. $D_{imy} = 2$ would mean a regression expression of $P^{max}_{imy} = (1+r_m)((1+r_m)(P^{min}_{imy}+k_m)+k_m)$.

To find an internally consistent fixed point, I start with an initial guess for the cost parameters ($\mathbb{C}^0$), solve for equilibrium using the procedure from section 4.1 so as to find $\mathbb{S}(\mathbb{C}^0)$ and $\mathbb{T}(\mathbb{C}^0)$, and then combine these with the price data and my estimation rules (equations 1.23 and 1.24) to re-estimate $\mathbb{C}^1(\mathbb{P}, \mathbb{S}(\mathbb{C}^0), \mathbb{T}(\mathbb{C}^0))$. I repeat this procedure until I converge to a fixed point for which $\mathbb{C}^{x+1}(\mathbb{P}, \mathbb{S}(\mathbb{C}^x), \mathbb{T}(\mathbb{C}^x)) = \mathbb{C}^x$.

Since the arbitrage conditions never bind if costs are prohibitively high, it is important to start the estimation procedure with a set of cost parameters ($\mathbb{C}^0$) that is a lower bound of the true parameters. A logical candidate is the set of cost parameters obtained by estimating equations 1.23 and 1.24 under the assumption that trade and storage occur always and everywhere (i.e. $\mathbb{T}$ and $\mathbb{S}$ include all crop-market (pair)-months, so $T_{mn} = 120$ for all mn and $D_{imy} = 11$ for all imy)[27]. Starting at this $\mathbb{C}^0$, it takes 11 iterations to converge to a fixed point.

Table 1.6 reports results of monthly interest rates r_m and additive storage costs k_m by region. The magnitudes of both parameters are high but on par with anecdotal evidence from Africa[28]. The relative size of k_m across regions matches exactly their ordering in terms of relative humidity (a major determinant of the cost of grain storage), from humid Central Africa and the West Coast through the arid Sahel. The relative size of r_m across regions is similar to their ordering in the World Bank's Doing Business indicators, in which countries in Central Africa consistently score the lowest and the West Coast receives relatively high scores in the Getting Credit component.

Table 1.6: Monthly Storage Cost Estimates by Region

	Southern	East/Horn	Central	West Coast	Sahel
r_m	0.0269***	0.0281***	0.0404***	0.0174***	0.0259***
	(0.0082)	(0.0034)	(0.0150)	(0.0029)	(0.0068)
k_m	0.0069***	0.0061***	0.0218**	0.0122***	0.0050**
	(0.0020)	(0.0011)	(0.0099)	(0.0013)	(0.0023)
Observations	240	506	156	604	506
Clusters	34	47	27	48	39

Note: Standard errors in () are block bootstrapped (10,000 iterations) at the cluster (market) level; * significant at 10%, ** at 5%, *** at 1%.

Trade cost estimates with standard errors for each of the 413 overland links in figure 1.3 are presented in the appendix. In order to compare trade cost estimates to one another, it is useful to convert them to cost per tonne-kilometer[29]. Among the 271 domestic links, the median estimated trade cost is \$0.287/t-km. The lowest estimated trade cost is along

[27] The fact that $\mathbb{C}^0$ is a lower bound also enables me to avoid the possibility of infinite loops (e.g. due to measurement error) by only updating τ_{mn} if $\tau_{mn}^{x+1} > \tau_{mn}^{x}$. This ensures monotonicity and hence convergence since costs are bounded above.

[28] For example, interviews I conducted with private traders in Tanzania and Malawi suggest that they face annual interest rates of 25–40%, while the World Food Programme's full cost of no-loss private storage in Zambia is approximately 0.010 USD/kg.

[29] Tonne (abbreviated t) refers to the metric ton (1000 kg).

the heavily-used paved road between Mombasa and Nairobi, Kenya ($0.049/t-km) while the highest trade costs include the virtually-impassable dirt track between Kananga and Tshikapa, D.R. Congo ($3.34/t-km) and the dirt road between Rumbek and Wau, South Sudan ($3.57/t-km), along which trade was often slowed or blocked due to flooding and land mines during the study period. Table 1.7 compares my trade cost estimates to estimates of freight rates from trucking surveys along 4 *major* African corridors reported in Taravaninthorn and Raballand 2009.

Table 1.7: Comparison of Trade Cost Estimates with Trucking Surveys

	TR 2009	My Estimate
Johannesburg-Lusaka	$0.077/t-km	$0.108/t-km
Mombasa-Kampala	$0.074/t-km	$0.189/t-km
Douala-N'Djamena	$0.106/t-km	$0.197/t-km
Accra-Bamako	$0.131/t-km	$0.269/t-km

The fact that my estimates are higher than baseline freight rates likely reflects the significant additional components of trade costs (information costs, tariffs, risk of losses, etc.) beyond transport costs in the African context[30]. The same study reports estimated freight rates from elsewhere in the world: $0.02/t-km in Pakistan, $0.035 in Brazil, $0.04 in the US, and $0.05 in China and the European Union. My median trade cost estimate from Africa is thus over 5 times higher than transport costs elsewhere in the world. For my counterfactual analysis, I will lower trade costs in Africa to $0.05/t-km, the highest of these reported freight rates from elsewhere in the world. In advanced agricultural markets, trade costs are unlikely to have significant components beyond baseline freight rates. In the appendix, I analyse price differences for maize along 11 direct transportation links between 8 markets within the US using analogous price data from the same period and find a median price difference of $0.012/t-km with only 1.1% of observations higher than $0.05/t-km.

Atkin and Donaldson 2015 estimate the distance-dependent component of intra-national trade costs in Ethiopia and Nigeria by observing how prices of specific manufactured goods increase as they travel further from their entry port or production point and compare them to analogous estimates for the US. They estimate that the effect of distance on trade costs is 3.19 times higher in Ethiopia than in the US and 5.40 times higher in Nigeria than in the US when using road distance as their distance metric. In comparison, I estimate an average overall trade cost of $0.257/t-km for intra-national links in Ethiopia and $0.437/t-km for intra-national links in Nigeria, 5.14 and 8.74 times higher than the benchmark freight rate of $0.05/t-km from Taravaninthorn and Raballand 2009. The ratio of Nigerian to

[30]The recent trade literature has established that there are other significant components to overall trade costs beyond transport costs (see for instance Anderson and Van Wincoop 2004). Allen 2014 finds that information frictions account for roughly half of overall trade costs in agricultural markets in the Philippines. Sotelo 2015 estimates overall trade costs 2.5 times higher than freight rates in the agricultural sector in Peru. Aker et al 2014 find agricultural trade costs of at least 20% to cross the "border" between two ethnic groups in Niger.

Ethiopian intra-national trade costs that I find (1.70) is reassuringly close to that of Atkin and Donaldson 2015 (1.69), while the apparently larger ratios of African trade costs to US trade costs that I find are likely due to the significant non-distance-dependent components of trade costs that Atkin and Donaldson 2015 do not explicitly measure. Table 1.8 groups the 33 African countries with at least one domestic link by level of average estimated intra-national trade cost.

Table 1.8: Comparative Levels of Average Intra-National Estimated Trade Costs by Country

Level	Trade Cost Range	Countries (Alphabetical)
Low	\$0.10–0.20/t-km	Burkina Faso, Chad, Malawi, Mali, Namibia, Niger, Zambia, Zimbabwe
Medium	\$0.20–0.30/t-km	Cameroon, Congo, Ethiopia, Guinea, Liberia, Senegal, Sierra Leone, Sudan, Tanzania
High	\$0.35–0.60/t-km	Benin, Côte d'Ivoire, Ghana, Kenya, Mauritania, Mozambique, Nigeria, Rwanda, Somalia, Uganda, Togo
Extreme	>\$0.75/t-km	Burundi, Central African Republic, D.R. Congo, Eritrea, South Sudan

In table 1.9, I explore correlations between my overland trade cost estimates and link characteristics through reduced-form regressions. Column (1) shows that crossing an international border is correlated with a \$0.0681 increase in trade costs (\$68/tonne) and that longer distances are correlated with a \$0.119/t-km increase in trade costs. In column (2) I interact the distance variable with indicator variables for whether the link is fully paved (52.5%), partially or fully unpaved (44.3%), or is a water-based route across a lake or along a river (3.2%)[31]. Distance is not significantly correlated with trade costs for paved links but is correlated with a \$0.183/t-km increase in trade costs for partially or fully unpaved links and a \$0.314/t-km increase in trade costs for water-based links. In columns (3) and (4) I repeat these regressions including an indicator variable for whether at least one of the towns in a link has a population over 500,000 but find that this is not significantly correlated with trade costs.

In table 1.10, I focus just on the 142 overland links that cross international borders within Africa. Distance and a difference in colonial language are not significantly correlated with higher trade costs for international links. The absence of a regional trade agreement between the countries is correlated with significantly higher trade costs[32]. A higher score on the Transparency International Corruption Perceptions Index is correlated with lower trade costs as is a higher score on the border and customs clearance efficiency component of the World Bank Logistics Performance Index[33], although these correlations lose significance when all variables are included in column (5).

[31] Data on paved roads is obtained from 2002 Michelin Maps, a widely-cited authority for accurate information on road quality in Africa (see for instance Burgess et al 2015). Water-based routes include 10 riverine links in the Congo River basin and 3 links crossing Lake Tanganyika.

[32] Regional trade agreements included in this analysis are SADC, EAC, CEMAC, and ECOWAS.

[33] CPI: 2013 rankings, score 0–100, higher score for less perception of corruption. LPI: 2014 rankings, score 1–5, higher score for better performance. For both indices, the scores of each country in a given link are added together to obtain the regressor.

Table 1.9: Correlation of Overland Trade Costs with Link Characteristics

	(1)	(2)	(3)	(4)
International	0.0681***	0.0552***	0.0679***	0.0553***
	(0.0169)	(0.0163)	(0.0169)	(0.0163)
Distance (km)	1.19E-04***		1.19E-04***	
	(3.95E-05)		(3.96E-05)	
Distance*paved		–3.41E-05		–4.07E-05
		(4.46E-05)		(4.50E-05)
Distance*unpaved		1.83E-04***		1.84E-04***
		(4.09E-05)		(4.09E-05)
Distance*water		3.14E-04***		3.14E-04***
		(8.64E-05)		(8.64E-05)
Town pop'n $> 500,000$			–0.00390	0.0159
			0.0161	(0.0156)
Constant	0.102***	0.120***	0.104***	0.113***
	(0.0183)	(0.0177)	(0.0201)	(0.0192)
Observations	413	413	413	413

Note: Standard errors in (); * significant at 10%, ** at 5%, *** at 1%.

Table 1.10: Correlation of Overland International Trade Costs with Link Characteristics

	(1)	(2)	(3)	(4)	(5)
Distance (km)	1.04E-04	6.14E-05	7.68E-05	6.89E-05	5.39E-05
	(1.16E-04)	(9.78E-05)	(1.05E-04)	(1.03E-04)	(9.92E-05)
Different language	0.0177				–0.0166
	(0.0460)				(0.0392)
No FTA		0.170***			0.140**
		(0.051)			(0.0615)
CPI index (sum)			–0.00435***		–8.57E-04
			(0.00124)		(0.00178)
LPI customs index (sum)				–0.140***	–0.0346
				(0.0368)	(0.0547)
Constant	0.166***	0.131***	0.442***	0.827***	0.361*
	(0.0521)	(0.0387)	(0.0830)	(0.164)	(0.187)
Observations	142	142	142	142	142
Clusters	75	75	75	75	75

Note: Robust standard errors in () clustered by country pair; * significant at 10%, ** at 5%, *** at 1%.

My trade cost estimation also includes trade costs between 30 African ports and the world market (Bangkok for rice and the US Gulf for other crops), which I estimate in the same way as overland trade costs as part of the iterative process outlined above. The median port-to-world-market trade cost I estimate is \$0.275/kg or \$275/tonne with over 70% of links having costs between \$100 and \$500/tonne. This compares to an average monthly transport cost of \$50/tonne from the US Gulf to Durban, South Africa over the study period, as reported by the International Grains Council. Durban is the largest port in sub-Saharan Africa, handling four times more cargo than the largest of the 30 ports I consider with one-quarter of the dwell time, and it is strategically located on major global shipping lanes (African Development Bank 2010, Kgare et al 2011). The higher range of costs I estimate for the ports I consider likely reflects lesser-used routes, increased port congestion with longer wait times, higher tariffs and non-tariff barriers, etc. In the appendix, I show that higher sea trade costs are correlated with smaller port populations, lower port volumes, lower Corruption Perception Indices, and higher tariffs on grains, although none of the correlations are statistically significant, which is likely due to the small sample size and the idiosyncratic nature of port costs. For my main counterfactual, I lower sea trade costs to \$50/tonne to match the freight rate to Durban.

1.4.4 Goodness of Fit

Having estimated both the demand parameters and the cost parameters, I proceed to use the estimated parameters to solve the model for equilibrium storage, trade, consumption, and prices of every grain in every market in every month. Before proceeding to my counterfactual analysis in the next section, it is important to verify the goodness of fit of the baseline estimated model. Of the four equilibrium variables, the only one I observe at the monthly, market level is prices, so I focus on comparing the model-generated equilibrium prices to the price data.

Figure 1.5 shows the actual maize price series from the 4 markets in Kenya and Tanzania from figure 1.1 together with the model-generated price series for these markets. In general, the correlation of the levels of the actual and model-generated price series is high. The correlation coefficient for the average prices for a given market and crop is 0.787. Within markets for all pairs of two crops, the model correctly predicts which crop has a higher average price 83.3% of the time.

The correlation of the model-generated prices and the price data *within a particular price series* seems lower, although the goodness of fit is more difficult to measure. The median correlation coefficient within price series is 0.385. As is clear from the sample price series in figure 1.5, there are many month-to-month price fluctuations (due to new information, government interventions, etc.) that cannot be explained by the parsimonious data used by the representative traders in my model. It is also the case that the correlation coefficient does not fully reflect the goodness of fit of the price series. The maize price series from figure 1.5, for instance, have within series correlation coefficients of 0.136 (Mandera), 0.217 (Nairobi), 0.171 (Arusha), and 0.174 (Songea) for this period despite the fact that the overall shapes

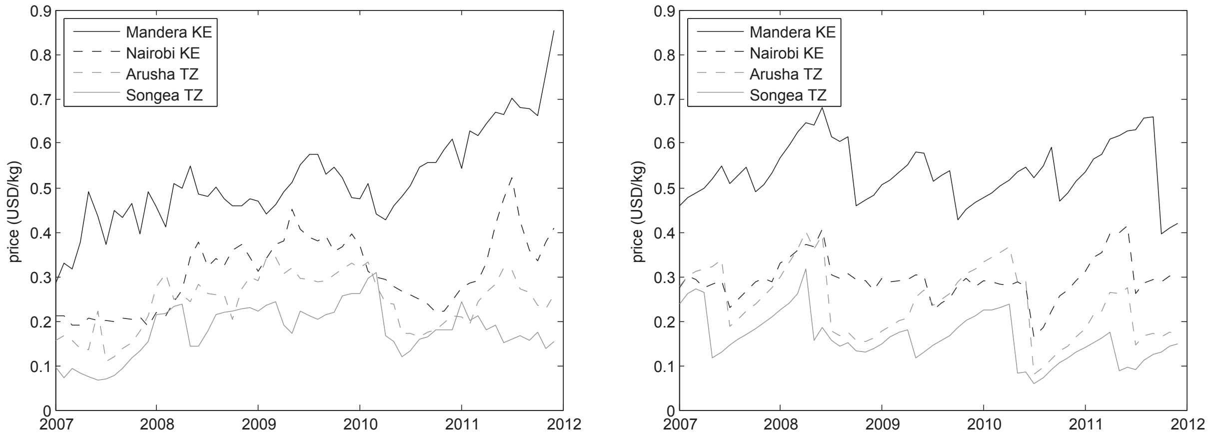

Figure 1.5: Actual Maize Price Series (left) and Model-Generated Baseline Price Series (right) for 4 Markets in East Africa, January 2007 – December 2011

of the series (including the timing of peaks and troughs) appear quite similar between the data and the model.

In addition to monthly, market-level prices, I also observe annual, country-level trade flows as reported in national trade statistics and compiled by CEPII's BACI project (Gaulier and Zignago 2010), which includes 37 of my 42 countries of interest as well as the rest of the world, which I group together into a 38th country[34]. Although these data are much less detailed than my model-generated trade data (1,510 vs. 55,440 observations), I can aggregate up my monthly, market-level equilibrium trade quantities and compare them to the annual, country-level data. In table 1.11, I compare net trade flows (exports minus imports) in the model and the data at different levels of aggregation. The first four rows compare net trade flows at the country level without distinguishing between specific origins and destinations, while in the bottom four rows I attempt to make this distinction by assigning observed trade with non-contiguous partner countries to the adjacent country through which such trade would have to pass so as to enable comparison with my model-generated trade flows.

Correlation coefficients between net trade flows in the model and the data are generally very high, although they are somewhat lower at the lowest levels of aggregation. Despite high correlation coefficients, the model appears to perform only moderately well at predicting whether net trade flows are positive, negative, or zero in the data. However, this is largely due to sign discrepancies for very small or zero net trade flows. Once trade flows below a minimum threshold (T_{min} = 10,000 t/year) are dropped, the model predicts the correct sign for net trade flows for well above 80% of observations at all levels of aggregation. Discrepancies between the model and the data — particularly for small trade volumes — are likely due in part to the existence of significant informal grain trade flows across borders in many parts of sub-Saharan Africa, which are not captured by official trade statistics. Tschirley and Jayne

[34]The missing countries are Botswana, Lesotho, Namibia, and Swaziland, which together with South Africa form the Southern African Customs Union (SACU), and South Sudan, which until 2011 was part of Sudan.

Table 1.11: Goodness of Fit of Net Trade Flows at Different Levels of Aggregation

	Correlation	Observations	Correct Sign	$\lvert T \rvert > T_{min}$	Correct Sign
Country	0.993	38	84.2%	36	86.1%
Country-Year	0.956	380	84.5%	328	90.5%
Country-Crop	0.897	83	75.9%	51	86.3%
Country-Year-Crop	0.837	830	68.7%	457	86.7%
Country Pair	0.902	91	60.4%	36	83.3%
Country Pair-Year	0.782	910	58.5%	313	89.1%
Country Pair-Crop	0.730	151	53.0%	45	84.4%
Country Pair-Year-Crop	0.615	1510	50.6%	348	89.4%

2010, for instance, cite estimates of informal, unrecorded cross-border trade flows of maize between Malawi, Mozambique, Tanzania, Zambia, and Zimbabwe exceeding 100,000 t/year.

Having estimated the model and established that it can reproduce both the price data and annual, country-level trade data reasonably well, in the next section I conduct my counterfactual analysis in which I compare equilibrium outcomes under the baseline model to outcomes under counterfactuals in which I change some of the demand parameters, cost parameters, or exogenous variables.

1.5 Counterfactual Results

In this section, I present my counterfactual analysis and robustness checks. In my main counterfactual, I lower trade costs within sub-Saharan Africa and between sub-Saharan Africa and the world market to match benchmark freight rates elsewhere in the world. In two extensions, I explore the extent to which the gains from lower trade costs can be realized by focusing on a few key trade corridors and how the impact of agricultural technology adoption depends on trade costs.

1.5.1 Main Counterfactual: Lowering Trade Costs

What would be the gains from lowering trade costs in sub-Saharan Africa to match levels elsewhere in the world? To answer this question, I re-solve the model replacing just the trade cost parameters with values equivalent to \$0.05/t-km for overland market links and \$50/tonne for port-to-world-market links, in line with baseline freight rates from the rest of the world discussed previously[35]. Importantly, this counterfactual does not reduce trade costs to zero (which would be impossible to achieve) but reduces them to match existing transport costs elsewhere in the world, a level which is potentially achievable. Empirically — as shown in the appendix — price differences for grains between locations within the US and between the US Gulf and other major world markets rarely exceed these benchmark

[35]This means that trade costs from the world market to an African port in this counterfactual are equivalent to overland trade costs for a distance of 1,000 km within Africa.

values, suggesting that transport costs make up most if not all of trade costs for grains in advanced countries and on the world market. This is consistent with the generally low or non-existent tariffs on grains in advanced countries and the low or non-existent information and search costs in these markets, where grains meeting standard quality specifications are traded on organized commodity exchanges.

For my counterfactual analysis, I continue to use the values of the exogenous variables (population, harvest, and world prices) from my period of interest (May 2003 – April 2013). I re-solve the model month-by-month as before with only the trade cost parameters changed and compare the resulting equilibrium to my original one. Thus while my results show the effects of lowering trade costs for this particular period, the impact of lower trade costs could be larger or smaller during other periods where the exogenous variables are substantially different. Figure 1.6 compares the model-generated price series under actual high trade costs from figure 1.5 to the model-generated price series under counterfactual low trade costs for the 4 markets from figure 1.1.

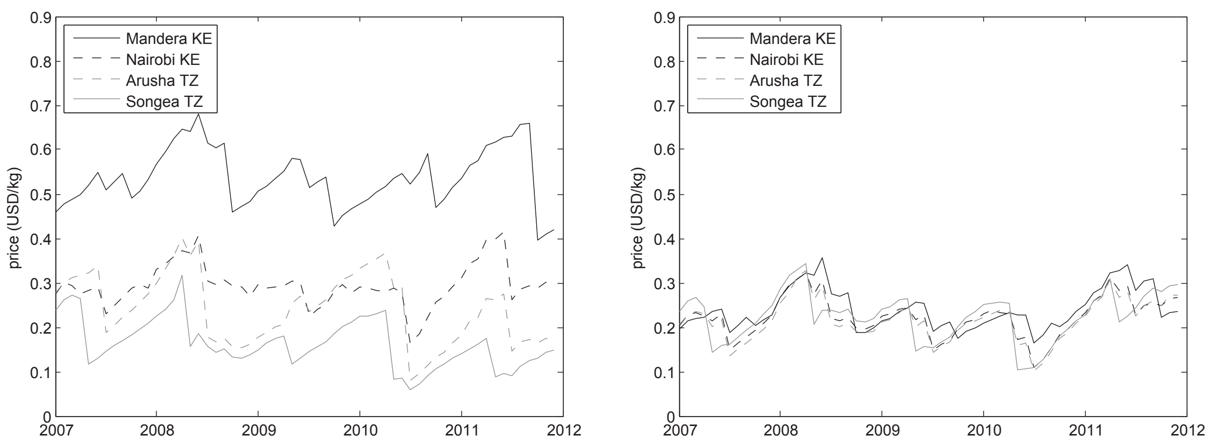

Figure 1.6: Model-Generated Baseline Price Series (left) and Model-Generated Counterfactual Price Series (right) for 4 Markets in East Africa, January 2007 – December 2011

Table 1.12 presents results from my main counterfactual, aggregated across space and time to include all 229 markets in 41 countries[36] and all 120 months in my 10-year period of interest. On aggregate, lower trade costs lead to a 46.4% drop in the average grain price index (from \$0.54 to \$0.29/kg). The counterfactual average grain price index of \$0.29/kg is in the 14th percentile of the baseline distribution of average grain price indices across markets, while the highest market-level average grain price index in the counterfactual (\$0.51/kg in Impfondo, Congo) is lower than the median in the baseline distribution. Lower prices lead to a decrease in agricultural revenues net of trade and storage costs by \$117.4 billion (−42.1%) and a decrease in expenditure on grains by \$226.4 billion (−44.1%). The direction of these aggregate results is explained by the fact that Africa as a whole is a net importer of

[36]Johannesburg, South Africa is excluded as I have treated it like the world market in my model.

grain, with most consumers and producers facing artificially high prices that fall once trade costs are lowered. Imports of grain from the world market increase by 32.0 million tonnes (17.5%), although the value of grain imports declines due to lower trade costs. Expenditure on trade costs declines substantially as does expenditure on storage costs (due to lower interest payments for storing cheaper grain and some substitution of trade for storage). Consumption of the outside good increases as less income is spent on grains. Overall welfare gains are equivalent to 2.2% of GDP over the 10-year period (a $125.0 billion equivalent variation), with the benefits of lower consumer prices outweighing the income losses in the agricultural sector.

Table 1.12: Aggregate Results from Main Counterfactual

	Quantity	Percent
Average Grain Price Index	–$0.25/kg*** ($0.01/kg)	–46.4%*** (1.0%)
Net Agricultural Revenues	–$117.4 billion*** ($10.2 billion)	–42.1%*** (1.7%)
Expenditure on Grains	–$226.4 billion*** ($14.1 billion)	–44.1%*** (1.0%)
Net Grain Imports – Quantity	+32.0 million tonnes*** (4.6 million tonnes)	+17.5%*** (1.8%)
Net Grain Imports – Value	–$16.2 billion*** ($1.2 billion)	–20.9%*** (0.9%)
Gross Trade Volumes	+537.7 million tonnes*** (48.4 million tonnes)	+65.9%*** (6.4%)
Expenditure on Trade Costs	–$65.5 billion*** ($3.0 billion)	–72.8%*** (1.0%)
Expenditure on Storage Costs	–$27.3 billion*** ($1.6 billion)	–41.0%*** (2.0%)
Consumption of Outside Good	+$109.0 billion*** ($4.7 billion)	+2.1%*** (0.1%)
Welfare	+$125.0 billion EV*** ($5.6 billion EV)	+2.2%*** (0.1%)

Note: Standard errors in () are bootstrapped (40 iterations) as described in the text; * significant at 10%, ** at 5%, *** at 1%.

Standard errors in table 1.12 were obtained using a computationally-intensive bootstrapping procedure with 40 iterations. For each iteration, I re-solved the model for equilibrium storage, trade, consumption, and prices under both high and low trade costs using different demand and cost parameter estimates obtained by re-sampling the data used to estimate each parameter with replacement. Due to the lengthy run-time, I limit my iterations to 40 and do not report standard errors for the later counterfactuals in this chapter.

In addition to the direct effect on price levels, lowering trade costs also affects local price volatility. In absolute terms, the average standard deviation of prices for the 511 grain price series falls from 0.188 to 0.123 (–34.5%) under low trade costs. However, in relative terms, the average coefficient of variation increases from 0.330 to 0.387 (+17.4%) due to the fall in the mean prices. A similar distinction holds for the frequency of high price events. In absolute terms, the frequency of grain prices over 1 USD/kg falls dramatically from 12.5% to 0.9% when trade costs are lowered. In relative terms, the frequency of grain prices exceeding double the series mean increases slightly from 2.0% to 2.1%. Lowering trade costs does therefore appear to be effective at preventing local prices from far exceeding regional and international levels as they have during events like the Horn of Africa famine (figure 1.1), but relative price volatility remains significant as high storage costs and similar agricultural calendars within regions mean that seasonal price fluctuations continue to be substantial (as seen in figure 1.6).

The aggregate results in table 1.12 do not reflect the heterogeneity of the effects of reducing trade costs across African markets and countries. Table 1.13 summarizes this heterogeneity by grouping markets and countries according to the sign of the changes they experience in their average grain price index, their net agricultural revenues, and their overall welfare when trade costs are lowered. The 181 markets (79.0%) and 37 countries in Group A are primarily net grain importers and experience changes similar to the continent-wide aggregate with falling prices and revenues and increasing welfare. The 14 markets (6.1%) and 2 countries (Malawi and Zambia) in Group B are primarily net grain exporters who experience price increases, revenue increases, and welfare increases under lower trade costs. This is not the case for all exporting regions: the 24 markets (10.5%) in Group C are net exporters that experience price decreases, revenue decreases, and welfare losses. These are mostly landlocked surplus regions (e.g. in the Sahel) that experience negative terms-of-trade effects when the urban and coastal regions they trade with are able to access cheaper grain imports from the world market. Finally, a small group of 10 markets (4.4%) and 2 countries (Sierra Leone and Zimbabwe) in Group D experience price decreases, revenue gains, and welfare gains due to their particular crop mix and/or their changing export position over time.

Table 1.13: Heterogeneous Effects of Reducing Trade Costs

	Group A	Group B	Group C	Group D
Price Index	−	+	−	−
Net Agricultural Revenues	−	+	−	+
Welfare	+	+	−	+
Markets	181	14	24	10
Countries	37	2	0	2

The results discussed thus far reflect the effects of reducing trade costs in the short run when factors of production cannot reallocate between sectors. In the longer run, the large price changes that my model predicts under lower trade costs are likely to lead to the reallocation of factors of production. In the majority of markets (Group A), the decrease in the relative price of grains would lead to a shift of factors of production out of agriculture and into the outside good sector. Using my production model developed previously, I use the actual harvests and the baseline equilibrium prices to back out the implied productivity shocks B_{imt} and then re-solve the counterfactual with an endogenous supply response using different values for the price elasticity of supply η. Roberts and Schlenker (2013) estimate the year-to-year price elasticity of supply for staple grains at 0.097. In the longer run, η may be larger (closer to $\eta = 0.5$), while a value of $\eta = 1$ would be considered unusually high in the agriculture literature.

Table 1.14: Aggregate Results with Supply Response

	$\eta = 0$	$\eta = 0.1$	$\eta = 0.5$	$\eta = 1$
Average Grain Price Index	–46.4%	–45.2%	–42.8%	–41.7%
Net Agricultural Revenues	–42.1%	–41.4%	–40.0%	–33.7%
Expenditure on Grains	–44.1%	–42.4%	–39.1%	–37.5%
Net Grain Imports – Quantity	+32.0 million t	+64.0 million t	+113.1 million t	+39.9 million t
Welfare	+2.2%	+2.2%	+2.4%	+2.5%

Table 1.14 compares results for key aggregate variables with an endogenous supply response for $\eta = 0.1$, $\eta = 0.5$, and $\eta = 1$ to results from the original counterfactual with no supply response ($\eta = 0$). As η increases, aggregate agricultural production in Africa falls, leading to a slightly smaller fall in prices, expenditure on grains, and net agricultural revenues (for which the price effect is larger than the quantity effect). Welfare, buoyed by increased income through increased production of the outside good, increases by more than before. Net grain imports from the rest of the world increase substantially as η increases, helping make up for the lower level of agricultural production within Africa[37]. The magnitude and direction of the changes in the aggregate variables remain similar to the base case, even when allowing for a large supply response ($\eta = 1$).

1.5.2 Robustness Checks and Alternate Approaches

My model and estimation strategy included several important assumptions. In this section, I explore the effects of relaxing some of these assumptions.

When defining market catchment areas, I allocated all agricultural production in my 42 countries of interest to the 230 markets in my network. As an alternative, I define market catchment areas for all 263 markets on my initial ideal list and then drop production in the catchment areas of the 33 markets for which I was unable to obtain price data. Re-solving the model for both baseline and counterfactual scenarios using these revised production data does not change my results substantially. Results for all indicators in table 1.12 are well within 95% confidence intervals constructed using the standard errors reported there.

[37]This trend appears to reverse in the rightmost column ($\eta = 1$), but this is due to unrealistically large increases in production in 9 markets for which extremely low baseline equilibrium prices in some harvest periods imply unrealistically large productivity shocks when $\eta = 1$. Net grain exports from these 9 markets increase by over 100 million tonnes when moving from $\eta = 0.5$ to $\eta = 1$. The increased production in these 9 markets is also behind the much smaller loss in net agricultural revenues in this column.

For my baseline estimation, I used the Cobb-Douglas elasticity of substitution ($\sigma = 1$) and set the price elasticity of demand for grains to match the estimate of Roberts and Schlenker 2013 ($\epsilon = -0.066$). Both of these values are at the lower end of elasticity estimates in the literature. In table 1.15, I compare my baseline results to results obtained using larger elasticities ($\sigma = 3$ and $\epsilon = -0.5$) in my estimation. Each time I change an elasticity, I re-estimate the other demand parameters (α_{im} and A_m) using the new elasticities, re-solve the model under both existing high trade costs and counterfactual low trade costs, and report the aggregate effects of lowering trade costs in table 1.15. Increasing the elasticity of substitution σ to 3 has virtually no impact on my aggregate results[38]. Increasing the price elasticity of demand ϵ to -0.5 leads to less of a fall in expenditure on grains and net agricultural revenues, as consumers increase expenditure more under lower prices. However, the average fall in the grain price index is nearly the same as before, with net grain imports from the world market increasing by nearly eight times as much to cover increased demand. The overall welfare increase from decreasing trade costs does not change significantly from my baseline case.

Table 1.15: Comparison to Results Using Different Elasticities

	$\sigma = 1$ $\epsilon = -0.066$	$\sigma = 3$ $\epsilon = -0.066$	$\sigma = 1$ $\epsilon = -0.5$
Average Grain Price Index	–46.4%	–46.4%	–40.6%
Net Agricultural Revenues	–42.1%	–42.0%	–27.6%
Expenditure on Grains	–44.1%	–44.3%	–21.6%
Net Grain Imports – Quantity	+32.0 million t	+40.8 million t	+249.9 million t
Welfare	+2.2%	+2.1%	+2.2%

I next analyse the effects of my assumption about trader expectations, which is necessary for model tractability but is likely to lead to underestimates of equilibrium storage by eliminating the effects of uncertainty. To evaluate the extent to which this assumption affects my results, I build 30 individual, small-scale, tractable models of grain storage and trade with full rational expectations in which harvests and world prices are stochastic. For the purposes of these models, I collapse all months, all grains, and all markets in each country into a single annual national harvest for which I calculate a sample mean and variance over my 10 year period of interest. For 20 countries with ports or direct access to Johannesburg, South Africa, I build a model for each country with just that country and the world market. For the remaining 21 countries, I build 10 models each consisting of a landlocked country, a coastal country, and the world market[39]. I choose a centrally-located major city

[38]This might seem surprising as the elasticity of substitution is in many trade models one of the key parameters determining the gains from trade (Arkolakis et al 2012), with the gains from lower trade costs expected to be smaller with a higher elasticity of substitution. Here the gains are only slightly smaller when σ is 3 because each grain is a homogeneous good without location-specific varieties and most markets are either exporters or importers of all grains, so substitution *between grains* is second-order.

[39]One of these models includes Rwanda and Burundi combined into a single landlocked country.

in each country and use my trade cost estimates to compute a single representative trade cost between each landlocked and coastal country and between each coastal country and the world market. I use my estimated demand parameters for each country as well as my estimated monthly storage cost parameters aggregated up to the annual level. For world prices, I compute a single annual world price index for each coastal country based on its harvest year and demand share parameters and calculate the sample variance of the month-to-month change in price of these indices over my 10 year period of interest. Putting all of this information together, I use the RECS solver in MATLAB to solve each of the 30 models and run simulations using actual observed harvest and world price shocks to solve for equilibrium storage, trade, price, and consumption in every country in every year under full rational expectations. I then re-solve each model under counterfactual low trade costs.

Despite volatile local harvests and high baseline trade costs, my results from this exercise indicate that inter-annual storage in Africa is limited even under full rational expectations, likely due to high storage costs and the position of most countries as net grain importers. Under existing high trade costs, an average of 2.0% of the grain harvest is stored inter-annually, and there is positive inter-annual storage in only 50 (12.5%) of the 400 total country-years in my 30 models. Under counterfactual low trade costs, an average of 0.3% of the grain harvest is stored inter-annually, and there is positive inter-annual storage in only 7 (1.8%) of the 400 total country-years in my 30 models, as cheaper trade serves as a partial substitute for storage.

The use of my assumption about trader expectations does appear to lead to underestimates of annual storage, but adjusting for these underestimates does not affect my main results. In my main model, under existing high trade costs, an average of 0.3% of the grain harvest is stored inter-annually, and there is positive inter-annual storage in just 1.5% of total market-crop-years, while under counterfactual low trade costs there is no inter-annual storage in any market-crop-year. To determine how allowing for full rational expectations affects my results, I re-solve my main model under both existing and counterfactual trade costs while restricting traders' choice of inter-annual storage of each grain in each market to equal the percentage of grain stored inter-annually in equilibrium for that country for that year in the results from my individual full rational expectations models. The percentage changes in net agricultural revenues, the average grain price index, expenditure on grains, and welfare are all within two tenths of a percentage point of my baseline results, and the results for all indicators in table 1.12 are well within 95% confidence intervals constructed using the standard errors reported there. Thus I conclude that my assumption about trader expectations does not have a statistically significant effect on my results.

Given the fact that inter-annual storage is limited, it is reasonable to ask to what extent my results would change if I used a more parsimonious model with no storage at all. In recent trade papers dealing with the agricultural sector (e.g. Costinot et al 2014), it is common to use annual data on production and farm-gate prices, the prices farmers receive when they sell their produce immediately after harvest. Using annual data, one can avoid having to deal with harvest cycles and intra-annual storage, which is necessary for there to be positive consumption in non-harvest months. To better understand the differences between this approach and the one I have used in this chapter, I use the harvest month price for each crop in each market from my baseline estimated model as the annual farm-gate price and build a new static model with all variables aggregated up to the annual level and no storage. I re-estimate trade costs for this new static annual model using the same approach as for my dynamic monthly model and then solve for equilibrium with both my new trade cost estimates and counterfactual low trade costs.

Trade cost estimates converge in 6 iterations for the static annual model, and each iteration takes only 2 minutes (less than 0.1% of the run-time for the dynamic monthly model). However, my trade cost estimates are 23.4% lower on average using the static annual model, and the overall welfare gain from lowering trade costs is 32.9% smaller than under the dynamic monthly model with storage. These differences can be explained by the pattern of equilibrium storage and trade described in Proposition 1. When production is widespread, trade between markets almost never occurs at the beginning of the harvest cycle when farm-gate prices are measured. During this period, local production and storage is used for consumption, spatial arbitrage conditions do not bind, and equilibrium price gaps are narrower. Instead, trade occurs primarily at the end of the harvest cycle once local stocks have been depleted, which is when equilibrium price gaps are wider and spatial arbitrage conditions bind. Using monthly data and a dynamic model with storage to identify more precisely when agricultural trade occurs thus seems important to avoid underestimating trade costs and their effects on welfare, particularly in developing country contexts with large seasonal price fluctuations. Further details on this exercise with graphical examples are contained in the appendix.

Having confirmed the robustness of my main results to the relaxation of several of my key assumptions and explored alternate approaches, I next turn my attention to two extensions in which I run additional counterfactuals to further explore the consequences of high trade costs in sub-Saharan Africa and the options for reducing them.

1.5.3 Extension: Trade Corridors

Reducing trade costs *everywhere* in Africa to match transport costs elsewhere in the world is likely not feasible in the short run. However, it may be feasible to reduce trade costs along certain high-priority routes. This section considers the extent to which some routes matter more than others for achieving the welfare effects of the main counterfactual. Even if a long-term goal of reducing trade costs everywhere is maintained, trade cost reduction will not be simultaneous, so the results in this section also shed light on welfare effects during the potentially long transitional period from a high trade cost to a low trade cost regime.

I start by looking at the effects of reducing trade costs along the 413 overland links within Africa while holding port-to-world-market sea trade costs constant and of reducing port-to-world-market sea trade costs while holding overland trade costs constant. Results in the second and third columns of table 1.16 indicate that while overland trade cost reduction accounts for over 70% of the overall welfare gain, nearly half of the overall welfare gain is achievable by just reducing sea trade costs between African ports and the world market.

Overland trade and sea trade are partial substitutes as both can reduce prices in grain-deficit markets.

Table 1.16: Aggregate Results with Trade Cost Reduction on Specific Links

	All Links	Just Land	Just Sea	Sea & 30 Land	Sea & 75 Land
Average Grain Price Index	–46.4%	–29.9%	–25.6%	–32.6%	–39.2%
Net Agricultural Revenues	–42.1%	–16.6%	–33.2%	–40.3%	–43.6%
Expenditure on Grains	–44.1%	–24.9%	–27.8%	–37.7%	–42.1%
Net Grain Imports	+32.0 mill t	–1.0 mill t	+43.0 mill t	+47.8 mill t	+41.3 mill t
Welfare	+2.2%	+1.6%	+1.0%	+1.6%	+1.9%

Since reducing port-to-world-market sea trade costs is likely more feasible than reducing overland trade costs everywhere in Africa, I start with this scenario and then look at whether adding trade cost reductions on a few key overland routes can substantially narrow the gap with my main counterfactual. I select key routes by first identifying the markets with the biggest welfare gaps between the "just sea" scenario in column 3 and the main counterfactual in column 1 and then identifying the most important overland links connecting these markets to their trading partners. In columns 4 and 5 of table 1.16, I show that adding trade cost reductions on just 30 overland links (7.3%) to the "just sea" scenario allows for over 70% of welfare gains to be achieved, and adding trade cost reductions on 75 overland links (18.2%) allows for 86% of welfare gains to be achieved.

These results are encouraging for policy-makers and multilateral donors who may have limited resources to invest in trade cost reduction. Generally speaking, the results suggest that investment in "trade corridors" of the type promoted by the African Development Bank and other institutional donors may be worthwhile. Although it is likely that the specific corridors I identify might not be the most important ones when other goods besides grains are considered, my corridor selection exercise, which is detailed in the appendix, suggests that certain types of corridors may be particularly beneficial. First, reducing trade costs from the world market all the way to "dry ports" in densely-populated inland areas like Addis Ababa, Ethiopia and Kinshasa, D.R. Congo can achieve major welfare gains even if trade costs from the dry ports to further-inland areas remain high. Second, reducing trade costs along inland corridors with imbalances or fluctuations in production and consumption (e.g. the trans-Sahelian highway) can lead to large gains without significant involvement of the world market. Third, targeting those inland areas isolated by extremely high trade costs (e.g. South Sudan) can lead to very large welfare improvements for those areas.

1.5.4 Extension: Technology Adoption and Trade Costs

In 2013, African cereal grain yields averaged 1.4 tonnes per hectare, compared to 3.1 in South Asia, 4.2 in Latin America, and 7.3 in the US. Low productivity in African agriculture is primarily due to the low use of inputs like fertilizer, and institutional donors and organizations like the Alliance for a Green Revolution in Africa (AGRA) are promoting technology adoption to narrow this productivity gap. This section uses my estimated model to look at the effects that widespread technology adoption in Africa would have under existing high trade costs and counterfactual low trade costs.

A complete model of technology adoption is beyond the scope of this chapter. Instead, I estimate what would happen if productivity everywhere in Africa doubled, i.e. if African cereal grain yields increased to 2.8 tonnes per hectare, which is much closer though still below levels elsewhere in the world. In the context of my model of production, this is equivalent to a doubling of all B_{imt}, which would double agricultural production in the short run ($\eta = 0$). Practically speaking, I implement this counterfactual by doubling the harvest (H_{imt}) in all markets and all time periods while keeping all other exogenous variables and parameters the same[40].

Table 1.17 compares results for key aggregate indicators from my main counterfactual (first column), counterfactuals with technology adoption under high trade costs (second column) and low trade costs (third column), and a combined counterfactual in which trade costs are lowered and technology adoption occurs (fourth column = first column + third column)[41]. Under high trade costs, technology adoption leads to a collapse of prices and agricultural revenues, as high trade costs confine much of the increased production to local markets with inelastic demand. Only 39 markets (17.0%) experience an increase in agricultural revenues, 37 of which are net importers for which increased production primarily serves to replace imports so that the price does not fall as much as in other markets[42]. In contrast, under low trade costs, agricultural revenues increase on aggregate and for 184 individual markets (80.3%), as much more of the increased production can be exported to deficit areas and the world market. Low trade costs are thus a prerequisite for widespread technology adoption to increase the incomes of African farmers.

Table 1.17: Aggregate Results with Technology Adoption

Baseline Counterfactual	High τ Low τ	High τ Double H	Low τ Double H	High τ Both
Average Grain Price Index	–46.4%	–58.6%	–14.2%	–60.2%
Net Agricultural Revenues	–42.1%	–71.4%	+12.4%	–29.7%
Net Grain Exports	–32.0 mill t	+254.1 mill t	+697.0 mill t	+665.0 mill t
Welfare	+2.2%	+2.6%	+2.2%	+4.4%

The net welfare effect of doubling productivity through technology adoption is similar in magnitude to the net welfare effect of lowering trade costs[43]. Although lower trade costs and productivity improvements are partial substitutes as both lead to lower prices in most

[40] In the appendix, I experiment with increasing production by less than 100% (10%, 20%,... 90%) and find that the effects always have the same sign, with lower percentages just leading to lower magnitudes.

[41] For ease of comparison, all percentage changes in table 1.17 are given in terms of the baseline equilibrium with existing high trade costs and low productivity.

[42] The other 2 markets are net exporters that have relatively cheap access to the world market even under high trade costs and/or have changing export positions over time.

[43] If policies that reduce agricultural trade costs also reduces trade costs for other sectors, the effect

markets, the combined welfare effect of both (4.4%) represents 92% of the sum of the effects of each intervention on its own (2.2% + 2.6% = 4.8%). These findings suggest that agricultural policy in Africa should give as much weight to trade cost reduction as to technology adoption and prioritize comprehensive approaches that include both.

1.6 Conclusion

In this chapter, I have built, estimated, and solved a dynamic model of agricultural storage and trade in sub-Saharan Africa and used it to estimate the gains from reducing trade costs to levels on par with the rest of the world. I began by assembling a new intra-national dataset of monthly prices and production of the 6 major staple cereal grains in 230 market catchment areas covering all 42 countries of continental sub-Saharan Africa over the ten-year period from May 2003 to April 2013. I then wrote down a dynamic model of storage and trade under uncertainty in which a representative consumer in each market chooses consumption of each grain and an outside good given prices and income in each period and a representative competitive trader in each market chooses how much of available grain to put into storage, sell locally, and import or export from other markets given current and expected stocks, harvests, world prices, and consumption demand across all markets in the network. I used my data to estimate both the model's demand parameters and its cost parameters (including trade costs for each of 413 overland links and between each of 30 ports and the world market). My storage and trade cost estimation strategy utilized a novel iterative approach to determine the markets and periods in which the storage and trade arbitrage conditions were binding. The median intra-national trade cost I estimated using this approach is over 5 times higher than benchmark freight rates elsewhere in the world.

After solving my estimated model for equilibrium storage, trade, consumption, and prices for every grain in every market in every month, I proceeded to re-solve the model for several counterfactual scenarios. In my main counterfactual, I lowered agricultural trade costs within Africa and between Africa and the world market to match transport costs elsewhere in the world. On aggregate, lower trade costs would have led to a large drop in grain prices, agricultural revenues, and expenditure on grains in sub-Saharan Africa during the study period, with an overall welfare gain equivalent to 2.2% of GDP. These findings change only slightly when allowing for reallocation of factors of production in the long run and are robust to alternative demand specifications and the relaxation of the key assumption about trader expectations that I used for tractability. There is significant variation in these effects between markets within Africa, with some markets experiencing increases in prices, revenue, and welfare, and others experiencing welfare losses due to terms-of-trade effects. Using a dynamic monthly model with storage is important for correctly identifying when agricultural trade occurs, particularly in contexts like this one with large seasonal price fluctuations. In my case, I showed that a static annual model underestimates trade costs by 23% and welfare

of lowering trade costs would likely be much larger than the effect of doubling productivity just in the agricultural sector.

effects by 33%.

In two extensions, I explored the extent to which investment in select trade corridors could achieve similar gains to continent-wide trade cost reduction and the degree to which the impact of productivity-enhancing technology adoption depends on trade costs. I showed that reducing port-to-world-market trade costs and trade costs along just 18% of the 413 overland links enables achievement of 86% of overall welfare gains, suggesting that a corridor-based approach to trade cost reduction may be efficient in this context. The effects of technology adoption are very different under existing high and counterfactual low trade costs. Doubling agricultural productivity leads to large declines in net agricultural revenues under existing high trade costs due to limited market access and inelastic local demand. In contrast, the same productivity change under counterfactual low trade costs leads to increases in net agricultural revenues as surplus production can be exported. The welfare gains from trade cost reduction and technology adoption are similar in magnitude and nearly additive when both occur together, highlighting the importance of prioritizing both in agricultural policy.

The findings in this chapter complement and need to be further complemented by micro-level studies looking at the components of trade costs, the impact of policies designed to reduce trade costs, and the size and nature of farm-to-hub-market trade costs. It is beyond the scope of this chapter to identify precise components of trade costs, but my trade cost estimates can be a useful starting point for studies that attempt to do so. Since intra-national price data on staple grains is relatively widely available for sub-Saharan African markets, these data could be used as the basis for evaluating the impact of specific policy interventions on trade costs and welfare using some of the techniques used in this chapter. Importantly, this chapter considered only trade costs between the 230 large hub markets in my dataset. Farm-to-hub-market trade costs are potentially even larger and their reduction would likely have a positive effect on farmer incomes, although the significant market power of traders in remote rural areas must be taken into account.

Aside from the findings of my counterfactuals, a major contribution of this chapter is the estimated model of African agricultural storage and trade in and of itself. The model can potentially be used to explore many additional counterfactuals beyond the few considered in this particular chapter, including the effects of events like climate change, international food price spikes, conflicts, and disease outbreaks on prices, revenues, and welfare in individual markets or countries or for the continent as a whole.

Chapter 2

Empirical Effects of Short-Term Export Bans: The Case of African Maize

2.1 Introduction

The prices of basic agricultural commodities have fluctuated dramatically over the last decade. In developing countries, where food expenditure makes up a large proportion of household consumption, these price fluctuations have led to a proliferation of policies to control or stabilize food prices. Temporary export restrictions have been particularly widespread, with at least 33 countries using some form of export restriction during the 2007 – 2008 food price spike and its aftermath, including 4 of the top 5 rice producers (China, India, Bangladesh, Vietnam) and 7 of the top 13 wheat producers (China, India, Russia, Pakistan, Ukraine, Argentina, Kazakhstan) (Sharma 2011). This chapter focuses on the most common and severe of such restrictions: the short-term export ban.

The literature on export restrictions has focused on understanding why countries implement them and the role they play in exacerbating international price spikes. Theoretically, export restrictions introduce welfare-reducing price distortions, with local farmers losing more than local consumers gain from lower domestic prices (Mitra and Josling 2009; Liefert et al. 2011). Governments likely implement export restrictions because they put more weight on consumers' interests than those of producers, are more concerned about negative deviations from the status quo than positive ones, or seek to avoid extreme events (Abbott 2011). Gouel and Jean (2015) have also shown that export restrictions can be part of an optimal dynamic food price stabilization policy when consumers are risk averse and insurance markets are incomplete. Regardless of their domestic rationale, the welfare effects on other countries appear to be unambiguously negative: by cutting off supply to the world market during times of high prices, export restrictions magnify international price fluctuations and have been criticized for representing a beggar-thy-neighbor approach to trade (Headey 2011; Martin and Anderson 2011; Anderson and Nelgen 2012).

This chapter provides new empirical evidence from East and Southern Africa that export bans do not always have the effects that governments (or economists) think they do. Unlike other parts of the world where export restrictions were one-time policies implemented during the 2007 – 2008 food price spike (e.g. Götz et al. 2013), export bans in East and Southern Africa are regularly used to respond to high international prices or domestic production shortfalls of maize, the main staple grain in the region. I use monthly, market-level maize price data from 49 large hub markets in 12 countries over a 10-year period during which 5 of these countries (Ethiopia, Kenya, Tanzania, Malawi, and Zambia) implemented 13 distinct export bans on maize. I document a surprising and robust empirical result: export bans in this region do not have a statistically significant effect on the gaps in prices between pairs of affected cross-border markets.

I compare my empirical results to results from simulations using the estimated dynamic monthly model of grain storage and trade in sub-Saharan Africa from the previous chapter, which includes nearly all of the same markets and cross-border trade routes. The model predicts a large and statistically significant increase in the gaps in prices between the affected cross-border markets due to the 13 export bans, even when traders are able to anticipate the bans with perfect foresight. The absence of an effect on the price gaps in the data matches a model simulation in which the export bans are not implemented. However, prices in *both* implementing and trading partner countries during export bans are significantly higher in the data than in the model simulation with no implementation.

Information collected from market participants in sub-Saharan Africa indicates that export bans are imperfectly enforced, with informal local traders as well as some formal traders who are able to secure export permits through back-door channels able to continue trading during bans. These alternative trade channels may be subject to capacity constraints, but these constraints appear to only bind at the very end of bans. However, the unpredictable, *ad hoc* nature of the bans and their enforcement appears to destabilize markets on both sides of the border. In addition to prices that are higher than they would have been without a ban, price volatility is also significantly higher in the implementing country.

Taken together, my results suggest that export bans in East and Southern Africa do not have their intended effects of stabilizing or lowering domestic prices or insulating them from high international prices and have unintended destabilizing consequences instead. Policymakers in the region (and perhaps elsewhere) should therefore re-evaluate their use even when they appear justified on political economy grounds. My results are also a cautionary note for studies that have used model-based simulations to estimate the effects of export restrictions (e.g. Ahmed et al. 2012; Diao and Kennedy 2016), as these effects are likely different in practice if the export restrictions in question are imperfectly enforced.

2.2 A Surprising Empirical Result

Maize is the primary staple grain produced and consumed in East and Southern Africa. Empirical evidence suggests that while imperfect competition is important in small, remote rural grain markets in sub-Saharan Africa, larger hub markets of the type considered here are competitive, with many traders and low firm concentration ratios (Osborne 2005; Aker 2010). Trade in the region is almost exclusively by diesel truck and is constrained by geography and the limited road network. Although most maize production is consumed domestically, maize is actively traded across all of the borders in the region. Formal maize trade volumes recorded in official trade statistics between the 12 countries considered here averaged 424,000 metric tons annually during the study period (Gaulier and Zignago 2010), with at least another 120,000 metric tons of unrecorded informal cross-border trade (Tschirley and Jayne 2010), together representing roughly 3% of the 19 million metric tons produced annually in the region.

Table 2.1: Dates of 13 Export Bans

Country	Start Month	End Month	Affected Pairs
Ethiopia	Jan-06	Jul-10	6
Ethiopia	Mar-11	Post-2011	6
Kenya	Oct-08	Post-2011	14
Malawi	Jul-05	Feb-07	7
Malawi	Apr-08	Aug-09	7
Malawi	Dec-11	Post-2011	7
Tanzania	Jul-03	Jan-06	18
Tanzania	Aug-06	Dec-06	18
Tanzania	Jan-08	Oct-10	18
Tanzania	May-11	Oct-11	18
Zambia	Pre-2002	Jul-03	7
Zambia	Mar-05	Jul-06	7
Zambia	May-08	Jul-09	7

My primary dataset consists of a panel of monthly maize price data from large hub markets (major towns) in East and Southern Africa assembled by the Famine Early Warning System Network (FEWS NET) and covering the 10-year period from January 2002 to December 2011. Using local newspaper archives and FEWS NET monitoring reports, I identified the starting and ending dates of 13 short-term export bans implemented by 5 countries during this period, ranging in duration from 4 to 54 months (table 2.1). I then selected the major markets on either side of the affected international borders from the FEWS NET database and identified the pairs of cross-border markets directly linked by transportation infrastructure. With competitive trade, any price change caused by an export ban should be detectable at these directly-linked cross-border markets, with markets further away from the border experiencing equivalent price changes if they are trading with the directly-linked markets and no price change otherwise. The resulting dataset includes 49 markets and 40 cross-border market pairs (figure 2.1). This includes an additional 6 markets in areas not covered by the FEWS NET database in western Tanzania, eastern Malawi, and northern Mozambique, which I added to my dataset using price data from the Ministries of Agriculture (Malawi and Mozambique) and of Industry, Trade, and Marketing (Tanzania) in these countries.

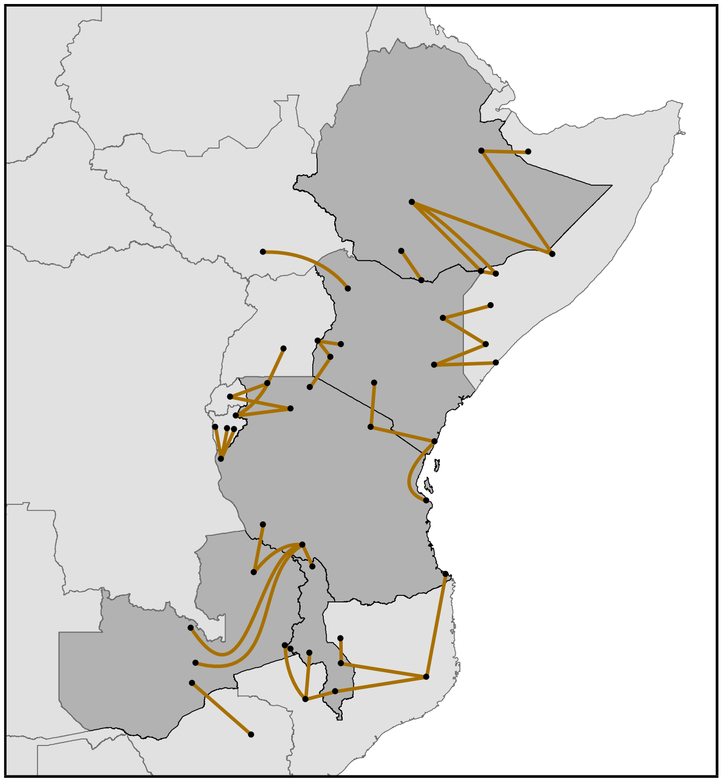

Figure 2.1: Map of 49 Markets and 40 Market Pairs in Dataset

The median market town has a population of 178,000, and the median market pair is separated by a road distance of 345 kilometers. All prices are expressed in US dollars per kilogram using monthly exchange rates provided by FEWS NET. The mean maize price across all markets and all periods is $0.274/kg. The price data is not complete as data collection began in some markets after January 2002 and there are a few missing observations throughout. The median price series has 102 of 120 possible observations, and 40 of the 49 markets have at least 6 years (72 observations) of data. Of 5,880 possible price observations, 1,435 (19%) are missing. I will show that my results are robust to restricting the panel to a more balanced subset.

Export bans are likely implemented during periods of high prices and are thus endogenous to prices. My main empirical specification estimates the effects of export bans on the *price gaps* between pairs of cross-border markets instead. Export bans are unlikely to be endogenous to price gaps, since the events that trigger them are unlikely to affect the costs of trade between the cross-border market pairs. In the following section, I confirm with model simulations that in the absence of any bans price gaps would not have been higher or lower during periods in which bans were in fact implemented than in periods in which they were not.

In theory, export bans work by increasing the costs of trade between cross-border market pairs (to infinity if the ban is perfectly enforced). The spatial price analysis literature has thought carefully about the relation between price gaps, which are observable, and total trade costs, which are typically unobservable (Fackler and Goodwin 2001). Under competitive trade, the price gap between a pair of markets is equivalent to the total trade costs between those markets if trade is occurring, which Baulch (1997) and others have called "regime 1." If trade is not occurring, the markets are in a segmented equilibrium (Baulch's "regime 2"), and the price gap between them is a lower bound on the total trade costs. The price gap may also temporarily exceed the trade costs if the markets are in disequilibrium following a shock (Baulch's "regime 3"). Regimes 1 and 3 motivate a regression of the form:

$$\Delta P_{ijt} = \beta B_{it} + \phi_{ij} + \epsilon_{ijt} \tag{2.1}$$

In equation 2.1, $\Delta P_{ijt} = P_{jt} - P_{it}$ is the price gap between market j and market i in month t, B_{it} is an indicator variable for an export ban affecting exports from market i to market j in month t, ϕ_{ij} is a directional market pair fixed effect capturing components of price differences that do not vary over time (e.g. baseline trade costs), and ϵ_{ijt} is a mean-zero error term reflecting the possibility of a shock that would cause price gaps to be greater or less than trade costs during a particular month t. In estimating equation 2.1, I exclude observations with negative price gaps so that a given market pair has a single observation per month in the direction of the positive price gap.

For markets with relatively low trade costs and consistent import-export relationships, restricting attention to regimes 1 and 3 would be appropriate. However, given the high trade costs in the agricultural sector in sub-Saharan Africa estimated in the previous chapter and the fact that maize is produced locally in all of the markets in my dataset, it is important to account for the possibility of regime 2 segmented equilibria in which export bans would have no effect because they are not binding. If I include these "no-trade" observations in my estimation, the resulting estimate of my parameter of interest β is a valid measure of the effects of export bans in a reduced-form sense conditional on market conditions at the time of ban implementation but is a downwardly-biased estimate of the effects of export bans conditional on the ban actually binding and preventing trade that would otherwise have occurred. Recent empirical evidence in contexts where regime 2 observations can be identified confirms this downward bias when all observations are included (Atkin and Donaldson 2015). In the regressions that follow, I experiment with different ways of identifying and excluding potential regime 2 no-trade observations and compare my subsequent results to my baseline reduced-form result using all observations.

Column 1 of table 2.2 shows results from the specification given in equation 2.1 with all observations. The mean of the dependent variable (the gap in prices between cross-border market pairs) is \$0.0853/kg. The point estimate for the effect of export bans on this gap is less than three-thousandths of a US cent or less than three-hundredths of a percent of the mean price gap and is not statistically significantly different from zero at any confidence level. I calculate standard errors directly because of the complicated nature of potential correlation between the residuals in my dataset. The standard approach with panel data (shown in column 2) would be to cluster at the market pair level to allow for correlation of residuals for a given market pair in different time periods. However, as is clear from the map in figure 2.1, the market pair structure also has features of a dyadic regression, with a single market often being a member of multiple market pairs. To deal with this additional source of correlation, I extend the approach of Fafchamps and Gubert (2007) for calculating consistent standard errors in cross-sectional dyadic regressions, allowing for correlation of residuals between any observations sharing at least one common market (even if those observations are in different time periods) while continuing to assume that residuals are independent across observations with no common markets. The standard errors calculated using this dyadic approach (column 1) are very close to those obtained by clustering at the market pair level (column 2).

Table 2.2: Basic Specification and Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
Export ban	0.0000214	0.0000214	–0.00139	–0.0154	0.00311	–0.00619
	(0.00959)	(0.00969)	(0.0100)	(0.0124)	(0.00559)	(0.0114)
Distance * Gas price			0.0000231			
			(0.0000158)			
Infrastructure			Yes			
Time trend				0.00128		
				(0.00110)		
Time fixed effects				Quarter		
Observations	3253	3253	3253	3253	3096	2579
Standard errors	Dyadic	Cluster: Pairs	Dyadic	Dyadic	Dyadic	Dyadic

Note: Robust standard errors in () calculated as indicated; *significant at 10%, ** at 5%, *** at 1%.

Using the standard errors from column 1 and the mean maize price of \$0.274/kg, I can reject an alternate hypothesis that export bans have an effect at least as large as that of a 5% export tax ($0.05 * \$0.274 = \$0.0137$/kg) at an 8% significance level. A 5% export tax is at the low end of short-term trade policy responses to commodity market price fluctuations — temporary export taxes of 25–40% are not uncommon (Sharma 2011). Of course, such taxes may (like export bans) not translate into empirical price differences, so the benchmark used here should be interpreted as the theoretical effect of a permanent 5% export tax.

The specification in equation 2.1 implicitly assumes that no other variables besides export bans systematically affect price gaps over time. In columns 3 and 4 of table 2.2, I introduce additional covariates to capture some of this potential temporal variation. Recent results from Dillon and Barrett (2016) highlight the importance of fuel prices for maize trade in East and Southern Africa. I construct monthly retail diesel price series in US dollars per liter at the national level for my 12 countries of interest (plus the breakaway republic of Somaliland) by using biennial observations from the International Fuel Prices project of GTZ (the German technical cooperation) to compute markups over the Dubai Fateh crude oil index (the most relevant for oil imports into East and Southern Africa) and filling in gaps between GTZ observations using markups inferred by linear interpolation. In column 3, I add a term interacting these fuel prices in the origin market with the distance to the destination market as well as a set of indicator variables for major infrastructure projects affecting particular cross-border links compiled from government ministries and local newspaper archives. The point estimate for the diesel-distance coefficient corresponds to the expected cost of a 10-metric ton truck consuming 23 liters per 100 kilometers (11 miles per gallon), although it is not statistically significant at conventional levels. In column 4, I include quarterly time fixed effects and a time trend instead. In both of these new specifications, the coefficient estimate on export bans is negative and not statistically different from zero. Similar results were obtained using monthly and annual fixed effects with and without a time trend as well as including all variables from both columns 3 and 4.

In column 5 of table 2.2, I exclude two outliers: the pairs involving Juba, South Sudan and Hargeisa, Somaliland, which have the highest and most volatile prices of the markets in my dataset. Their exclusion does not affect my results but does reduce the standard error on my export ban coefficient estimate. This enables me to reject my alternate hypothesis that the effect of export bans is as large as the theoretical effect of a 5% export tax at a 3% significance level. In column 6, I explore whether the unbalancedness of the panel is affecting my results by excluding all observations before January 2006, reducing my dataset from ten years to six. With this adjustment, of the 3,528 possible price observations in my new panel, only 171 (4.8%) are missing, as opposed to 19% in my original panel. My basic result that export bans do not have a statistically significant effect on the price gaps between pairs of affected cross-border markets remains unchanged.

In a further set of robustness checks not presented here, I interacted implementing country indicator variables with the export ban indicator variable to look at potential heterogeneous effects. Again, none of the coefficients were statistically different from zero, indicating that none of the countries' export bans had a statistically significant effect on the price gaps between pairs of affected cross-border markets.

I next consider the possibility that regime 2, segmented equilibrium observations are biasing my coefficient estimate towards zero. Suppose that export bans do increase price gaps significantly for market pair-periods where they prevent trade from occurring but that I am not detecting this increase because I am including many other observations of segmented equilibria where trade would not occur with or without an export ban. In this case, if I were to progressively drop increasing numbers of these regime 2 observations from my dataset my coefficient estimate should increase.

In figure 2.2, I experiment with two different ways of identifying and excluding potential regime 2 observations. Teravaninthorn and Raballand (2009) present data on transport prices for several major African transport corridors that range from \$0.07 to \$0.13 per metric ton-kilometer. In the previous chapter, I find that total trade costs are roughly double these baseline freight rates and are higher off of major corridors, with a median trade cost of \$0.29/t-km. Among the cross-border market pairs considered in this chapter, the maximum per-distance trade cost estimated in the previous chapter is \$0.70/t-km, and the maximum absolute trade cost is \$0.20/kg. Since trade costs are un upper bound on price gaps in regime 2, I proceed by dropping all observations in my dataset with price gaps below a

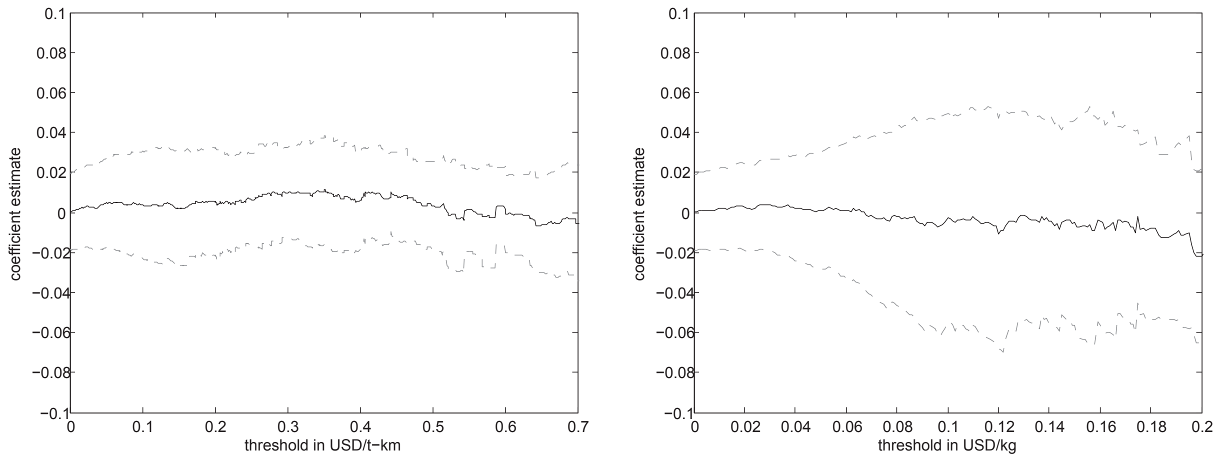

Figure 2.2: Estimate of Export Ban Coefficient (solid black) and Bounds of 95% Confidence Interval (dashed grey) with Increasing Threshold in USD/t-km (left) and USD/kg (right)

progressively increasing threshold. In the left panel of figure 2.2, I use the per-distance price gap and progressively drop observations from 0 up to \$0.70/t-km. In the right panel, I use the absolute price gap and progressively drop observations from 0 up to \$0.20/kg. At the maximum threshold, only 354 (10.9%) and 297 (9.1%) observations remain in the dataset. In both cases, the point estimate stays statistically insignificant and very close to zero, and there is no sign of an upward trend as I drop increasing numbers of potential regime 2 observations. I conclude that my failure to detect an effect of export bans on cross-border price gaps is not due to the presence of regime 2 observations.

2.3 Comparison to Model Simulations

In this section, I run simulations using the estimated dynamic monthly model of grain storage and trade in sub-Saharan Africa from the previous chapter to help understand the surprising empirical result from the previous section. The model consists of a representative consumer and a representative competitive trader in each of 230 large hub markets covering all 42 countries of continental sub-Saharan Africa. The model includes maize and five other major staple grains, and its demand, storage cost, and trade cost parameters were estimated using data from May 2003 – April 2013. Given monthly (expected) production, (expected) world prices, demand, storage costs, and trade costs, traders decide each month how much of each grain to sell locally, to put into storage in each of the 230 locations, and to trade along each of 413 overland bilateral transportation links as well as with the world market through 30 major ports. The model output includes equilibrium price series for each grain in each market.

I adjust the model to start and stop a year earlier so as to match the timeframe of the empirical exercise in the previous section and run three simulations. In the first simulation, I assume that export bans are not implemented so that trade is possible between cross-border market pairs during every month at the constant, pair-specific trade costs from the original estimated model. In the second simulation, I assume that the 13 export bans from table 2.1 are implemented and perfectly enforced and that traders are naïve, so the imposition and lifting of the bans takes traders by surprise. This means that prior to bans storage and trade decisions are made assuming that trade will always be possible at the constant, pair-specific trade costs, and during bans these decisions are made assuming that trade will never again be possible between the affected pairs (trade costs are infinite). In the third simulation, I assume that the bans are implemented and perfectly enforced but that traders have perfect foresight about the imposition and lifting of bans. This gives them the possibility of exporting prematurely before bans are imposed and storing for future exports during bans. Realistically, trader behavior is likely somewhere in between the second and third simulations, given that precise information about future discretionary government actions is not available but that some anticipation is certainly possible.

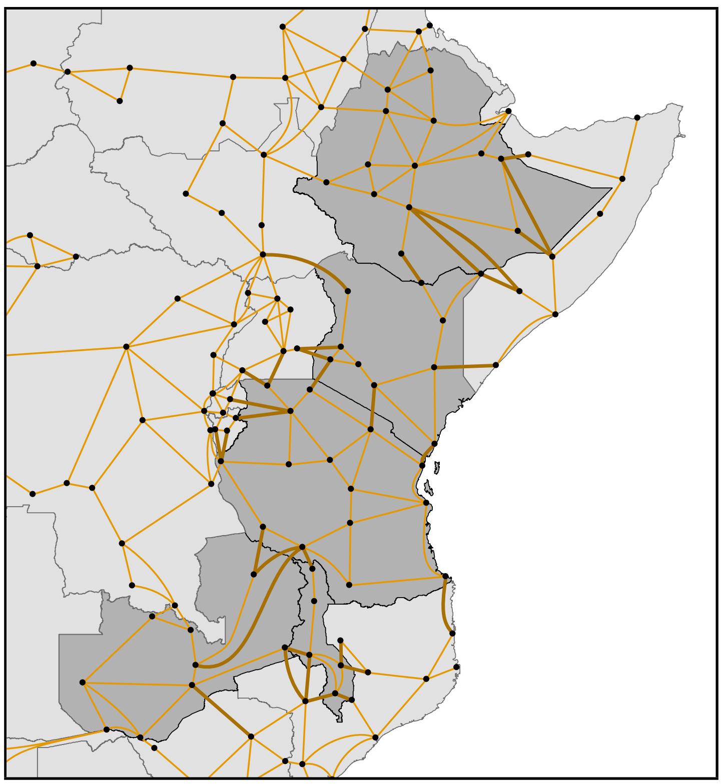

Figure 2.3: Map of 33 Selected Market Pairs (in bold) from Model

After solving month by month for the full continent-wide equilibrium for each of the three simulations, I extract the price series for the 47 markets and 33 market pairs corresponding most closely to the 49 markets and 40 market pairs from the dataset used in the previous section. Figure 2.3 highlights these market pairs against the backdrop of the other markets and transportation links in the continent-wide model. I then run the same regression from equation 2.1 using the price gaps for these market pairs from each of the model simulations (table 2.3). The results reported here do not change significantly when all affected cross-border pairs from the model (including those with Namibia, D.R. Congo, Eritrea, Sudan, and the world market) are included.

Table 2.3: Results Using Simulated Price Series

	No Bans	Naïve	Foresight
Export ban	–0.00359	0.301***	0.178***
	(0.00287)	(0.0726)	(0.0408)
Observations	2938	2958	2934

Note: Robust dyadic standard errors in (); *significant at 10%, ** at 5%, *** at 1%.

The results in table 2.3 are helpful for distinguishing between different explanations for my finding in the previous section that export bans do not have a statistically significant effect on the price gaps between cross-border markets. One possible explanation is that export bans do increase price gaps but are implemented during periods of abnormally small price gaps, which prevents me from detecting the effect. I can rule out this explanation using the first simulation, which shows that in the absence of export bans, the difference between the cross-border price gaps during periods when export bans were and were not actually implemented would not have been significantly different from zero. A second explanation is that export bans are not binding or that the trade flows they do prevent are so small that the bans do not have a significant effect on price gaps. I can rule out this explanation using the second simulation, which shows a very large effect of export bans on cross-border price gaps (significant at the 1% level) when traders do not anticipate ban imposition and lifting. The size of the effect is over four times larger than the average price gap of \$0.0853/kg. A third possible explanation is that since maize is storable and bans are temporary, traders are able to limit the actual effects of export bans when they can anticipate their imposition and lifting. The third simulation shows that perfect foresight would enable traders to cut the effect of export bans on cross-border price gaps nearly in half, but the effect is still large and statistically significant at the 1% level. Interviews with traders in the region confirm that high storage costs (including the high cost of capital) make it costly for them to hold on to stocks while waiting for a ban to be lifted.

Comparing my results from the model simulation without export ban implementation in the first column of table 2.3 with my results using the actual price data in table 2.2, it is clear that I cannot reject a hypothesis that export bans are simply not enforced. To shed additional light on this hypothesis, I run additional regressions looking at the effects of export bans on prices in both the origin markets in the export ban implementing countries and the destination markets in the trading partner countries. These regressions are of the form:

$$P_{it} = \beta B_{it} + \phi_i + \epsilon_{it} \tag{2.2}$$

for origin markets and

$$P_{jt} = \beta B_{it} + \phi_j + \epsilon_{jt} \tag{2.3}$$

for destination markets, where ϕ_i and ϕ_j are fixed effects for origin and destination markets respectively. I continue to restrict the data to the direction of the positive price gap so that a given market pair has a single origin market and destination market each period. I run these two regressions on the price data as well as the price series from each of the three model simulations (table 2.4).

Table 2.4: Price Regressions with Data and Model Simulations

	Data	Data	No Bans	No Bans
Dependent variable	Orig. price	Dest. price	Orig. price	Dest. price
Export ban	0.0624***	0.0574***	0.0220***	0.0183***
	(0.00887)	(0.0117)	(0.00444)	(0.00467)
Observations	3253	3253	2938	2938

	Naïve	Naïve	Foresight	Foresight
Dependent variable	Orig. price	Dest. price	Orig. price	Dest. price
Export ban	–0.0438***	0.256***	–0.0104	0.167***
	(0.0130)	(0.0509)	(0.0682)	(0.0312)
Observations	2958	2958	2934	2934

Note: Robust standard errors in () clustered by market;
*significant at 10%, ** at 5%, *** at 1%.

A concern with the specifications in equations 2.2 and 2.3 discussed previously is that export bans are likely endogenous to prices as they are ostensibly implemented during periods of high prices. Results in table 2.4 using the price series from the simulation with no bans confirm that in the absence of export bans, prices in both origin and destination markets would have been 2 US cents/kg higher during periods when bans were in fact in place than in periods when they were not. However, in the data, prices in both origin and destination markets are 6 US cents/kg higher during export ban periods, and the difference with the no-ban simulation is statistically significant. This suggests that export bans are in fact having some effect on market outcomes, although the empirical effects of export bans in the data are still very different from those in the model simulations in which the bans are fully enforced with either naïve traders or traders with perfect foresight. In both of these simulations, the price response to bans is more consistent with theory, with destination market prices increasing substantially and origin prices falling (naïve) or remaining statistically unchanged (perfect foresight).

The results from this section suggest that the lack of an effect of export bans on the price gaps between pairs of cross-border markets is consistent with the bans not being enforced and is not consistent with the bans being perfectly enforced, even if traders can anticipate the bans. However, the fact that prices in both origin and destination markets are higher during export bans than they would have been in the absence of bans suggests that the bans are affecting markets somehow. In the following section, I present information collected from market participants in the region about ban enforcement that helps explain these findings.

2.4 Imperfect Enforcement and Destabilizing Stabilization

As part of the research for this chapter, I obtained information about ban enforcement from market participants in Malawi, Tanzania, and Zambia, which together are responsible for 10 of the 13 export bans in my dataset. I conducted interviews with formal and informal private traders of all sizes, trader associations, farmers, government officials, and market observers including FEWS NET and the World Food Programme in these countries. I also visited six border points in the region during export bans.

The consensus among market participants is that export bans are implemented but imperfectly enforced. The formal export of maize requires an export permit, typically issued by the Ministry of Agriculture. When an export ban is imposed, permits are no longer issued. The bans shut down most of the formal maize trade, but maize continues to cross borders. Some formal traders (particularly those with the right political connections) are able to obtain export permits during bans through back-door channels. Informal traders, who may not be eligible for or choose to obtain export permits even during non-ban periods, are also able to continue moving maize across borders during bans. At official border points, informal traders often use bicycles, which are not regulated, to move maize between trucks on either side of the border. Informal traders also use unofficial border crossings along the long, porous land borders between countries in the region.

The total volume of maize that can be transported across affected borders during bans may be subject to capacity constraints. At and around official border points, market participants report that enforcement is positively correlated with volume, with border officials generally tolerating low volumes of informal trade during bans but initiating patrols and crackdowns when volumes increase. At one border point in Malawi, FEWS NET monitors estimate the volume of informal maize trade tolerated by officials to be 200 metric tons per month. This compares to formal export volumes that have occasionally been as high as 10,000 metric tons or more through this border point in non-ban months. At an unofficial border crossing I visited elsewhere, a single dugout canoe with a capacity of 0.7 metric tons is available to ferry maize between trucks across a river border during bans, allowing for the transport of approximately 1,000 metric tons per month.

Theoretically, if capacity constraints are binding during bans, the price gaps between pairs of affected cross-border markets should increase, which I do not observe in the data. However, anecdotal evidence suggests that bans are often lifted in response to complaints from farmers and traders about a lack of trading opportunities following bumper harvests, precisely the time when capacity constraints may start to bind. To assess this possibility, I divide the nine export bans for which I have start-to-finish data into quarters, drop observations from the other four bans, and redo my main specification with separate indicator variables for the first, second, third, and fourth quarters of export bans. Results in table 2.5 indicate that while price gaps are unchanged in the first three quarters of bans, they do exhibit a small but statistically significant increase in the final quarter of bans. This suggests that capacity constraints on informal cross-border trade generally only bind at the very end of bans, when large new harvests may make governments amenable to lifting the bans anyway.

Table 2.5: Effect on Price Gaps by Ban Quarter

1st quarter of ban	–0.00485
	(0.00667)
2nd quarter of ban	0.011831
	(0.00959)
3rd quarter of ban	0.0108
	(0.0163)
4th quarter of ban	0.0182**
	(0.00774)
Observations	3159

Note: Includes only bans with start-to-finish data. Robust dyadic standard errors in (); *significant at 10%, ** at 5%, *** at 1%.

Of potentially greater concern is that market participants report that the climate of uncertainty created by discretionary export bans with *ad hoc* enforcement and the diversion of trade away from formal, regulated traders to informal channels during export bans destabilize markets. Faced by fluctuations in bans, permit issuing, and enforcement, both formal and informal traders choose to engage less in long-term storage for future trade, in contractual agreements with cross-border purchasers (particularly those with long-term delivery commitments), and in long-distance trade across far-off borders where they have fewer connections and less local knowledge about informal channels. Instead, they prioritize short-term, non-contractual, local transactions. This potentially weakens the capacity of markets to respond efficiently to the harvest shortfalls or price increases that characterize export ban periods.

To see whether these destabilizing effects show up in the data, I compute the standard deviation of prices during export ban and non-export ban periods for each origin and destination market and re-run the regressions in equations 2.2 and 2.3 using the standard deviation of prices as my dependent variable (table 2.6). In the data, the standard deviation of prices for origin markets is 36% higher during export bans than its average in non-ban periods (statistically significant at the 1% level), whereas model simulations indicate no significant difference in standard deviation between ban and non-ban periods if the bans had not been implemented. The point estimate for the standard deviation of prices for destination markets is also much larger in the data than in the "no bans" simulation (23% of its non-ban average), but it is not statistically significant at conventional levels and is smaller than the effect in model simulations when bans are implemented and fully enforced.

Taken together, my results suggest that export bans are having very different effects

Table 2.6: Standard Deviation Regressions with Data and Model Simulations

	Data	Data	No Bans	No Bans
Dependent variable	Orig. SD	Dest. SD	Orig. SD	Dest. SD
Export ban	0.0238***	0.0198	0.00573	–0.00189
	(0.00833)	(0.0162)	(0.00971)	(0.00499)
Observations	78	82	52	64
Mean SD (no bans)	0.0662	0.0873	0.0648	0.0682
	Naïve	Naïve	Foresight	Foresight
Dependent variable	Orig. SD	Dest. SD	Orig. SD	Dest. SD
Export ban	0.00819	0.0661**	0.00936	0.0693**
	(0.00796)	(0.0296)	(0.00655)	(0.0299)
Observations	53	65	53	64
Mean SD (no bans)	0.0638	0.0654	0.0627	0.0676

Note: Robust standard errors in () clustered by market;
*significant at 10%, ** at 5%, *** at 1%.

than those intended by implementing country governments in East and Southern Africa. Rather than cutting off trade, export bans divert it to the informal sector. Rather than widening price gaps, export bans do not affect them. Rather than maintaining or lowering domestic prices and domestic price volatility, export bans appear to increase both. Export bans may thus be contributing to high and volatile domestic maize prices in a cycle that makes governments all the more inclined to implement them.

2.5 Conclusion

In this chapter, I have used monthly data on maize prices from 40 pairs of cross-border markets to investigate the empirical effects of 13 short-term export bans implemented by 5 countries in East and Southern Africa over a ten-year time period. My initial estimation yielded the surprising result that export bans do not have a statistically significant effect on cross-border price gaps. This result is robust to a variety of alternative specifications and modifications of the dataset, including the elimination of potential segmented equilibria in which the bans might not be binding. I am also able to reject a hypothesis that the effect of export bans on price gaps is at least as large as the theoretical effect of a 5% export tax.

I compared my empirical results to results from running the same regressions on price series obtained from three simulations using the estimated dynamic monthly model of grain storage and trade in sub-Saharan Africa from the previous chapter. The simulations enabled me to rule out several potential explanations for my surprising result, including that bans are implemented in periods of abnormally low price gaps, that bans are not binding, and that bans are ineffective due to trader anticipation. My results on price gaps are consistent with a model simulation in which bans are not implemented, but prices in both implementing country and trading partner markets are significantly higher during bans than in this simulation, as is price volatility in implementing country markets.

Information collected from market participants and visits to affected border points indicates that export bans in the region are imperfectly enforced. Export bans divert trade into the informal sector, which appears to be able to move enough maize across borders to keep price gaps from widening until market conditions change and the implementing government is ready to lift the ban. However, the increased prices and volatility during export ban periods compared to the model simulation with no bans suggest that the bans are destabilizing markets as traders shift into short-term, non-contractual, local transactions.

While it is already widely accepted that export bans are disruptive for trading partner countries, they can theoretically be justified by the countries that implement them, particularly those that weight consumers' welfare more than that of producers. My results, however, suggest that they may have unexpected empirical effects. Instead of stabilizing and lowering domestic prices, export bans in East and Southern Africa appear to destabilize markets, leading to increases in both domestic prices and domestic price volatility. Governments in the region should therefore reconsider their use of these policies even when they seem justified on political economy grounds.

Although many of my findings appear to depend on the institutional and geographic details of East and Southern Africa, these features are not unique to countries in the region. Many of the countries that implemented export restrictions during the 2007 – 2008 food price spike and its aftermath were developing countries with relatively weak institutions. Although countries like India that are mostly surrounded by water may find it easier to enforce trade policies, others like Ukraine have long and relatively porous land borders, and the active smuggling of rice from Indonesia to the Philippines suggests that even island countries are not immune to informal trade circumventing trade barriers. Moreover, chronologies of trade policies used during this period reveal how unpredictable and *ad hoc* they were in many countries (Sharma 2011, Headey 2011). The results presented here highlight how these types of discretionary stabilization policies can end up being destabilizing — even for the implementing countries themselves.

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Appendix A

A.1 Proofs of Propositions

Proposition 1. *Consider any two markets m and n. If m and n have identical storage costs then neither market stores and imports from the other simultaneously in equilibrium, i.e. for any month t and grain i:*

$$S_{int} > 0 \Rightarrow T_{imnt} \leq 0 \quad \text{and} \quad T_{imnt} > 0 \Rightarrow S_{int} = 0$$

with a symmetric condition holding for S_{imt} and trade from n to m.

Corollary 1. *Consider a particular harvest year for two markets m and n with net trade of grain i from m to n in equilibrium. Let the harvest year months be indexed s with the last month before the next harvest $\bar{s}$. Let the first month with trade from m to n be designated s^*. Then the following must be true for any grain i:*
(i) If $r_m \leq r_n$ and $k_m - k_n < \frac{r_m \tau_{mn}}{1+r_m}$, then $S_{ins} > 0$ for $s < s^* - 1$, $S_{ins} \geq 0$ for $s = s^* - 1$, $S_{ins} = 0$ for $s \geq s^*$, $T_{imns} \leq 0$ for $s < s^*$, and $T_{imns} > 0$ for $s \geq s^*$. Traders store first and trade later.
(ii) If $r_m \geq r_n$ and $k_m - k_n > \frac{r_m \tau_{mn}}{1+r_m}$, then $S_{ins} > 0$ for $s < s^* - 1$, $S_{ins} \geq 0$ for $s = s^* - 1$, $S_{ins} > 0$ for $s^* \leq s < \bar{s}$, $T_{imns^*} > 0$, and $T_{imns} \leq 0$ for all $s \neq s^*$. Trade from m to n only occurs in month s^*.
(iii) For any values of r_m, r_n, k_m, and k_n, the pattern of storage and trade will be the same as (i) if the following expression is negative and the same as (ii) if the following expression is positive:

$$(1 + r_m)k_m - (1 + r_n)k_n + (r_m - r_n)P_{ims^*} - r_n \tau_{mn}$$

Corollary 2. *Given a set of demand and cost parameters, there is a unique grain market equilibrium (competitive equilibrium).*

Proof. Let m and n have identical storage costs k and r. First note that the spatial arbitrage condition must hold in expectation in period $t + 1$:

$$\mathbb{E}_t[P_{in,t+1}] - \mathbb{E}_t[P_{im,t+1}] \leq \tau_{mn} \tag{A.1}$$

Suppose market n has both imports and storage of grain i in period t ($S_{int} > 0$ and $T_{imnt} > 0$). Then by equations 1.11 and 1.12:

$$S_{int} > 0 \Rightarrow P_{int} = \frac{\mathbb{E}_t[P_{in,t+1}]}{1+r} - k \tag{A.2}$$

$$T_{imnt} > 0 \Rightarrow P_{int} = P_{imt} + \tau_{mn} \tag{A.3}$$

Combining these two equations gives:

$$P_{imt} = \frac{\mathbb{E}_t[P_{in,t+1}]}{1+r} - k - \tau_{mn} \tag{A.4}$$

The temporal arbitrage condition for market m implies:

$$P_{imt} \geq \frac{\mathbb{E}_t[P_{im,t+1}]}{1+r} - k \tag{A.5}$$

Combining these two equations gives:

$$\frac{\mathbb{E}_t[P_{in,t+1}]}{1+r} - k - \tau_{mn} \geq \frac{\mathbb{E}_t[P_{im,t+1}]}{1+r} - k \tag{A.6}$$

$$\Rightarrow \mathbb{E}_t[P_{in,t+1}] - \mathbb{E}_t[P_{im,t+1}] \geq (1+r)\tau_{mn} > \tau_{mn} \tag{A.7}$$

Which is a contradiction of equation A.1, thus proving the main proposition.

For the first corollary, I allow for the possibility that $r_m \neq r_n$ and $k_m \neq k_n$ and use subscripts s for the months of the particular harvest year. Then equation A.6 becomes:

$$\frac{\mathbb{E}_s[P_{in,s+1}]}{1+r_n} - k_n - \tau_{mn} \geq \frac{\mathbb{E}_s[P_{im,s+1}]}{1+r_m} - k_m \tag{A.8}$$

$$\Rightarrow \frac{\mathbb{E}_s[P_{in,s+1}]}{1+r_n} - \frac{\mathbb{E}_s[P_{im,s+1}]}{1+r_m} \geq \tau_{mn} - (k_m - k_n) \tag{A.9}$$

Consider case (i) with $r_m \leq r_n$:

$$r_m \leq r_n \Rightarrow \frac{\mathbb{E}_s[P_{in,s+1}]}{1+r_n} - \frac{\mathbb{E}_s[P_{im,s+1}]}{1+r_m} \leq \frac{\mathbb{E}_s[P_{in,s+1}]}{1+r_m} - \frac{\mathbb{E}_s[P_{im,s+1}]}{1+r_m} \tag{A.10}$$

$$\Rightarrow \frac{\mathbb{E}_s[P_{in,s+1}]}{1+r_m} - \frac{\mathbb{E}_s[P_{im,s+1}]}{1+r_m} \geq \frac{\mathbb{E}_s[P_{in,s+1}]}{1+r_n} - \frac{\mathbb{E}_s[P_{im,s+1}]}{1+r_m} \geq \tau_{mn} - (k_m - k_n) \tag{A.11}$$

Now suppose that $k_m - k_n < \frac{r_m \tau_{mn}}{1+r_m}$. Then:

$$\frac{\mathbb{E}_s[P_{in,s+1}]}{1+r_m} - \frac{\mathbb{E}_s[P_{im,s+1}]}{1+r_m} \geq \tau_{mn} - (k_m - k_n) > \tau_{mn} - \frac{r_m \tau_{mn}}{1+r_m} \tag{A.12}$$

$$\Rightarrow \mathbb{E}_s[P_{in,s+1}] - \mathbb{E}_s[P_{im,s+1}] > \tau_{mn} \tag{A.13}$$

This is a contradiction of equation A.1, so the conditions of the main proposition hold. By definition, any months before s^* have $T_{imns} \leq 0$, with or without storage ($S_{ins} \geq 0$). In order to ensure positive grain consumption in these months, $S_{ins} > 0$ for $s < s^* - 1$. By the main proposition, $T_{imns^*} > 0 \Rightarrow S_{ins^*} = 0$. Now consider the month $s^* + 1$. Since there is no additional harvest and $S_{ins^*} = 0$, the only source of grain for consumption is imports, so $T_{imn,s^*+1} > 0$ and $S_{ins^*+1} = 0$. The same holds true for all $s \geq s^*$.

Now consider case (ii). Consider the first month with trade from m to n, s^*. Suppose that there is also expected trade from m to n in the following month, i.e. $\mathbb{E}[T_{imn,s^*+1}] > 0$. Then $S_m > 0$ as there is no subsequent harvest. Thus the following three arbitrage conditions are binding:

$$P_{ims^*} = P_{ins^*} - \tau_{mn} \tag{A.14}$$

$$\mathbb{E}_{s^*}[P_{im,s^*+1}] = \mathbb{E}_{s^*}[P_{in,s^*+1}] - \tau_{mn} \tag{A.15}$$

$$P_{ims^*} + k_m = \frac{\mathbb{E}_{s^*}[P_{im,s^*+1}]}{1+r_m} \tag{A.16}$$

Substituting the first and second of these conditions into the third I get:

$$P_{ins^*} - \tau_{mn} + k_m = \frac{\mathbb{E}_{s^*}[P_{in,s^*+1}] - \tau_{mn}}{1+r_m} \tag{A.17}$$

$$\Rightarrow P_{ins^*} + k_m - \frac{r_m\tau_{mn}}{1+r_m} = \frac{\mathbb{E}_{s^*}[P_{in,s^*+1}]}{1+r_m} \tag{A.18}$$

Now suppose that $r_m \geq r_n$ and $k_m - k_n > \frac{r_m\tau_{mn}}{1+r_m}$ (so that $k_m - \frac{r_m\tau_{mn}}{1+r_m} > k_n$). Then I get:

$$P_{ins^*} + k_n < \frac{\mathbb{E}_{s^*}[P_{in,s^*+1}]}{1+r_m} \leq \frac{\mathbb{E}_{s^*}[P_{in,s^*+1}]}{1+r_n} \Rightarrow P_{ins^*} + k_n < \frac{\mathbb{E}_{s^*}[P_{in,s^*+1}]}{1+r_n} \tag{A.19}$$

This is a contradiction of the temporal arbitrage condition for market n. The intuition is that with sufficiently higher storage costs in m it is cheaper to import first and store the imports in n for later consumption. Since having imports in s^* and in s^*+1 led to a contradiction and since s^* was the first month with imports, it follows that $T_{imns^*} > 0$ and $T_{imns} \leq 0$ for all $s \neq s^*$. With all imports concentrated in just one month (s^*), storage S_{ins} in market n must be strictly positive for all $s < \bar{s}$ (with the exception of $s^* - 1$) to ensure positive consumption in every month.

Now consider case (iii). Taking equation A.9 for month s^* and rearranging gives:

$$\begin{aligned}\mathbb{E}_{s^*}[P_{in,s^*+1}] - \mathbb{E}_{s^*}[P_{im,s^*+1}] \geq (1+r_m)(1+r_n)\tau_{mn} - (1+r_m)(1+r_n)(k_m - k_n) \\ + r_n\mathbb{E}_{s^*}[P_{im,s^*+1}] - r_m\mathbb{E}_{s^*}[P_{in,s^*+1}]\end{aligned} \tag{A.20}$$

For case (i) to hold the right-hand side of this expression must be larger than τ_{mn}, i.e.:

$$(1+r_m)(1+r_n)\tau_{mn} - (1+r_m)(1+r_n)(k_m - k_n) + r_n\mathbb{E}_{s^*}[P_{im,s^*+1}] - r_m\mathbb{E}_{s^*}[P_{in,s^*+1}] > \tau_{mn} \tag{A.21}$$

Substituting in for $\mathbb{E}_{s^*}[P_{in,s^*+1}]$ using the spatial arbitrage condition (which holds with equality for s^*+1 in case (i)) gives:

$$\Rightarrow (1+r_m)(1+r_n)\tau_{mn} - (1+r_m)(1+r_n)(k_m - k_n) + r_n\mathbb{E}_{s^*}[P_{im,s^*+1}] - r_m(\mathbb{E}_{s^*}[P_{im,s^*+1}] + \tau_{mn}) > \tau_{mn} \tag{A.22}$$

$$\Rightarrow k_m - k_n < \frac{r_n\tau_{mn}}{(1+r_n)} + \frac{r_n\mathbb{E}_{s^*}[P_{im,s^*+1}]}{(1+r_m)(1+r_n)} - \frac{r_m\mathbb{E}_{s^*}[P_{im,s^*+1}]}{(1+r_m)(1+r_n)} \tag{A.23}$$

Substituting in for $\mathbb{E}_{s^*}[P_{im,s^*+1}]$ using the temporal arbitrage condition (which holds with equality for m in s^* in case (i)) gives:

$$\Rightarrow k_m - k_n < \frac{r_n \tau_{mn}}{(1+r_n)} + \frac{r_n(P_{ims^*} + k_m)}{(1+r_n)} - \frac{r_m(P_{ims^*} + k_m)}{(1+r_n)} \tag{A.24}$$

$$\Rightarrow (1+r_m)k_m - (1+r_n)k_n + (r_m - r_n)P_{ims^*} - r_n\tau_{mn} < 0 \tag{A.25}$$

Now taking equation A.18 and rearranging gives:

$$\frac{1+r_m}{1+r_n}(P_{ins^*} + k_m) - \frac{r_m \tau_{mn}}{1+r_n} = \frac{\mathbb{E}_{s^*}[P_{in,s^*+1}]}{1+r_n} \tag{A.26}$$

For case (ii) to hold the left-hand side of this expression must be larger than $P_{ins^*} + k_n$, i.e.:

$$\frac{1+r_m}{1+r_n}(P_{ins^*} + k_m) - \frac{r_m \tau_{mn}}{1+r_n} > P_{ins^*} + k_n \tag{A.27}$$

$$\Rightarrow (1+r_m)k_m - (1+r_n)k_n > r_n P_{ins^*} - r_m P_{ins^*} + r_m \tau_{mn} \tag{A.28}$$

Substituting in for P_{ins^*} using the spatial arbitrage condition (which holds with equality for s^*) gives:

$$(1+r_m)k_m - (1+r_n)k_n > r_n(P_{ims^*} + \tau_{mn}) - r_m(P_{ims^*} + \tau_{mn}) + r_m\tau_{mn} \tag{A.29}$$

$$\Rightarrow (1+r_m)k_m - (1+r_n)k_n + (r_m - r_n)P_{ims^*} - r_n\tau_{mn} > 0 \tag{A.30}$$

This completes the proof of the first corollary.

For the second corollary, suppose there exist two different grain market equilibria with the second equilibrium denoted by the prime symbol. Consider first the case of a system of two markets m and n with no world market for a single harvest year.

Suppose there is no trade between the markets in either equilibrium. Given that the harvest in each market is exogenous, $\sum_t H_{imt} = \sum_t Q_{imt} = \sum_t Q'_{imt}$. The temporal arbitrage conditions must hold with equality between all periods in each market to ensure positive consumption in every period. If there were two different sets of prices satisfying the temporal arbitrage conditions with equality then $P_{imt} > P'_{imt}$ or vice versa for all t, implying $\sum_t Q_{imt} < \sum_t Q'_{imt}$ or vice versa, a contradiction. Therefore $P_{imt} = P'_{imt} \Rightarrow Q_{imt} = Q'_{imt} \Rightarrow S_{imt} = S'_{imt}$ for every grain, market, and month, so the equilibria are identical, a contradiction.

Now suppose there is trade between the markets in one equilibrium and there is no trade between the markets in the other equilibrium. If the markets were in autarky (no trade allowed) then there would be a unique equilibrium (as shown above). Now they open up to trade. If there is a no-trade equilibrium then the autarky price gaps are always less than or equal to trade costs. If there is a trade equilibrium then the autarky price gaps exceed trade costs in some periods. Since there is a unique autarky equilibrium, this is a contradiction.

Now suppose there is trade between the markets in both equilibria. Without loss of generality let m by the exporting market and n the importing market. Given the exogenous harvest in each market, $\sum_t H_{imt} + \sum_t H_{int} = \sum_t Q_{imt} + \sum_t Q_{int} = \sum_t Q'_{imt} + \sum_t Q'_{int}$. The overall pattern of storage and trade is determined by the first corollary (case (i) or case (ii)). In either case, the price of a particular grain in every market in every period is connected to the price in any other market-period by a series of temporal or spatial arbitrage conditions that must hold with equality. If there were two sets of prices such that the relevant arbitrage conditions were satisfied with equality then $\sum_t Q_{imt} + \sum_t Q_{int} \neq \sum_t Q'_{imt} + \sum_t Q'_{int}$, a contradiction. Therefore $P_{imt} = P'_{imt} \Rightarrow Q_{imt} = Q'_{imt}$ for every grain and month for both m and n, which in turn implies by the first corollary that $T_{imnt} = T'_{imnt}$, $S_{imt} = S'_{imt}$, and $S_{int} = S'_{int}$, so the equilibria are identical, a contradiction.

Now allow for multiple harvest years with storage possible between years. Initial entering stocks in the very first period are exogenous and hence identical for the two equilibria. Consider the first harvest year and the first inter-harvest storage decision. With identical available supply and identical expectations, traders will make the same inter-harvest storage decision in both equilibria, with the location of the inter-harvest storage determined by the proposition and first corollary. With identical entering stocks, harvests, and inter-harvest storage, $\sum_t Q_{imt} + \sum_t Q_{int} = \sum_t Q'_{imt} + \sum_t Q'_{int}$ for the first harvest year, so the results above hold. For the second harvest year, identical inter-harvest storage from the first year and identical exogenous harvests imply identical total available supply again, so the same arguments hold. Thus the equilibria are identical, a contradiction.

Now consider extending the two-market multi-year case to many markets (still with no world market). Assume that there are no knife-edge cases, i.e. cases where grain can pass from one market to another market elsewhere in the network by two routes with identical costs. By analogy to the two-market case, any two equilibria must have the same subset of markets linked by trade. For this subset of markets, inter-harvest storage decisions are identical across equilibria and $\sum_m \sum_t Q_{imt} = \sum_m \sum_t Q'_{imt}$ within harvest years. As in the two-market case, for each harvest year, the price of a particular grain in every market in every period is connected to the price in every other market-period by a series of temporal or spatial arbitrage conditions that must hold with equality and are determined by the first corollary. If there were two sets of prices such that the relevant arbitrage conditions were satisfied with equality then $\sum_m \sum_t Q_{imt} \neq \sum_m \sum_t Q'_{imt}$, a contradiction. Therefore $P_{imt} = P'_{imt} \Rightarrow Q_{imt} = Q'_{imt}$ for every grain-market-month, which in turn implies by the first corollary that $T_{imnt} = T'_{imnt}$ and $S_{imt} = S'_{imt}$, so the equilibria are identical, a contradiction.

Now consider extending the multi-market multi-year case to include the world market with perfectly elastic supply and monthly price uncertainty. Each month, traders (who have identical expectations) make supply allocation plans for current and future months based on price expectations. Consider two different plans for a particular month t. If neither or only one of these plans includes trade with the world market, there is a contradiction by the arguments above. Suppose both plans include trade with the world market. The trade pattern with the world market is determined as in the first corollary. For a given plan, planned prices in all markets connected by trade to the world market in all periods connected by storage to the period with trade with the world market are pinned down by the expected world market price. Since both plans have the same trade pattern, $P_{imt} = P'_{imt} \Rightarrow Q_{imt} = Q'_{imt}$ for every grain, market, and month, which in turn implies by the first corollary that $T_{imnt} = T'_{imnt}$ and $S_{imt} = S'_{imt}$, so the plans are identical, a contradiction. Since a given plan for a particular month t is unique, all equilibrium P_{imt}, Q_{imt}, S_{imt}, and T_{imnt} for that month will be unique. By extension, the grain market equilibrium for all months will be unique.

A unique grain market equilibrium implies a unique competitive equilibrium. This completes the proof. $\square$

A.2 Market Selection

Table A1, which begins on the next page, includes three lists of markets by country and town population (in thousands). "Markets A" is my initial list of 178 towns with a population of at least 100,000 that are at least 200 kilometers apart[1]. When two towns of over 100,000 population are closer than 200 kilometers the larger is chosen. Population data is from national censuses of different years as reported on various online databases (e.g. citypopulation.de) and should be taken as approximate. "Markets B" includes all "Markets A" plus 85 additional towns that are either towns located at important transport hubs (road junctions or ports) or additional major towns in countries with high initial population-to-market ratios. This is my ideal list of 263 markets for which I attempted to obtain price data. "Markets C" is the list of 230 markets in my final network. This includes 218 of the 263 markets on my ideal list for which I was able to obtain price data as well as an additional 12 markets with price data which are located close to 12 of the missing markets and which I therefore use as substitutes (indicated in italics in the table).

Table A2, which follows table A1, shows the population-to-market ratios by country for the three sets of markets (A, B, and C). In adding markets to generate the ideal list of markets (Markets B), the population-to-market ratios in the initial list (Markets A) were used as one criterion. In the ideal list of markets, only Nigeria and Ethiopia — the two most populous countries — have population-to-market ratios above 4 million. In the final network (Markets C), the three countries with more than two missing markets (Angola, Cameroon, and Uganda) are the only ones besides Nigeria and Ethiopia that are significantly above this threshold.

[1]Note that Johannesburg is the only town included in South Africa due to its special treatment in my model.

Table A.1: List of Markets by Country and Town Population

Country	Markets A	Population	Markets B	Population	Markets C	Population
Angola	Luanda	2584	Luanda	2584	Luanda	2584
	Cabinda	378	Cabinda	378		
	Huambo	333	Huambo	333		
	Lubango	251	Lubango	251		
	Malanje	157	Malanje	157		
	Lobito	145	Lobito	145		
	Uige	116	Uige	116		
			Luena	85		
			Saurimo	78		
Benin	Cotonou	818	Cotonou	818	Cotonou	818
	Parakou	227	Parakou	227	Parakou	227
	Kandi	150	Kandi	150	*Malanville*	*36*
	Natitingou	120	Natitingou	120	Natitingou	120
Botswana	Gaborone	186	Gaborone	186	Gaborone	186
			Francistown	83		
Burk. Faso	Ouagadougou	1182	Ouagadougou	1182	Ouagadougou	1182
	Bobo Dioul.	436	Bobo Dioul.	436	Bobo Dioul.	436
			Ouahigouya	71		
			Fada Ngo.	41	Fada Ngo.	41
			Dedougou	38	Dedougou	38
Burundi	Bujumbura	340	Bujumbura	340	Bujumbura	340
			Gitega	47	Gitega	47
			Muyinga	45	Muyinga	45
Cameroon	Douala	1907	Douala	1907	Douala	1907
	Yaounde	1818	Yaounde	1818	Yaounde	1818
	Bamenda	270	Bamenda	270	Bamenda	270
	Garoua	236	Garoua	236	Garoua	236
	Maroua	201	Maroua	201		
	Ngaoundere	153	Ngaoundere	153		
			Kousseri	89		
			Bertoua	88		
C.A.R.	Bangui	623	Bangui	623	Bangui	623
			Berberati	77		
			Bambari	41	Bambari	41
			Bouar	40		
			Bangassou	32	Bangassou	32
Chad	Ndjamena	818	Ndjamena	818	Ndjamena	818
	Moundou	141	Moundou	141	Moundou	141
	Sarh	119	Sarh	119	Sarh	119
			Abeche	77	Abeche	77
Congo	Brazzaville	1373	Brazzaville	1373	Brazzaville	1373
	Pointe-Noire	715	Pointe-Noire	715	Pointe-Noire	715
			Impfondo	34	Impfondo	34

Country	Markets A	Population	Markets B	Population	Markets C	Population
C.d.I.	Abdijan	3677	Abdijan	3677	Abdijan	3677
	Bouake	567	Bouake	567	Bouake	567
	Daloa	216	Daloa	216	Daloa	216
	San Pedro	197	San Pedro	197		
	Korhogo	167	Korhogo	167	*Odienne*	*43*
			Man	139	Man	139
			Abengourou	71	Abengourou	71
D.R.C.	Kinshasa	8901	Kinshasa	8901	Kinshasa	8901
	Lubumbashi	1630	Lubumbashi	1630	Lubumbashi	1630
	Mbuji-Mayi	1559	Mbuji-Mayi	1559	Mbuji-Mayi	1559
	Kisangani	868	Kisangani	868	Kisangani	868
	Bukavu	707	Bukavu	707	Bukavu	707
	Tshikapa	524	Tshikapa	524	Tshikapa	524
	Kolwezi	451	Kolwezi	451	Kolwezi	451
	Goma	377	Goma	377	Goma	377
	Kikwit	370	Kikwit	370	Kikwit	370
	Bunia	327	Bunia	327	Bunia	327
	Mbandaka	324	Mbandaka	324	Mbandaka	324
	Matadi	291	Matadi	291	Matadi	291
	Butembo	204	Butembo	204	Butembo	204
	Isiro	175	Isiro	175	Isiro	175
	Kindu	164	Kindu	164	Kindu	164
	Kamina	144	Kamina	144	Kamina	144
	Bandundu	137	Bandundu	137	Bandundu	137
	Gemena	133	Gemena	133	*Zongo*	*33*
	Bumba	103	Bumba	103	*Gbadolite*	*48*
			Kananga	967	Kananga	967
			Uvira	337	Uvira	337
			Kalemie	92	Kalemie	92
Djibouti	Djibouti	624	Djibouti	624	Djibouti	624
Eritrea	Asmara	650	Asmara	650	Asmara	650
			Teseney	65		
			Massawa	37	Massawa	37

Country	Markets A	Population	Markets B	Population	Markets C	Population
Ethiopia	Addis Ab.	3041	Addis Ab.	3041	Addis Ab.	3041
	Dire Dawa	274	Dire Dawa	274	Dire Dawa	274
	Mekele	272	Mekele	272	Mekele	272
	Gondar	254	Gondar	254	Gondar	254
	Awasa	213	Awasa	213	Awasa	213
	Jimma	149	Jimma	149	Jimma	149
	Dessie	148	Dessie	148	Dessie	148
			Bahir Dar	191	Bahir Dar	191
			Jijiga	147	Jijiga	147
			Arba Minch	96		
			Nekemte	89	Nekemte	89
			Gode	68	Gode	68
			Adwa	41		
			Gambela	39	Gambela	39
			Moyale	34	*Yabelo*	*18*
Gabon	Libreville	591	Libreville	591	Libreville	591
	Port Gentil	112	Port Gentil	112		
Gambia	Banjul	524	Banjul	524	Banjul	524
Ghana	Accra	2070	Accra	2070	Accra	2070
	Kumasi	2035	Kumasi	2035	Kumasi	2035
	Tamale	371	Tamale	371	Tamale	371
	Sek. Tak.	539	Sek. Tak.	539	Sek. Tak.	539
			Ho	105	Ho	105
			Wa	71	Wa	71
			Bolgatanga	66	Bolgatanga	66
Guinea	Conakry	1400	Conakry	1400	Conakry	1400
	Nzerekore	178	Nzerekore	178	Nzerekore	178
	Boke	147	Boke	147		
	Kankan	142	Kankan	142	Kankan	142
			Gueckedou	96		
			Mamou	60	*Labe*	*59*
G. Bissau	Bissau	388	Bissau	388	Bissau	388

Country	Markets A	Population	Markets B	Population	Markets C	Population
Kenya	Nairobi	3138	Nairobi	3138	Nairobi	3138
	Mombasa	939	Mombasa	939	Mombasa	939
	Kisumu	388	Kisumu	388	Kisumu	388
	Garissa	116	Garissa	116	Garissa	116
			Nakuru	308	Nakuru	308
			Eldoret	289	Eldoret	289
			Mandera	88	Mandera	88
			Wajir	82	Wajir	82
			Lodwar	48	Lodwar	48
			Isiolo	46		
			Moyale	38	Moyale	38
Lesotho	Maseru	218	Maseru	218	Maseru	218
Liberia	Monrovia	1022	Monrovia	1022	Monrovia	1022
	Gbarnga	57	Gbarnga	57	Gbarnga	57
Malawi	Lilongwe	647	Lilongwe	647	Lilongwe	647
	Blantyre	585	Blantyre	585	Blantyre	585
	Mzuzu	175	Mzuzu	175	Mzuzu	175
			Mangochi	40	Mangochi	40
			Karonga	34	Karonga	34
Mali	Bamako	1809	Bamako	1809	Bamako	1809
	Sikasso	226	Sikasso	226	Sikasso	226
	Segou	131	Segou	131	Segou	131
	Kayes	127	Kayes	127	Kayes	127
	Mopti	114	Mopti	114	Mopti	114
			Gao	87	Gao	87
Mauritania	Nouakchott	719	Nouakchott	719	Nouakchott	719
			Nouadhibou	90		
			Adel Bagrou	58	Adel Bagrou	58
			Kiffa	40	*Tintane*	*22*
Mozambique	Maputo	1766	Maputo	1766	Maputo	1766
	Beira	546	Beira	546	Beira	546
	Nampula	478	Nampula	478	Nampula	478
	Chimoio	239	Chimoio	239	Chimoio	239
	Quelimane	193	Quelimane	193	Quelimane	193
	Tete	156	Tete	156	Tete	156
	Lichinga	142	Lichinga	142	Lichinga	142
	Pemba	141	Pemba	141	Pemba	141
	Gurue	117	Gurue	117	*Cuamba*	*95*
	Xai Xai	116	Xai Xai	116	Xai Xai	116
	Maxixe	106	Maxixe	106	Maxixe	106
			Nacala	208	Nacala	208
			Milange	30	Milange	30

Country	Markets A	Population	Markets B	Population	Markets C	Population
Namibia	Windhoek	268	Windhoek	268	Windhoek	268
			Rundu	58	*Kat. Mulilo*	*28*
			Walvis Bay	52	*Swakopmund*	*44*
			Oshakati	37	Oshakati	37
Niger	Niamey	1303	Niamey	1303	Niamey	1303
	Zinder	275	Zinder	275	Zinder	275
	Maradi	206	Maradi	206	Maradi	206
	Agadez	124	Agadez	124	Agadez	124
	Tahoua	123	Tahoua	123	Tahoua	123
	Arlit	112	Arlit	112	Arlit	112
			Diffa	48	Diffa	48
Nigeria	Lagos	8029	Lagos	8029	Lagos	8029
	Kano	3249	Kano	3249	Kano	3249
	Kaduna	1459	Kaduna	1459	Kaduna	1459
	Pt. Harcourt	1054	Pt. Harcourt	1054	Pt. Harcourt	1054
	Benin City	1052	Benin City	1052	Benin City	1052
	Maiduguri	972	Maiduguri	972	Maiduguri	972
	Ilorin	756	Ilorin	756	Ilorin	756
	Jos	742	Jos	742	Jos	742
	Enugu	593	Enugu	593	Enugu	593
	Sokoto	501	Sokoto	501	Sokoto	501
	Okene	445	Okene	445	*Lokoja*	*90*
	Calabar	431	Calabar	431	Calabar	431
	Makurdi	249	Makurdi	249	Makurdi	249
	Gombe	231	Gombe	231	Gombe	231
	Yola	218	Yola	218	Yola	218
	Abuja	160	Abuja	160	Abuja	160
	Gashua	110	Gashua	110		
			Ibadan	3078	Ibadan	3078
			Katsina	387	Katsina	387
			Akure	370	Akure	370
Rwanda	Kigali	745	Kigali	745	Kigali	745
			Butare	90	Butare	90
			Gisenyi	84	Gisenyi	84
Senegal	Dakar	1999	Dakar	1999	Dakar	1999
	Ziguinchor	162	Ziguinchor	162	Ziguinchor	162
	St. Louis	131	St. Louis	131	St. Louis	131
			Touba	428	Touba	428
			Kaolack	174	Kaolack	174
			Tambacounda	75	Tambacounda	75
S. Leone	Freetown	773	Freetown	773	Freetown	773
	Bo	150	Bo	150	Bo	150
			Kabala	14	Kabala	14

Country	Markets A	Population	Markets B	Population	Markets C	Population
Somalia	Mogadishu	1353	Mogadishu	1353	Mogadishu	1353
	Hargeisa	1200	Hargeisa	1200	Hargeisa	1200
	Bosaso	700	Bosaso	700	Bosaso	700
	Galkayo	545	Galkayo	545	Galkayo	545
	Kismayo	183	Kismayo	183	Kismayo	183
	Baidoa	158	Baidoa	158	Baidoa	158
			Berbera	233		
			Beledweyne	67	Beledweyne	67
			Garoowe	57	Garoowe	57
South Africa	Johannesburg	957	Johannesburg	957	Johannesburg	957
South Sudan	Juba	372	Juba	372	Juba	372
	Wau	151	Wau	151	Wau	151
	Malakal	139	Malakal	139	Malakal	139
			Yambio	40		
			Rumbek	32	Rumbek	32
			Bor	27	Bor	27
Sudan	Khartoum	4273	Khartoum	4273	Khartoum	4273
	Nyala	493	Nyala	493	Nyala	493
	Port Sudan	395	Port Sudan	395	Port Sudan	395
	El Obeid	345	El Obeid	345	El Obeid	345
	Kassala	299	Kassala	299	Kassala	299
	Al Qadarif	269	Al Qadarif	269	Al Qadarif	269
	Al Fashir	218	Al Fashir	218	Al Fashir	218
	Kostil	213	Kostil	213	Kostil	213
	Ad Damazin	137	Ad Damazin	137	Ad Damazin	137
	El Geneina	134	El Geneina	134	El Geneina	134
	Atbarah	112	Atbarah	112		
			Kadugli	67	Kadugli	67
Swaziland			Mbabane	95	Mbabane	95

Country	Markets A	Population	Markets B	Population	Markets C	Population
Tanzania	Dar es Salaam	4365	Dar es Salaam	4365	Dar es Salaam	4365
	Mwanza	707	Mwanza	707	Mwanza	707
	Arusha	416	Arusha	416	Arusha	416
	Dodoma	411	Dodoma	411	Dodoma	411
	Mbeya	385	Mbeya	385	Mbeya	385
	Tanga	273	Tanga	273	Tanga	273
	Tabora	227	Tabora	227	Tabora	227
	Kigoma	215	Kigoma	215	Kigoma	215
	Sumbawanga	210	Sumbawanga	210	Sumbawanga	210
	Songea	203	Songea	203	Songea	203
	Musoma	178	Musoma	178	Musoma	178
	Iringa	151	Iringa	151	Iringa	151
	Singida	150	Singida	150	Singida	150
	Bukoba	129	Bukoba	129	Bukoba	129
	Mtwara	108	Mtwara	108	Mtwara	108
	Mpanda	102	Mpanda	102		
Togo	Lome	729	Lome	729	Lome	729
	Sokode	118	Sokode	118	*Kara*	*104*
Uganda	Kampala	1660	Kampala	1660	Kampala	1660
	Gulu	154	Gulu	154	Gulu	154
			Lira	108	Lira	108
			Mbale	92		
			Jinja	90	Jinja	90
			Mbarara	84	Mbarara	84
			Kasese	74		
			Masaka	74		
			Arua	59	Arua	59
			Masindi	45	Masindi	45
Zambia	Lusaka	2147	Lusaka	2147	Lusaka	2147
	Kitwe	410	Kitwe	410	Kitwe	410
	Chipata	117	Chipata	117	Chipata	117
	Livingstone	113	Livingstone	113	Livingstone	113
	Kasama	102	Kasama	102	Kasama	102
			Kabwe	193	Kabwe	193
			Solwezi	91	Solwezi	91
			Mongu	52	Mongu	52
Zimbabwe	Harare	1607	Harare	1607	Harare	1607
	Bulawayo	713	Bulawayo	713	Bulawayo	713
	Mutare	194	Mutare	194	Mutare	194
			Masvingo	81	Masvingo	81
			Hwange	37	Hwange	37

Table A.2: Population (2010, Millions) per Market by Country

Country	Popn	Mkts A	Pop/Mkt	Mkts B	Pop/Mkt	Mkts C	Pop/Mkt
Angola	19.55	7	2.79	9	2.17	1	19.55
Benin	9.51	4	2.38	4	2.38	4	2.38
Botswana	1.97	1	1.97	2	0.98	1	1.97
Burk. Faso	15.54	2	7.77	5	3.11	4	3.89
Burundi	9.23	1	9.23	3	3.08	3	3.08
Cameroon	20.62	6	3.44	8	2.58	4	5.16
C.A.R.	4.35	1	4.35	5	0.87	3	1.45
Chad	11.72	3	3.91	4	2.93	4	2.93
Congo	4.11	2	2.06	3	1.37	3	1.37
C.d.I.	18.98	5	3.80	7	2.71	6	3.16
D.R.C.	62.19	19	3.27	22	2.83	22	2.83
Djibouti	0.83	1	0.83	1	0.83	1	0.83
Eritrea	5.74	1	5.74	3	1.91	2	2.87
Ethiopia	87.10	7	12.44	15	5.81	13	6.70
Gabon	1.56	2	0.78	2	0.78	1	1.56
Gambia	1.68	1	1.68	1	1.68	1	1.68
Ghana	24.26	4	6.07	7	3.47	7	3.47
Guinea	10.88	4	2.72	6	1.81	4	2.72
G. Bissau	1.59	1	1.59	1	1.59	1	1.59
Kenya	40.91	4	10.23	11	3.72	10	4.09
Lesotho	2.01	1	2.01	1	2.01	1	2.01
Liberia	3.96	1	3.96	2	1.98	2	1.98
Malawi	15.01	3	5.00	5	3.00	5	3.00
Mali	13.99	5	2.80	6	2.33	6	2.33
Mauritania	3.61	1	3.61	4	0.90	3	1.20
Mozambique	23.97	11	2.18	13	1.84	13	1.84
Namibia	2.18	1	2.18	4	0.54	4	0.54
Niger	15.89	6	2.65	7	2.27	7	2.27
Nigeria	159.71	17	9.39	20	7.99	19	8.41
Rwanda	10.84	1	10.84	3	3.61	3	3.61
Senegal	12.95	3	4.32	6	2.16	6	2.16
Sierra Leone	5.75	2	2.88	3	1.92	3	1.92
Somalia	9.64	6	1.61	9	1.07	8	1.20
South Africa	NA	1	NA	1	NA	1	NA
South Sudan	9.94	3	3.31	6	1.66	5	1.99
Sudan	35.65	11	3.24	12	2.97	11	3.24
Swaziland	1.19	1	1.19	1	1.19	1	1.19
Tanzania	44.97	16	2.81	16	2.81	15	3.00
Togo	6.31	2	3.15	2	3.15	2	3.15
Uganda	33.99	2	16.99	10	3.40	7	4.86
Zambia	13.22	5	2.64	8	1.65	8	1.65
Zimbabwe	13.08	3	4.36	5	2.62	5	2.62
Total	842.31	178	4.73	263	3.20	230	3.66

A.3 Grain Types and Data Sources

Table A3, which begins on the next page, lists the seasonal regime and the grain types for each of the 230 markets in my final network. 112 markets fall into the Northern Hemisphere zone (N) with a single annual grain harvest in October, 70 markets fall into the Equatorial zone (E) with a larger grain harvest (two-thirds of the annual total) in July and a smaller grain harvest (one-third of the annual total) in December, and 48 markets fall into the Southern Hemisphere zone (S) with a single annual grain harvest in May.

To determine the grain types for each market, I first made a list for each country of all cereal grains constituting at least 5% of national cereal grain production. I excluded barley (Eritrea and Ethiopia) and fonio (Guinea) as they are relatively minor grains. I then searched for available price data for these grains and removed a few from the final list so as to have contiguous areas for each grain for my trade network. My final list includes 76% of the grains on the initial list, with the missing grains relatively minor in terms of share of national cereal grain production. 86% of total cereal grain production in my countries of interest is covered by a grain price series in its associated market.

Table A4, which follows table A3, lists the data sources by country for my price data. Most series were obtained from secondary sources, particularly the online databases maintained by the World Food Programme's VAM unit and FAO's GIEWS project. However, table A3 also includes the primary sources from which these databases obtained their price data. Although the price data are often collected by different government ministries in different countries, the methodology is typically quite similar and the mandate usually falls into one of three categories: (i) agricultural market information systems (MIS) intended to provide information to farmers and traders on market prices in different locations; (ii) price monitoring by national statistics offices for the monthly consumer price index (CPI); or (iii) food security monitoring by agencies like the World Food Programme.

Table A.3: Seasonal Regime and Grain Types by Market

Country	Market	Season	Maize	Millet	Rice	Sorghum	Teff	Wheat
Angola	Luanda	E	X					
Benin	Cotonou	N	X		X			
	Malanville	N	X			X		
	Natitingou	N	X		X	X		
	Parakou	N	X		X			
Botswana	Gaborone	S	X					
Burk. Faso	Bobo Dioulasso	N		X		X		
	Dedougou	N		X		X		
	Fada Ngourma	N		X		X		
	Ouagadougou	N		X		X		
Burundi	Bujumbura	E	X			X		
	Gitega	E	X			X		
	Muyinga	E	X			X		
Cameroon	Bamenda	N	X		X			
	Douala	N	X		X			
	Garoua	N	X		X			
	Yaounde	N	X		X			
C.A.R.	Bambari	E	X		X			
	Bangassou	E	X		X			
	Bangui	E	X		X			
Chad	Abeche	N		X		X		
	Moundou	N		X		X		
	Ndjamena	N	X	X	X	X		
	Sarh	N		X		X		
Congo	Brazzaville	E			X			
	Impfondo	E			X			
	Pointe Noire	E			X			
C.d.I.	Abengourou	N	X		X			
	Abidjan	N	X		X			
	Bouake	N	X		X			
	Daloa	N	X		X			
	Man	N	X		X			
	Odienne	N	X		X			

Country	Market	Season	Maize	Millet	Rice	Sorghum	Teff	Wheat
D.R. Congo	Bandundu	E	X		X			
	Bukavu	E	X		X			
	Bunia	E	X		X			
	Butembo	E	X		X			
	Gbadolite	E	X		X			
	Goma	E	X		X			
	Isiro	E	X		X			
	Kalemie	S	X		X			
	Kamina	S	X		X			
	Kananga	E	X		X			
	Kikwit	E	X		X			
	Kindu	E	X		X			
	Kinshasa	E	X		X			
	Kisangani	E	X		X			
	Kolwezi	S	X		X			
	Lubumbashi	S	X		X			
	Matadi	E	X		X			
	Mbandaka	E	X		X			
	Mbuji Mayi	E	X		X			
	Tshikapa	E	X		X			
	Uvira	E	X		X			
	Zongo	E	X		X			
Djibouti	Djibouti	N			X			
Eritrea	Asmara	N				X		
	Massawa	N				X		
Ethiopia	Addis Ababa	N	X			X	X	X
	Awasa	N	X			X	X	X
	Bahir Dar	N	X			X	X	X
	Dessie	N	X			X	X	X
	Dire Dawa	N	X			X	X	X
	Gambela	N	X			X	X	X
	Gode	E	X			X		X
	Gondar	N	X			X		X
	Jijiga	E	X			X		X
	Jimma	N	X			X	X	X
	Mekele	N	X			X	X	X
	Nekemte	N	X			X	X	
	Yabelo	E	X					X
Gabon	Libreville	N			X			
Gambia	Banjul	N	X	X	X	X		

Country	Market	Season	Maize	Millet	Rice	Sorghum	Teff	Wheat
Ghana	Accra	N	X	X	X	X		
	Bolgatanga	N	X	X	X	X		
	Ho	N	X		X			
	Kumasi	N	X	X	X	X		
	Sekondi Takoradi	N	X		X			
	Tamale	N	X	X	X	X		
	Wa	N	X	X	X	X		
Guinea	Conakry	N			X			
	Kankan	N			X			
	Labe	N			X			
	Nzerekore	N			X			
Guinea Bissau	Bissau	N	X	X	X	X		
Kenya	Eldoret	E	X					
	Garissa	E	X					
	Kisumu	E	X					
	Lodwar	E	X					
	Mandera	E	X					
	Mombasa	E	X					
	Moyale	E	X					
	Nairobi	E	X					
	Nakuru	E	X					
	Wajir	E	X					
Lesotho	Maseru	S	X					
Liberia	Gbarnga	N			X			
	Monrovia	N			X			
Malawi	Blantyre	S	X					
	Karonga	S	X					
	Lilongwe	S	X					
	Mangochi	S	X					
	Mzuzu	S	X					
Mali	Bamako	N		X	X	X		
	Gao	N		X	X	X		
	Kayes	N		X	X	X		
	Mopti	N		X	X	X		
	Segou	N		X	X	X		
	Sikasso	N		X	X	X		
Mauritania	Adel Bagrou	N			X	X		
	Nouakchott	N			X	X		
	Tintane	N			X	X		

Country	Market	Season	Maize	Millet	Rice	Sorghum	Teff	Wheat
Mozambique	Beira	S	X		X			
	Chimoio	S	X		X			
	Cuamba	S	X		X			
	Lichinga	S	X		X			
	Maputo	S	X		X			
	Maxixe	S	X		X			
	Milange	S	X		X			
	Nacala	S	X		X			
	Nampula	S	X		X			
	Pemba	S	X		X			
	Quelimane	S	X		X			
	Tete	S	X		X			
	Xai Xai	S	X		X			
Namibia	Katima Mulilo	S	X					
	Oshakati	S	X					
	Swakopmund	S	X					
	Windhoek	S	X					
Niger	Agadez	N		X		X		
	Arlit	N		X		X		
	Diffa	N		X		X		
	Maradi	N		X		X		
	Niamey	N		X		X		
	Tahoua	N		X		X		
	Zinder	N		X		X		
Nigeria	Abuja	N	X	X	X	X		
	Akure	N	X	X	X	X		
	Benin City	N	X	X	X	X		
	Calabar	N	X	X	X	X		
	Enugu	N	X	X	X	X		
	Gombe	N	X	X	X	X		
	Ibadan	N	X	X	X	X		
	Ilorin	N	X	X	X	X		
	Jos	N	X	X	X	X		
	Kaduna	N	X	X	X	X		
	Kano	N	X	X	X	X		
	Katsina	N	X	X	X	X		
	Lagos	N	X	X	X	X		
	Lokoja	N	X	X	X	X		
	Maiduguri	N	X	X	X	X		
	Makurdi	N	X	X	X	X		
	Port Harcourt	N	X	X	X	X		
	Sokoto	N	X	X	X	X		
	Yola	N	X	X	X	X		

Country	Market	Season	Maize	Millet	Rice	Sorghum	Teff	Wheat
Rwanda	Butare	E	X			X		
	Gisenyi	E	X			X		
	Kigali	E	X			X		
Senegal	Dakar	N	X	X	X	X		
	Kaolack	N	X	X	X	X		
	Saint Louis	N	X	X	X	X		
	Tambacounda	N	X	X	X	X		
	Touba	N	X	X	X	X		
	Ziguinchor	N	X	X	X	X		
Sierra Leone	Bo	N			X			
	Freetown	N			X			
	Kabala	N			X			
Somalia	Baidoa	E	X			X		
	Beledweyne	E	X			X		
	Bosaso	E	X			X		
	Galkayo	E	X			X		
	Garoowe	E	X			X		
	Hargeisa	E	X			X		
	Kismayo	E	X			X		
	Mogadishu	E	X			X		
South Africa	Johannesburg	S	X					
South Sudan	Bor	N	X			X		
	Juba	E	X			X		
	Malakal	N	X			X		
	Rumbek	N	X			X		
	Wau	N	X			X		
Sudan	Ad Damazin	N		X		X		X
	Al Fashir	N		X		X		X
	Al Qadarif	N		X		X		X
	El Geneina	N		X		X		X
	El Obeid	N		X		X		X
	Kadugli	N		X		X		X
	Kassala	N		X		X		X
	Khartoum	N		X		X		X
	Kosti	N		X		X		X
	Nyala	N		X		X		X
	Port Sudan	N		X		X		X

Country	Market	Season	Maize	Millet	Rice	Sorghum	Teff	Wheat
Swaziland	Mbabane	S	X					
Tanzania	Arusha	E	X		X			
	Bukoba	E	X		X			
	Dar es Salaam	E	X		X			
	Dodoma	E	X		X			
	Iringa	S	X		X			
	Kigoma	E	X		X			
	Mbeya	S	X		X			
	Mtwara	S	X		X			
	Musoma	E	X		X			
	Mwanza	E	X		X			
	Singida	E	X		X			
	Songea	S	X		X			
	Sumbawanga	S	X		X			
	Tabora	E	X		X			
	Tanga	E	X		X			
Togo	Kara	N	X		X	X		
	Lome	N	X		X	X		
Uganda	Arua	E	X					
	Gulu	E	X			X		
	Jinja	E	X			X		
	Kampala	E	X			X		
	Lira	E	X			X		
	Masindi	E	X			X		
	Mbarara	E	X			X		
Zambia	Chipata	S	X					
	Kabwe	S	X					
	Kasama	S	X					
	Kitwe	S	X					
	Livingstone	S	X					
	Lusaka	S	X					
	Mongu	S	X					
	Solwezi	S	X					
Zimbabwe	Bulawayo	S	X					
	Harare	S	X					
	Hwange	S	X					
	Masvingo	S	X					
	Mutare	S	X					
	Total		180	64	126	110	9	23

Table A.4: Primary and Secondary Data Sources by Country

Country	Markets	Series	Primary Source	Secondary Source
Angola	1	1	National Institute of Statistics	
Benin	4	9	Min. of Ag., Livestock, & Fisheries	FAO GIEWS
Botswana	1	1	Central Statistics Office	BIDPA
Burk. Faso	4	8	Afrique Verte	FAO GIEWS
Burundi	3	6	World Food Programme	USAID FEWS NET
Cameroon	4	8	National Institute of Statistics	FAO GIEWS
C.A.R.	3	6	World Food Programme	WFP VAM
Chad	4	10	USAID FEWS NET	FAO GIEWS
Congo	3	3	World Food Programme	WFP VAM
C.d.I.	6	12	World Food Programme	WFP VAM
D.R.C.	22	44	FAO-DRC & Min. of Ag. & Rural Dev.	
Djibouti	1	1	Dept. of Stat. & Demog. Studies	USAID FEWS NET
Eritrea	2	2	UN OCHA Eritrea	FAO GIEWS
Ethiopia	13	46	Ethiopian Grain Trade Enterp.; WFP	FAO GIEWS; WFP VAM
Gabon	1	1	Ministry of Economy and Planning	FAO GIEWS
Gambia	1	4	Bureau of Statistics	WFP VAM
Ghana	7	24	Ministry of Food and Agriculture	FAO GIEWS; WFP VAM
Guinea	4	4	World Food Programme	WFP VAM
G. Bissau	1	4	World Food Programme	WFP VAM
Kenya	10	10	Min. of Ag., Livestock, & Fisheries; NDMA; RATIN	USAID FEWS NET; FAO GIEWS
Lesotho	1	1	Bureau of Statistics	FAO GIEWS
Liberia	2	2	World Food Programme	WFP VAM
Malawi	5	5	Min. of Agriculture and Food Security	
Mali	6	18	Afrique Verte	FAO GIEWS
Mauritania	3	6	World Food Programme	WFP VAM
Mozamb.	13	26	Ministry of Agriculture	WFP VAM
Namibia	4	4	Namibia Statistics Agency	
Niger	7	14	Min. of Trade & Priv. Sec. Promotion	FAO GIEWS; WFP VAM
Nigeria	19	76	National Bureau of Statistics	D. Donaldson
Rwanda	3	6	Min. of Ag. & Animal Resources	WFP VAM
Senegal	6	24	Food Security Commission	WFP VAM
S. Leone	3	3	World Food Programme	WFP VAM
Somalia	8	16	Food Security & Nut. Analysis Unit	
S. Africa	1	1	South African Futures Exchange	FAO GIEWS
S. Sudan	5	10	World Food Programme	WFP VAM
Sudan	11	33	World Food Programme; Food Security Information for Action	WFP VAM; FAO GIEWS
Swaziland	1	1	Ministry of Agriculture	WFP VAM
Tanzania	15	30	Min. of Industry, Trade, & Marketing	WFP VAM
Togo	2	6	Min. of Ag., Livestock, & Fisheries	FAO GIEWS
Uganda	7	13	Infotrade Uganda; Farmgain Africa	WFP VAM; USAID FEWS NET
Zambia	8	8	Central Statistics Office	WFP VAM
Zimbabwe	5	5	World Food Programme	WFP VAM
Total	230	512		

A.4 Retail and Wholesale Price Series

390 (76%) of the 512 price series are identified as retail price series for quantities ranging from 0.5 to 3.5 kg, while the remainder are identified as wholesale price series for quantities ranging from 50 to 100 kg. Table A5 on the next page reports results from a statistical test of 37 series from 17 markets in 5 countries for which both "retail" and "wholesale" prices are available. My null hypothesis is that retail prices and wholesale prices are not significantly different, which is consistent with interviews of market participants suggesting that separate retail and wholesale markets typically do not exist and that prices per kilogram often do not vary with quantity sold. To test this hypothesis, I subtract each wholesale price series from its respective retail price series and then regress each resulting series of differences on a constant. I fail to reject the null for 9 of 37 series (24.3%), I find retail prices significantly greater than wholesale prices for 23 of 37 series (62.2%), and I find wholesale prices significantly greater than retail prices for 5 of 37 series (13.5%). Interestingly, all 9 of the 9 series from 4 large commercial capital cities have retail price series significantly greater than wholesale price series, suggesting that more sophisticated, separate markets may exist in these environments. These 4 cities all have populations over 1 million, whereas the remaining 28 series come from cities with populations less than 500,000. Without the 9 series from the large cities, exactly 50% of the remaining 28 series have retail prices significantly greater than wholesale prices while 50% have retail prices not different or significantly smaller than wholesale price series.

While I cannot reject my null hypothesis of equality, the results of the test are somewhat inconclusive. If there were a significant difference between retail and wholesale prices in some markets, it would be problematic for my estimation of trade costs in cases where a market with wholesale price series is directly connected to a market with retail price series. Fortunately, such cases are few – only 60 of the 413 links in my network (14.5%). Of these, only 29 (7.0%) involve a city with a population larger than 500,000. In table A6, I compare my estimated trade costs along these 29 links to estimated trade costs along similar nearby links with identical series types (wholesale-wholesale or retail-retail). Although direct comparisons are difficult to make due to the particularities of each link, the costs per t-km of the 29 potentially affected links do not appear to be systematically larger than those of their comparison links. The estimated trade costs along the 29 potentially affected links are also all much higher than the counterfactual trade cost of \$0.05/t-km, suggesting that any small bias in my trade cost estimates for these links due to retail-wholesale price discrepancies would not affect my results significantly.

Table A.5: Statistical Test of Retail–Wholesale Price Difference

Market	Country	Crop	Observ.	Coefficient	Std. Error	Result	Large City
Ad Damazin	Sudan	Millet	79	0.0935***	(0.0143)	+	
		Sorghum	86	0.0629***	(0.0067)	+	
Addis Ababa	Ethiopia	Maize	52	0.2525***	(0.0173)	+	X
		Sorghum	64	0.1875***	(0.0132)	+	X
		Teff	72	0.0373***	(0.0036)	+	X
		Wheat	72	0.0812***	(0.0066)	+	X
Agadez	Niger	Millet	76	–1.49E-04	(0.0031)	=	
		Sorghum	49	–4.79E-04	(0.0049)	=	
Al Fashir	Sudan	Millet	82	0.0458***	(0.0110)	+	
		Sorghum	60	0.1203***	(0.0147)	+	
Bahir Dar	Ethiopia	Teff	71	–0.0106**	(0.0048)	–	
		Wheat	67	0.0263***	(0.0063)	+	
Dar es Salaam	Tanzania	Maize	100	0.1646***	(0.0090)	+	X
		Rice	79	0.0937***	(0.0118)	+	X
Dire Dawa	Ethiopia	Maize	41	0.1972***	(0.0162)	+	
		Sorghum	55	0.0360***	(0.0081)	+	
		Teff	65	0.0775***	(0.0175)	+	
El Geneina	Sudan	Millet	72	–0.0153*	(0.0086)	=	
		Sorghum	66	–0.0259**	(0.0107)	–	
El Obeid	Sudan	Millet	109	0.0171*	(0.0086)	=	
		Sorghum	94	0.0228***	(0.0065)	+	
Kadugli	Sudan	Millet	71	0.0345*	(0.0185)	=	
		Sorghum	103	0.0176***	(0.0059)	+	
		Wheat	43	–0.0134	(0.0204)	=	
Kampala	Uganda	Maize	118	0.0840***	(0.0025)	+	X
Maradi	Niger	Millet	76	–1.17E-04	(0.0024)	=	
		Sorghum	76	–0.0098***	(0.0033)	–	
Mekele	Ethiopia	Teff	66	0.0362***	(0.0097)	+	
Niamey	Niger	Millet	76	0.0593***	(0.0030)	+	X
		Sorghum	76	0.0865***	(0.0032)	+	X
Nyala	Sudan	Millet	72	0.0136	(0.0101)	=	
		Sorghum	70	0.0139**	(0.0058)	+	
Port Sudan	Sudan	Millet	91	0.0788***	(0.0183)	+	
		Sorghum	96	0.0086**	(0.0037)	+	
		Wheat	55	0.0064	(0.0174)	=	
Zinder	Niger	Millet	76	–0.0328***	(0.0037)	–	
		Sorghum	52	–0.0213***	(0.0039)	–	

Note: * significant at 10%, ** at 5%, *** at 1%. Result column indicates whether the retail price is greater than (+), less than (–), or not different from (=) the wholesale price at 5% significance.

Table A.6: Estimated Trade Costs Along Potentially Affected Links and Nearby Comparison Links

Potentially Affected Link	τ_{mn}	Dist.	/t-km	Comparison Link	τ_{mn}	Dist.	/t-km
Monrovia LR – Bo SL	0.238	357	0.667	F'town SL – Conak. GN	0.398	311	1.279
B'ko ML – Odienne CI	0.091	406	0.225	Odienne CI – Kankan GN	0.120	301	0.398
B'ko ML – Kankan GN	0.160	372	0.429	Labe GN – Tambac. SN	0.179	422	0.424
B'ko ML – Adel Bag. MR	0.110	431	0.256	Kayes ML – Tambac. SN	0.088	284	0.309
B'ko ML – Tintane MR	0.394	704	0.560				
Ouaga. BF – Kara TG	0.132	531	0.248	Ouaga. BF – Bolgat. GH	0.096	212	0.451
Niam. NE – Gao ML	0.127	447	0.284	Niamey NE – Malanv. BJ	0.083	297	0.281
Niam. NE – Fada Ng. BF	0.152	292	0.520				
Accra GH – Lome TG	0.249	192	1.298	Cotonou BJ – Lagos NG	0.188	120	1.563
Kumasi GH – Abeng. CI	0.161	266	0.606	Abeng. CI – Bouake CI^d	0.211	346	0.611
Abidj. CI – Sek.-Tak. GH	0.163	321	0.509	Abidj. CI – Bouake CI^d	0.147	351	0.418
Bouake CI – Sikasso ML	0.061	492	0.123	Sikasso ML – Bobo D. BF	0.022	176	0.122
Luanda AO – Matadi CD	1.074	920	1.168	Matadi CD – Kinsh. CD^d	0.366	362	1.012
Luanda AO – Kinsh. CD	1.041	531	1.960				
Jo'burg ZA – Maseru LS	0.071	420	0.168	Jo'burg ZA – Mbab. SZ	0.089	357	0.251
Jo'burg ZA – Gabor. BW	0.114	366	0.312	Bulaw. ZW – Masv. ZW^d	0.118	283	0.415
Jo'burg ZA – Map. MZ	0.213	545	0.391				
Jo'burg ZA – Wind. NA	0.260	1365	0.190				
Jo'burg ZA – Bulaw. ZW	0.081	863	0.093				
Jo'burg ZA – Masv. ZW	0.111	827	0.134				
Map. MZ – Mbabane SZ	0.100	221	0.451	Map. MZ – Xai Xai MZ^d	0.105	216	0.485
Nairobi KE – Garissa KE^d	0.202	366	0.553	Garissa KE – Wajir KE^d	0.155	323	0.480
Momb. KE – Garissa KE^d	0.151	463	0.327				
Kigali RW – Mwanza TZ	0.079	533	0.147	Kigali RW – Mbarara UG	0.141	242	0.582
Kamp. UG – Bukoba TZ	0.136	299	0.456	Kigali RW – Mbarara UG	0.141	242	0.582
Khar. SD – Ad Dam. SD^d	0.112	533	0.211	Ad Dam. SD – Kosti SD^d	0.077	352	0.220
Khar. SD – Kosti SD^d	0.062	317	0.196	Khar. SD – Al Qad. SD^d	0.066	356	0.186
Asmara ER – Mekele ET	0.560	311	1.801	Asmara ER – Gondar ET	0.611	538	1.136
Asmara ER – Kassala SD	0.689	428	1.610				

Note: ^{d} Domestic link

A.5 Derivation of Inverse Demand and Welfare

In this section I derive expressions for inverse demand and welfare (indirect utility). The consumer's utility maximization problem is as follows:

$$\max_{\{Q_{imt}\}_{i\in I_m},X_{mt}} \frac{\theta_{mt}\left(\left[\sum_{i\in I_m}\alpha_{im}^{1/\sigma}Q_{imt}^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}\right)^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} + X_{mt} \text{ such that } \sum_{i\in I_m} P_{imt}Q_{imt} + X_{mt} \leq Y_{mt}$$

The first order condition for X_{mt} is $\lambda = 1$ where λ is the Lagrange multiplier. The first order condition for any grain i is:

$$\theta_{mt}\left(\left[\sum_{j\in I_m}\alpha_{jm}^{1/\sigma}Q_{jmt}^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}\right)^{1/\epsilon}\left[\sum_{j\in I_m}\alpha_{jm}^{1/\sigma}Q_{jmt}^{(\sigma-1)/\sigma}\right]^{1/(\sigma-1)}\alpha_{im}^{1/\sigma}Q_{imt}^{-1/\sigma} = \lambda P_{imt} = P_{imt}$$

Rearranging and letting $\theta_{mt}^{-\epsilon} = A_m N_{mt}$ gives the inverse demand function for any grain i:

$$P_{imt} = \frac{\alpha_{im}^{1/\sigma}}{Q_{imt}^{1/\sigma}} * \frac{Q_{mt}^{1/\sigma+1/\epsilon}}{(A_m N_{mt})^{1/\epsilon}}$$

where $Q_{mt} = \left[\sum_{i\in I_m}\alpha_{im}^{1/\sigma}Q_{imt}^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}$ is the CES quantity index (the grain composite).

I next turn to deriving an expression for welfare (indirect utility). Rearranging the previous expression gives the demand function for any grain i:

$$Q_{imt} = \frac{\alpha_{im}}{P_{imt}^{\sigma}} * \frac{Q_{mt}^{1+\sigma/\epsilon}}{(A_m N_{mt})^{\sigma/\epsilon}}$$

Taking the ratio of any two such equations for grains j and i gives:

$$\frac{Q_{jmt}}{Q_{imt}} = \frac{\alpha_{jm}P_{imt}^{\sigma}}{\alpha_{im}P_{jmt}^{\sigma}}$$

$$\Rightarrow Q_{jmt} = \frac{\alpha_{jm}Q_{imt}P_{imt}^{\sigma}}{\alpha_{im}P_{jmt}^{\sigma}}$$

$$\Rightarrow P_{jmt}Q_{jmt} = \frac{\alpha_{jm}P_{jmt}^{1-\sigma}Q_{imt}P_{imt}^{\sigma}}{\alpha_{im}}$$

$$\Rightarrow \sum_{j\in I_m} P_{jmt}Q_{jmt} = \frac{Q_{imt}P_{imt}^{\sigma}}{\alpha_{im}}\sum_{j\in I_m}\alpha_{jm}P_{jmt}^{1-\sigma}$$

$$\Rightarrow Q_{imt} = \frac{\alpha_{im}\sum_{j\in I_m}P_{jmt}Q_{jmt}}{P_{imt}^{\sigma}\sum_{j\in I_m}\alpha_{jm}P_{jmt}^{1-\sigma}}$$

I can use this last expression to rewrite the grain composite as follows:

$$Q_{mt} = \left[\sum_{i\in I_m} \alpha_{im}^{1/\sigma} Q_{imt}^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)} = \frac{\sum_{j\in I_m} P_{jmt}Q_{jmt}}{\sum_{j\in I_m} \alpha_{jm}P_{jmt}^{1-\sigma}} \left[\sum_{i\in I_m} \alpha_{im}^{1/\sigma}\left(\frac{\alpha_{im}}{P_{imt}^{\sigma}}\right)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}$$

$$\Rightarrow Q_{mt} = \frac{\sum_{j\in I_m} P_{jmt}Q_{jmt}}{\sum_{j\in I_m} \alpha_{jm}P_{jmt}^{1-\sigma}} \left[\sum_{i\in I_m} \alpha_{im}P_{imt}^{1-\sigma}\right]^{\sigma/(\sigma-1)}$$

$$\Rightarrow Q_{mt} = \frac{\sum_{j\in I_m} P_{jmt}Q_{jmt}}{\left[\sum_{j\in I_m} \alpha_{jm}P_{jmt}^{1-\sigma}\right]^{1/(1-\sigma)}} = \frac{\sum_{j\in I_m} P_{jmt}Q_{jmt}}{P_{mt}}$$

where $P_{mt} = \left[\sum_{j\in I_m} \alpha_{jm}P_{jmt}^{1-\sigma}\right]^{1/(1-\sigma)}$ is the CES grain price index. Plugging this into the demand function derived above gives:

$$Q_{imt} = \frac{\alpha_{im}}{P_{imt}^{\sigma}} * \frac{\left(\frac{\sum_{j\in I_m} P_{jmt}Q_{jmt}}{P_{mt}}\right)^{1+\sigma/\epsilon}}{(A_mN_{mt})^{\sigma/\epsilon}}$$

$$\Rightarrow P_{imt}Q_{imt} = \alpha_{im}P_{imt}^{1-\sigma} * \frac{\left(\frac{\sum_{j\in I_m} P_{jmt}Q_{jmt}}{P_{mt}}\right)^{1+\sigma/\epsilon}}{(A_mN_{mt})^{\sigma/\epsilon}}$$

$$\Rightarrow \sum_{j\in I_m} P_{jmt}Q_{jmt} = \sum_{j\in I_m} \alpha_{jm}P_{jmt}^{1-\sigma} * \frac{\left(\frac{\sum_{j\in I_m} P_{jmt}Q_{jmt}}{P_{mt}}\right)^{1+\sigma/\epsilon}}{(A_mN_{mt})^{\sigma/\epsilon}}$$

$$\Rightarrow \left(\sum_{j\in I_m} P_{jmt}Q_{jmt}\right)^{-\sigma/\epsilon} = \frac{P_{mt}^{-\sigma(1+1/\epsilon)}}{(A_mN_{mt})^{\sigma/\epsilon}}$$

$$\Rightarrow \sum_{j\in I_m} P_{jmt}Q_{jmt} = A_mN_{mt}P_{mt}^{\epsilon+1}$$

Plugging this into the expression for the quantity index derived above gives:

$$Q_{mt} = A_mN_{mt}P_{mt}^{\epsilon}$$

I next plug the two previous expressions into the utility function to obtain indirect utility V_{mt}:

$$U_{mt} = \theta_{mt}\frac{Q_{mt}^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} + X_{mt} = (A_mN_{mt})^{-\frac{1}{\epsilon}}\frac{Q_{mt}^{1+\frac{1}{\epsilon}}}{1+\frac{1}{\epsilon}} + Y_{mt} - \sum_{j\in I_m} P_{jmt}Q_{jmt}$$

$$\Rightarrow V_{mt} = \frac{\epsilon}{\epsilon+1}A_mN_{mt}P_{mt}^{\epsilon+1} + Y_{mt} - A_mN_{mt}P_{mt}^{\epsilon+1}$$

$$\Rightarrow V_{mt} = Y_{mt} - \frac{1}{\epsilon+1}A_mN_{mt}P_{mt}^{\epsilon+1}$$

This last expression is identical to equation 6 in the main text.

A.6 Demand Parameters

To estimate the elasticity of substitution (σ) I use standard techniques for CES utility. First note that:

$$Q_{mt} = A_m N_{mt} P_{mt}^{\epsilon} \Rightarrow \frac{Q_{mt}^{\sigma/\epsilon}}{(A_m N_{mt})^{\sigma/\epsilon}} = P_{mt}^{\sigma}$$

Plugging this in to the demand function derived in the previous section gives:

$$Q_{imt} = \frac{\alpha_{im}}{P_{imt}^{\sigma}} * \frac{Q_{mt}^{1+\sigma/\epsilon}}{(A_m N_{mt})^{\sigma/\epsilon}} \Rightarrow Q_{imt} = \frac{\alpha_{im}}{P_{imt}^{\sigma}} Q_{mt} P_{mt}^{\sigma}$$

Multiplying both sides by P_{imt} gives expenditure of grain i:

$$P_{imt} Q_{imt} = \alpha_{im} P_{imt}^{1-\sigma} Q_{mt} P_{mt}^{\sigma}$$
$$\Rightarrow \sum_{j \in I_m} P_{jmt} Q_{jmt} = \sum_{j \in I_m} \alpha_{jm} P_{jmt}^{1-\sigma} Q_{mt} P_{mt}^{\sigma}$$

Combining the previous two equations gives the following expression for the expenditure share on grain i (s_{imt}):

$$s_{imt} \equiv \frac{P_{imt} Q_{imt}}{\sum_{j \in I_m} P_{jmt} Q_{jmt}} = \frac{\alpha_{im} P_{imt}^{1-\sigma}}{\sum_{j \in I_m} \alpha_{jm} P_{jmt}^{1-\sigma}}$$

Taking the natural logarithm of both sides then gives:

$$\ln s_{imt} = \ln \alpha_{im} + (1-\sigma) \ln P_{imt} - \ln \left(\sum_{j \in I_m} \alpha_{jm} P_{jmt}^{1-\sigma} \right)$$

Using data on consumption and prices I then run the following regression:

$$\ln s_{imt} = \mu_{im} + \beta \ln P_{imt} + \mu_{mt} + v_{imt}$$

where μ_{im} and μ_{mt} are crop-country and country-year fixed effects and v_{imt} is an error term. My estimate for σ is then $1 - \beta$.

A simple OLS regression yields an estimate of $\beta = 0.49$, implying an estimate of $\sigma = 1 - 0.49 = 0.51$, with a clustered standard error of 0.21. However, OLS is unlikely to yield consistent estimates of β since equilibrium prices are affected by unobserved demand shocks, i.e. $Cov(P_{imt}, v_{imt}) \neq 0$. I therefore use an instrumental variables regression with the landed world price as the instrument. I define the landed world price Z_{imt} as the world price plus the average price difference between the world price and the country's largest city, which is a lower bound on trade costs. Crops with no world price (millet, teff) are excluded. The identifying assumption is that $Cov(Z_{imt}, v_{imt}) = 0$, i.e. that the landed world price only affects the expenditure share through its effect on local prices.

The first stage regression is as follows:

$$\ln P_{imt} = \mu_{im} + \gamma \ln Z_{imt} + \mu_{mt} + v_{imt}$$

which yields an estimate of $\gamma = 0.495$ with an unclustered standard error of 0.073 and a standard error of 0.202 when clustering by country-crop (387 observations, 56 clusters). There is thus a strong positive correlation between the landed world price and local prices in Africa, which is to be expected given Africa's position as a net grain importer. The first stage F statistic is 45.7 without clustering and 6.0 with clustering by country-crop.

The full instrumental variables regression yields an estimate of $\beta = 0.10$, implying an estimate of $\sigma = 1 - 0.10 = 0.90$, with a clustered standard error of 0.18 and a 95% confidence interval for σ of $[0.56, 1.25]$. The estimated σ is close to the Cobb-Douglas benchmark of $\sigma = 1$, implying that expenditure shares are only slightly affected by price changes, if at all.

For a particular σ (e.g. $\sigma = 1$ in my baseline case, $\sigma = 3$ in my robustness checks) I proceed to estimate the associated set of α_{im} by estimating individual regressions for each country m of the form:

$$(\ln s_{imt} - (1 - \sigma) \ln P_{imt}) = \mu_{im} + \mu_{mt} + v_{imt}$$

and backing out the α_{im} parameters from the coefficients on the fixed effect indicator variables μ_{im}. To compute standard errors, I bootstrap by resampling the data with replacement (10,000 iterations).

To estimate the price elasticity of grain demand (ϵ), I first compute the price and quantity indices for the relevant σ and its associated set of α_{im}. For my baseline case, I set $\sigma = 1$, so I use the Cobb-Douglas price and quantity indices: $P_{mt} = \prod_{i \in I_m} P_{imt}^{\alpha_{im}}$ and $Q_{mt} = \prod_{i \in I_m} \left(\frac{Q_{imt}}{\alpha_{im}}\right)^{\alpha_{im}}$. As shown in the previous section, overall grain demand in terms of price and quantity indices is given by:

$$Q_{mt} = A_m N_{mt} P_{mt}^{\epsilon}$$

Letting q_{mt} denote per-capita grain consumption gives:

$$q_{mt} \equiv \frac{Q_{mt}}{N_{mt}} = A_m P_{mt}^{\epsilon}$$
$$\Rightarrow \ln q_{mt} = \ln A_m + \epsilon \ln P_{mt}$$

I then run the following regression:

$$\ln q_{mt} = \mu_m + \epsilon \ln P_{mt} + v_{mt}$$

where μ_m are country fixed effects. A simple OLS regression yields an estimate of $\epsilon = -0.256$ with a clustered standard error of 0.071. However, once again OLS is unlikely to yield consistent estimates of ϵ since equilibrium prices are affected by unobserved demand shocks, i.e. $Cov(P_{mt}, v_{mt}) \neq 0$. I therefore again use an instrumental variables regression with the landed world price index Z_{mt} as the instrument (local prices of millet and teff are used in this index as necessary). The identifying assumption is that $Cov(Z_{mt}, v_{mt}) = 0$, i.e. that the landed world price index only affects the expenditure share through its effect on local prices.

The first stage regression is as follows:

$$\ln P_{mt} = \mu_m + \gamma \ln P_{mt} + v_{mt}$$

which yields an estimate of $\gamma = 1.02$ with a standard error of 0.12 when clustering by country (289 observations, 28 clusters). The clustered first stage F statistic is 70.3. Once again there is a strong positive correlation between the world price indices and the local price indices in Africa.

The full instrumental variables regression yields an estimate of $\epsilon = -0.136$ with a clustered standard error of 0.116 and a 95% confidence interval for ϵ of $[-0.363, 0.091]$. The estimated ϵ is close to zero, consistent with the estimate of Roberts and Schlenker 2013 of -0.066.

The last parameters to estimate are the demand shifters A_m. Given a particular σ, an associated estimated set of α_{im}, and a particular ϵ, I estimate A_m as an average across years:

$$A_m = \frac{1}{T} \sum_t \frac{Q_{mt}}{N_{mt} P_{mt}^{\epsilon}}$$

To compute standard errors, I implement a two-stage bootstrap procedure with 10,000 iterations in which I first re-estimate the set of α_{im} and then the associated average A_m.

Table A7 on the next page reports estimates for A_m and α_{im} for 20 individual countries (above the line) and 8 groups of countries (below the line). Country groups were formed due to the limited number of annual observations. Countries with less than 7 observations were given special priority for group formation. Groups were formed from contiguous countries having the same set of grains and similar per-capita consumption of each grain. The maximum number of annual observations for a given country is 9 as trade data for 2013 was unavailable at the time of estimation.

Table A.7: Demand Parameter Estimates for 28 Countries or Country Groups

	A	α_{maize}	α_{millet}	α_{rice}	$\alpha_{sorghum}$	α_{teff}	α_{wheat}	Observ.
Benin	179.4***	0.329***		0.614***	0.058***			9
	(10.1)	(0.034)		(0.037)	(0.004)			
Burkina Faso	170.5***		0.421***		0.579***			7
	(7.5)		(0.009)		(0.009)			
Cameroon	90.7***	0.618***		0.382***				8
	(3.2)	(0.015)		(0.015)				
Chad	115.9***	0.145***	0.363***	0.140***	0.352***			9
	(4.9)	(0.007)	(0.015)	(0.005)	(0.011)			
Côte d'Ivoire	101.4***	0.172***		0.828***				7
	(3.8)	(0.008)		(0.008)				
Djibouti	45.0***			1***				9
	(5.5)			(0)				
Eritrea	38.3***				1***			3
	(11.0)				(0)			
Ethiopia	143.0***	0.210***			0.176***	0.308***	0.306***	7
	(5.2)	(0.006)			(0.010)	(0.015)	(0.011)	
Ghana	102.5***	0.401***	0.074***	0.436***	0.088***			7
	(5.2)	(0.024)	(0.006)	(0.021)	(0.007)			
Kenya	79.1***	1***						9
	(2.9)	(0)						
Malawi	169.0***	1***						9
	(14.7)	(0)						
Mali	234.7***		0.285***	0.515***	0.201***			7
	(13.2)		(0.018)	(0.017)	(0.007)			
Mauritania	70.1***			0.680***	0.320***			5
	(4.4)			(0.049)	(0.049)			
Mozambique	70.0***	0.602***		0.398***				8
	(4.2)	(0.027)		(0.027)				
Niger	251.2***		0.766***		0.234***			9
	(11.8)		(0.006)		(0.006)			
Nigeria	166.9***	0.218***	0.257***	0.223***	0.302***			7
	(7.4)	(0.011)	(0.009)	(0.013)	(0.015)			
Somalia	29.6***	0.590***			0.410***			9
	(2.6)	(0.033)			(0.033)			
Tanzania	98.1***	0.561***		0.439***				7
	(5.7)	(0.025)		(0.025)				
Togo	158.9***	0.400***		0.406***	0.194***			9
	(3.3)	(0.013)		(0.011)	(0.008)			
Uganda	72.1***	0.833***			0.167***			2
	(0.7)	(0.002)			(0.002)			

	A	α_{maize}	α_{millet}	α_{rice}	$\alpha_{sorghum}$	α_{teff}	α_{wheat}	Observ.
Angola/	48.8***	1***						9
Bots./Namib.	(10.2)	(0)						
Burundi/	31.6***	0.627***			0.373***			12
Rwanda	(3.7)	(0.026)			(0.026)			
C.A.R./	32.1***	0.712***		0.288***				14
D.R.C.	(2.1)	(0.018)		(0.018)				
Congo/	40.6***			1***				8
Gabon	(1.7)			(0)				
Gambia/	170.6***	0.125***	0.229***	0.570***	0.076***			19
G. Biss./Sen.	(9.0)	(0.011)	(0.024)	(0.030)	(0.006)			
Guinea/	108.3***			1***				17
Lib/S. Leone	(5.4)			(0)				
Leso./Swazi.	105.5***	1***						16
Zam./Zim.	(7.8)	(0)						
South Sudan/	212.7***	0.018***	0.089***		0.465***		0.428***	5
Sudan	(10.1)	(0.005)	(0.008)		(0.026)		(0.033)	

A.7 Trade Cost Parameters

Table A8, which begins on the next page, shows estimated trade costs τ_{mn} for each of the 413 overland links in my model. Each link is only listed once, i.e. a link with a given "Market 1" is only listed if its "Market 2" has not yet been listed as a "Market 1". Links are listed by country of "Market 1" (both domestic and overland international links are included). Observations listed are observations with trade on the last iteration in which trade costs for that particular link were estimated prior to convergence. Standard errors were obtained by bootstrapping (10,000 iterations) using this set of final-iteration observations for resampling with replacement. Distances are in kilometers, with cost per tonne-kilometer (with standard errors) also reported.

Table A9, which follows Table A8, shows estimated trade costs τ_{mn} for the 47 links between 30 African ports and the world market (Bangkok for rice and the US Gulf for maize, sorghum, and wheat). Whether or not a port is linked to Bangkok and/or the US Gulf depends on its mix of crops. Observations and standard errors are obtained using the same procedure as for table A8. Over 70% of links have costs between \$0.10 and \$0.50/kg (\$100 – \$500/tonne). The lowest cost ports (\$70 – \$100/tonne) are Nacala (Mozambique), Mombasa (Kenya), Mogadishu (Somalia), and Dakar (Senegal) while the highest cost ports (>\$1000/tonne) are Angola (Luanda), Massawa (Eritrea), and Bissau (Guinea-Bissau).

Table A10, which follows Table A9, shows correlations between these port to world market trade costs and port characteristics. Although none of the correlations are significant at the 5% level (which is likely due to the small sample size and the idiosyncratic nature of port costs), most of the point estimates have the expected signs, with higher costs correlated with smaller port populations, lower port volumes, lower Corruption Perception Indices, and higher import tariffs. Import tariffs were obtained for the relevant grains from the World Bank's World Integrated Trade Solution (WITS). "High Volume" is an indicator variable for whether the port handled more than 500,000 TEUs in 2007 (African Development Bank 2010).

Table A.8: Estimated Overland Trade Costs

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Botswana	Gaborone	Jo'burg	0.1142	0.0076	366	0.3120	0.0209	52
Lesotho	Maseru	Jo'burg	0.0707	0.0087	420	0.1683	0.0207	31
Malawi	Blantyre	Lilongwe	0.0536	0.0236	365	0.1468	0.0647	2
	Blantyre	Mangochi	0.0601	0.0137	191	0.3147	0.0717	17
	Blantyre	Milange	0.0883	0.0185	115	0.7682	0.1609	14
	Blantyre	Tete	0.0609	0.0227	215	0.2835	0.1055	4
	Karonga	Mzuzu	0.0530	0.0088	222	0.2389	0.0396	21
	Karonga	Mbeya	0.1131	0.0359	161	0.7023	0.2227	5
	Lilongwe	Mangochi	0.0558	0.0097	272	0.2053	0.0356	5
	Lilongwe	Mzuzu	0.0323	0.0022	358	0.0901	0.0060	92
	Lilongwe	Tete	0.0533	0.0079	370	0.1441	0.0212	15
	Lilongwe	Chipata	0.0644	0.0044	145	0.4441	0.0306	95
	Mangochi	Cuamba	0.0804	0.0049	205	0.3924	0.0238	40
	Mangochi	Lichinga	0.0665	0.0139	221	0.3008	0.0631	14
Mozamb.	Beira	Chimoio	0.0989	0.0132	204	0.4848	0.0648	36
	Beira	Quelimane	0.0424	0.0100	487	0.0871	0.0206	12
	Chimoio	Maxixe	0.1286	0.0084	677	0.1900	0.0124	90
	Chimoio	Quelimane	0.1516	0.0179	552	0.2747	0.0324	20
	Chimoio	Tete	0.1919	0.0272	381	0.5036	0.0715	44
	Chimoio	Mutare	0.0597	0.0210	96	0.6218	0.2189	3
	Cuamba	Lichinga	0.3503	0.0528	315	1.1119	0.1678	9
	Cuamba	Nampula	0.1566	0.0242	358	0.4374	0.0676	46
	Maputo	XaiXai	0.1047	0.0112	216	0.4847	0.0520	34
	Maputo	Mbabane	0.0997	0.0117	221	0.4510	0.0531	24
	Maputo	Jo'burg	0.2131	0.0115	545	0.3910	0.0211	38
	Maxixe	XaiXai	0.0738	0.0111	256	0.2883	0.0432	30
	Milange	Quelimane	0.0833	0.0159	320	0.2603	0.0498	19
	Nacala	Nampula	0.0744	0.0141	192	0.3875	0.0736	27
	Nampula	Pemba	0.0926	0.0067	404	0.2293	0.0167	79
	Nampula	Quelimane	0.0488	0.0041	551	0.0885	0.0075	76
	Pemba	Mtwara	0.1822	0.0341	445	0.4095	0.0766	18
	Tete	Chipata	0.1590	0.0213	379	0.4196	0.0561	9
	Tete	Harare	0.0324	0.0075	383	0.0845	0.0195	14
Namibia	K.Mulilo	Oshakati	0.1634	0.0137	1114	0.1467	0.0123	14
	K.Mulilo	Windhoek	0.1026	0.0228	1226	0.0837	0.0186	12
	K.Mulilo	Livingstone	0.2864	0.0345	208	1.3772	0.1657	10
	K.Mulilo	Mongu	0.3367	0.0174	312	1.0792	0.0557	15
	Oshakati	Windhoek	0.0902	0.0118	716	0.1259	0.0165	14
	Swakopmund	Windhoek	0.0279	0.0040	362	0.0771	0.0111	16
	Windhoek	Jo'burg	0.2600	0.0058	1365	0.1905	0.0043	16
Swaziland	Mbabane	Jo'burg	0.0894	0.0062	357	0.2505	0.0175	89

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Zambia	Chipata	Lusaka	0.0368	0.0044	572	0.0644	0.0077	46
	Kabwe	Kasama	0.1438	0.0325	721	0.1994	0.0451	4
	Kabwe	Kitwe	0.0425	0.0023	221	0.1922	0.0104	119
	Kabwe	Lusaka	0.0571	0.0068	140	0.4081	0.0485	24
	Kabwe	Mbeya	0.0921	0.0228	986	0.0934	0.0231	14
	Kasama	Mbeya	0.0935	0.0142	400	0.2337	0.0354	11
	Kasama	Sumbawanga	0.0902	0.0113	287	0.3144	0.0393	17
	Kitwe	Solwezi	0.0362	0.0059	223	0.1625	0.0265	22
	Kitwe	Lubumbashi	0.8285	0.3733	187	4.4306	1.9961	5
	Livingstone	Lusaka	0.0323	0.0041	477	0.0678	0.0086	27
	Livingstone	Mongu	0.0854	0.0165	508	0.1680	0.0325	10
	Livingstone	Hwange	0.1884	0.0110	117	1.6103	0.0938	9
	Lusaka	Mongu	0.0662	0.0145	607	0.1091	0.0238	9
	Lusaka	Harare	0.0807	0.0092	493	0.1636	0.0187	24
	Mongu	Solwezi	0.1750	0.0106	591	0.2961	0.0179	3
	Solwezi	Lubumbashi	0.4837	0.0522	166	2.9139	0.3144	60
Zimbabwe	Bulawayo	Harare	0.0344	0.0081	447	0.0769	0.0181	32
	Bulawayo	Hwange	0.0422	0.0094	339	0.1245	0.0278	9
	Bulawayo	Masvingo	0.1175	0.0065	283	0.4152	0.0230	4
	Bulawayo	Johannesburg	0.0805	0.0214	863	0.0933	0.0248	10
	Harare	Masvingo	0.0485	0.0033	294	0.1648	0.0111	39
	Harare	Mutare	0.0155	0.0095	254	0.0608	0.0374	11
	Masvingo	Mutare	0.0500	0.0082	298	0.1678	0.0274	3
	Masvingo	Johannesburg	0.1110	0.0061	827	0.1342	0.0073	40
Angola	Luanda	Kinshasa	1.0407	0.0187	531	1.9599	0.0353	4
	Luanda	Matadi	1.0745	0.0667	920	1.1679	0.0725	4
Burundi	Bujumbura	Gitega	0.0706	0.0034	101	0.6986	0.0332	184
	Bujumbura	Uvira	0.1002	0.0060	31	3.2335	0.1949	60
	Bujumbura	Butare	0.1755	0.0554	162	1.0834	0.3419	7
	Bujumbura	Kigoma	0.1225	0.0090	229	0.5350	0.0393	34
	Gitega	Muyinga	0.0842	0.0031	96	0.8773	0.0320	183
	Gitega	Kigoma	0.0847	0.0192	218	0.3885	0.0880	18
	Muyinga	Butare	0.0811	0.0039	118	0.6871	0.0327	108
	Muyinga	Mwanza	0.1016	0.0134	423	0.2402	0.0317	33
C.A.R.	Bambari	Bangassou	0.3381	0.0386	353	0.9577	0.1093	48
	Bambari	Bangui	0.6447	0.0457	385	1.6744	0.1188	14
	Bambari	Gbadolite	0.4744	0.0806	250	1.8975	0.3226	23
	Bangassou	Gbadolite	0.4891	0.0863	290	1.6866	0.2976	11
	Bangui	Impfondo	0.1576	0.0259	320	0.4924	0.0808	5
	Bangui	Zongo	0.4158	0.0895	2	207.8856	44.7520	4
Congo	Brazzaville	Impfondo	0.2016	0.0489	780	0.2584	0.0628	9
	Brazzaville	PointeNoire	0.1169	0.0302	548	0.2133	0.0551	10
	Brazzaville	Kinshasa	0.3888	0.0602	4	97.2042	15.0425	14
	Impfondo	Mbandaka	0.4169	0.0229	352	1.1845	0.0652	10

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
D.R.C.	Bandundu	Kikwit	0.3097	0.0610	395	0.7841	0.1545	18
	Bandundu	Kinshasa	0.3963	0.0584	395	1.0033	0.1479	18
	Bandundu	Mbandaka	0.4737	0.0712	580	0.8167	0.1227	20
	Bukavu	Goma	0.2805	0.0366	199	1.4097	0.1839	42
	Bukavu	Kindu	0.4623	0.0291	695	0.6652	0.0418	119
	Bukavu	Kisangani	0.3585	0.0137	641	0.5593	0.0213	119
	Bukavu	Uvira	0.3384	0.0388	137	2.4700	0.2832	41
	Bukavu	Butare	0.1966	0.0163	147	1.3375	0.1112	48
	Bunia	Butembo	0.3463	0.0559	251	1.3798	0.2227	27
	Bunia	Isiro	0.2737	0.0321	486	0.5632	0.0660	40
	Bunia	Kisangani	0.3564	0.0127	706	0.5049	0.0179	120
	Bunia	Juba	0.2254	0.0131	633	0.3560	0.0207	59
	Bunia	Arua	0.2819	0.0170	256	1.1013	0.0666	5
	Bunia	Gulu	0.3151	0.0386	350	0.9004	0.1103	13
	Butembo	Goma	0.3609	0.0933	313	1.1531	0.2980	8
	Butembo	Mbarara	0.1645	0.0109	303	0.5430	0.0359	25
	Gbadolite	Mbandaka	0.5745	0.0806	675	0.8511	0.1195	2
	Gbadolite	Zongo	0.5942	0.1088	404	1.4708	0.2692	2
	Goma	Gisenyi	0.1481	0.0239	9	16.4538	2.6558	35
	Isiro	Kisangani	0.4951	0.1192	577	0.8581	0.2065	9
	Isiro	Juba	0.2966	0.0179	674	0.4401	0.0265	43
	Kalemie	Kamina	0.3238	0.0379	990	0.3271	0.0383	40
	Kalemie	Kindu	0.4430	0.0325	802	0.5524	0.0406	120
	Kalemie	Uvira	0.7118	0.2536	312	2.2814	0.8129	2
	Kalemie	Kigoma	0.3550	0.0467	148	2.3986	0.3153	31
	Kamina	Kolwezi	0.3372	0.0407	512	0.6586	0.0795	37
	Kamina	Lubumbashi	0.2104	0.0305	578	0.3640	0.0528	42
	Kamina	MbujiMayi	0.2612	0.0353	458	0.5702	0.0770	35
	Kananga	Kisangani	0.3761	0.0399	1282	0.2934	0.0311	120
	Kananga	MbujiMayi	0.5579	0.2753	179	3.1169	1.5379	6
	Kananga	Tshikapa	0.7875	0.2223	236	3.3371	0.9420	5
	Kikwit	Kinshasa	0.3412	0.0404	347	0.9832	0.1164	42
	Kikwit	Tshikapa	0.4704	0.0275	519	0.9064	0.0530	118
	Kindu	Kisangani	0.4090	0.1099	592	0.6910	0.1857	34
	Kindu	MbujiMayi	0.7201	0.1357	752	0.9576	0.1804	8
	Kinshasa	Matadi	0.3663	0.0257	362	1.0119	0.0711	117
	Kinshasa	Mbandaka	0.3287	0.0154	620	0.5302	0.0248	120
	Kisangani	Mbandaka	0.1624	0.0187	976	0.1664	0.0192	89
	Kolwezi	Lubumbashi	0.2304	0.0167	304	0.7578	0.0549	112
	Mbandaka	Zongo	0.2274	0.0318	672	0.3384	0.0474	55
	Uvira	Kigoma	0.1787	0.0165	172	1.0390	0.0961	54

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Kenya	Eldoret	Kisumu	0.0508	0.0156	117	0.4342	0.1334	10
	Eldoret	Lodwar	0.2718	0.0126	367	0.7406	0.0345	109
	Eldoret	Nakuru	0.0224	0.0017	155	0.1444	0.0112	64
	Eldoret	Jinja	0.0693	0.0054	268	0.2585	0.0203	25
	Garissa	Mombasa	0.1514	0.0117	463	0.3269	0.0252	103
	Garissa	Nairobi	0.2024	0.0201	366	0.5529	0.0549	36
	Garissa	Wajir	0.1552	0.0069	323	0.4804	0.0213	115
	Garissa	Kismayo	0.2042	0.0055	410	0.4981	0.0134	4
	Kisumu	Nakuru	0.1075	0.0207	183	0.5877	0.1133	5
	Kisumu	Musoma	0.0743	0.0046	307	0.2421	0.0150	82
	Kisumu	Jinja	0.1623	0.0054	238	0.6821	0.0226	25
	Lodwar	Juba	0.1741	0.0197	641	0.2716	0.0307	50
	Mandera	Wajir	0.1687	0.0237	420	0.4016	0.0565	11
	Mandera	Baidoa	0.2629	0.0125	269	0.9773	0.0465	109
	Mandera	Awasa	0.1598	0.0171	704	0.2270	0.0242	31
	Mombasa	Nairobi	0.0246	0.0014	500	0.0493	0.0028	108
	Mombasa	Tanga	0.1103	0.0138	164	0.6727	0.0844	14
	Moyale	Wajir	0.4087	0.0287	258	1.5839	0.1112	2
	Moyale	Yabelo	0.0979	0.0083	213	0.4594	0.0391	67
	Nairobi	Nakuru	0.0388	0.0033	159	0.2439	0.0210	39
	Nairobi	Arusha	0.1556	0.0003	269	0.5785	0.0010	2
Rwanda	Butare	Gisenyi	0.0655	0.0238	202	0.3240	0.1180	2
	Butare	Kigali	0.0972	0.0144	123	0.7906	0.1171	23
	Gisenyi	Kigali	0.0905	0.0082	151	0.5996	0.0543	49
	Gisenyi	Mbarara	0.0785	0.0115	299	0.2625	0.0383	7
	Kigali	Mwanza	0.0786	0.0329	533	0.1474	0.0618	11
	Kigali	Mbarara	0.1409	0.0342	242	0.5820	0.1415	10
Somalia	Baidoa	Mogadishu	0.0604	0.0037	247	0.2447	0.0150	112
	Baidoa	Awasa	0.3026	0.0446	891	0.3396	0.0500	6
	Beledweyne	Galkayo	0.1293	0.0062	389	0.3325	0.0158	176
	Beledweyne	Mogadishu	0.0494	0.0024	339	0.1459	0.0070	182
	Beledweyne	Gode	0.0903	0.0088	263	0.3432	0.0334	101
	Beledweyne	Jijiga	0.1001	0.0052	599	0.1672	0.0087	118
	Bosaso	Garoowe	0.1210	0.0065	443	0.2731	0.0146	191
	Galkayo	Garoowe	0.4358	0.0728	230	1.8947	0.3164	8
	Garoowe	Hargeisa	0.3701	0.0478	594	0.6230	0.0804	5
	Hargeisa	Jijiga	0.1663	0.0065	165	1.0081	0.0397	149
	Kismayo	Mogadishu	0.0698	0.0203	485	0.1438	0.0418	10

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Tanzania	Arusha	Dodoma	0.0712	0.0115	423	0.1682	0.0271	13
	Arusha	Musoma	0.0693	0.0122	504	0.1375	0.0243	27
	Arusha	Singida	0.0642	0.0104	350	0.1834	0.0297	37
	Arusha	Tanga	0.0464	0.0074	436	0.1065	0.0170	37
	Bukoba	Mwanza	0.0628	0.0086	434	0.1446	0.0197	63
	Bukoba	Kampala	0.1363	0.0114	299	0.4560	0.0380	2
	Bukoba	Mbarara	0.1799	0.0115	313	0.5747	0.0367	25
	DaresSalaam	Dodoma	0.0669	0.0128	449	0.1490	0.0285	47
	DaresSalaam	Iringa	0.0686	0.0038	501	0.1369	0.0077	174
	DaresSalaam	Mtwara	0.0640	0.0068	559	0.1144	0.0122	52
	DaresSalaam	Tanga	0.0595	0.0122	355	0.1675	0.0345	57
	Dodoma	Iringa	0.0765	0.0033	265	0.2886	0.0124	174
	Dodoma	Singida	0.0925	0.0112	250	0.3699	0.0448	37
	Iringa	Mbeya	0.0740	0.0069	336	0.2201	0.0205	74
	Iringa	Songea	0.0594	0.0030	436	0.1362	0.0069	134
	Kigoma	Sumbawanga	0.1178	0.0113	536	0.2197	0.0211	34
	Kigoma	Tabora	0.1190	0.0099	716	0.1663	0.0138	59
	Mbeya	Songea	0.0622	0.0031	423	0.1472	0.0073	132
	Mbeya	Sumbawanga	0.0757	0.0041	317	0.2388	0.0130	149
	Mtwara	Songea	0.0996	0.0129	655	0.1521	0.0197	20
	Musoma	Mwanza	0.0743	0.0089	223	0.3330	0.0397	67
	Mwanza	Singida	0.1024	0.0104	475	0.2156	0.0218	38
	Mwanza	Tabora	0.0707	0.0111	367	0.1927	0.0304	24
	Singida	Tabora	0.1839	0.0175	357	0.5151	0.0490	16
Uganda	Arua	Gulu	0.0590	0.0091	232	0.2545	0.0394	9
	Arua	Juba	0.5288	0.0422	336	1.5737	0.1257	12
	Gulu	Kampala	0.0755	0.0064	339	0.2227	0.0188	50
	Gulu	Lira	0.0580	0.0036	135	0.4293	0.0267	50
	Gulu	Masindi	0.0877	0.0059	175	0.5010	0.0339	14
	Gulu	Juba	0.8681	0.0850	281	3.0892	0.3027	15
	Jinja	Kampala	0.0649	0.0045	79	0.8214	0.0574	50
	Kampala	Lira	0.0864	0.0073	342	0.2527	0.0214	34
	Kampala	Masindi	0.1442	0.0459	214	0.6737	0.2147	3
	Kampala	Mbarara	0.3276	0.0673	265	1.2364	0.2540	3
	Lira	Masindi	0.0702	0.0090	180	0.3898	0.0502	14
Djibouti	Djibouti	AddisAbaba	0.1481	0.0192	920	0.1610	0.0209	53
	Djibouti	Dessie	0.1333	0.0151	548	0.2432	0.0276	98
	Djibouti	DireDawa	0.1411	0.0197	323	0.4368	0.0610	58
Eritrea	Asmara	Massawa	0.4333	0.0709	110	3.9394	0.6447	2
	Asmara	Gondar	0.6112	0.0419	538	1.1360	0.0779	16
	Asmara	Mekele	0.5602	0.0468	311	1.8012	0.1504	14
	Asmara	Kassala	0.6892	0.0533	428	1.6103	0.1245	16

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Ethiopia	AddisAbaba	Awasa	0.0843	0.0046	272	0.3100	0.0168	222
	AddisAbaba	BahirDar	0.1069	0.0112	551	0.1941	0.0203	44
	AddisAbaba	Dessie	0.0612	0.0059	385	0.1590	0.0152	59
	AddisAbaba	DireDawa	0.0349	0.0013	507	0.0688	0.0026	299
	AddisAbaba	Jimma	0.0490	0.0018	306	0.1600	0.0058	283
	AddisAbaba	Nekemte	0.1202	0.0064	325	0.3699	0.0197	147
	Awasa	Gode	0.1498	0.0068	629	0.2382	0.0108	134
	Awasa	Jimma	0.1876	0.0432	416	0.4509	0.1039	12
	Awasa	Yabelo	0.1260	0.0077	295	0.4271	0.0262	96
	BahirDar	Dessie	0.0537	0.0024	474	0.1134	0.0051	273
	BahirDar	Gondar	0.0389	0.0016	176	0.2208	0.0088	224
	BahirDar	Nekemte	0.0575	0.0027	399	0.1442	0.0067	148
	BahirDar	AdDamazin	0.1034	0.0058	466	0.2219	0.0124	112
	Dessie	Gondar	0.0582	0.0067	528	0.1102	0.0127	78
	Dessie	Mekele	0.0603	0.0053	388	0.1555	0.0136	103
	DireDawa	Jijiga	0.1178	0.0097	155	0.7597	0.0626	78
	Gambela	Jimma	0.1162	0.0050	420	0.2768	0.0120	136
	Gambela	Nekemte	0.1511	0.0056	390	0.3875	0.0144	92
	Gambela	Malakal	0.2816	0.0831	445	0.6328	0.1867	11
	Gode	Jijiga	0.0934	0.0092	572	0.1632	0.0160	40
	Gondar	Mekele	0.0468	0.0022	599	0.0781	0.0036	221
	Gondar	AlQadarif	0.2117	0.0274	357	0.5929	0.0766	31
	Jimma	Nekemte	0.0875	0.0055	244	0.3588	0.0227	155
S. Sudan	Bor	Malakal	0.4707	0.0433	472	0.9971	0.0916	63
	Bor	Juba	0.2114	0.0215	200	1.0571	0.1077	37
	Juba	Rumbek	0.7834	0.0966	678	1.1554	0.1425	34
	Malakal	AdDamazin	0.4076	0.0322	484	0.8421	0.0666	80
	Malakal	Kadugli	0.3680	0.0331	334	1.1018	0.0990	79
	Malakal	Kosti	0.3487	0.0350	500	0.6975	0.0699	69
	Rumbek	Wau	0.8301	0.0749	226	3.6732	0.3312	42
	Wau	Kadugli	0.4991	0.0542	610	0.8182	0.0889	48
Sudan	AdDamazin	AlQadarif	0.0683	0.0032	523	0.1307	0.0061	169
	AdDamazin	Khartoum	0.1124	0.0081	533	0.2109	0.0152	89
	AdDamazin	Kosti	0.0774	0.0139	352	0.2198	0.0394	12
	AlFashir	ElGeneina	0.1326	0.0108	352	0.3768	0.0308	126
	AlFashir	ElObeid	0.1442	0.0127	613	0.2352	0.0208	98
	AlFashir	Nyala	0.0755	0.0089	194	0.3894	0.0459	72
	AlQadarif	Kassala	0.0779	0.0056	271	0.2873	0.0208	101
	AlQadarif	Khartoum	0.0662	0.0032	356	0.1859	0.0091	254
	AlQadarif	Kosti	0.0360	0.0018	396	0.0910	0.0044	209
	ElGeneina	Nyala	0.1391	0.0050	376	0.3700	0.0133	240
	ElGeneina	Abeche	0.0555	0.0026	197	0.2816	0.0130	217
	ElObeid	Kadugli	0.0941	0.0043	262	0.3592	0.0162	211
	ElObeid	Kosti	0.0354	0.0020	311	0.1139	0.0064	222
	Kassala	PortSudan	0.0951	0.0032	575	0.1654	0.0056	252
	Khartoum	Kosti	0.0622	0.0016	317	0.1963	0.0052	292
	Khartoum	PortSudan	0.0611	0.0037	821	0.0744	0.0045	214

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Benin	Cotonou	Parakou	0.1162	0.0129	425	0.2735	0.0304	37
	Cotonou	Lagos	0.1875	0.0154	120	1.5627	0.1284	113
	Cotonou	Lome	0.0957	0.0041	147	0.6513	0.0278	240
	Malanville	Parakou	0.1461	0.0763	320	0.4566	0.2384	4
	Malanville	Niamey	0.0834	0.0034	297	0.2810	0.0115	88
	Malanville	Sokoto	0.1050	0.0192	334	0.3144	0.0576	16
	Natitingou	Parakou	0.1500	0.0685	217	0.6914	0.3159	4
	Natitingou	FadaNgo.	0.1718	0.0287	253	0.6790	0.1134	15
	Natitingou	Kara	0.1051	0.0068	119	0.8833	0.0571	110
	Parakou	Ibadan	0.1142	0.0210	301	0.3794	0.0699	14
	Parakou	Ilorin	0.1164	0.0094	284	0.4099	0.0332	70
	Parakou	Kara	0.1281	0.0369	200	0.6407	0.1845	10
Burk. Faso	BoboDiou.	Dedougou	0.0222	0.0016	179	0.1238	0.0090	82
	BoboDiou.	Ouagadougou	0.0228	0.0014	356	0.0639	0.0039	82
	BoboDiou.	Wa	0.1386	0.0056	313	0.4429	0.0178	82
	BoboDiou.	Mopti	0.0532	0.0106	475	0.1120	0.0224	8
	BoboDiou.	Segou	0.0675	0.0055	377	0.1791	0.0145	4
	BoboDiou.	Sikasso	0.0215	0.0017	176	0.1223	0.0097	82
	Dedougou	Ouagadougou	0.0263	0.0013	225	0.1170	0.0059	128
	FadaNgo.	Ouagadougou	0.0538	0.0088	223	0.2414	0.0396	33
	FadaNgo.	Niamey	0.1517	0.0026	292	0.5196	0.0089	104
	Ouagadougou	Bolgatanga	0.0955	0.0170	212	0.4505	0.0800	20
	Ouagadougou	Kara	0.1317	0.0203	531	0.2481	0.0382	18
Cameroon	Bamenda	Douala	0.0686	0.0042	305	0.2248	0.0138	158
	Bamenda	Yaounde	0.1053	0.0031	368	0.2862	0.0085	200
	Bamenda	Calabar	0.1774	0.0268	331	0.5361	0.0808	20
	Bamenda	Enugu	0.2563	0.0205	511	0.5016	0.0402	2
	Douala	Yaounde	0.1092	0.0058	236	0.4627	0.0247	101
	Douala	Calabar	0.1254	0.0063	453	0.2768	0.0140	103
	Douala	Enugu	0.1697	0.0154	632	0.2685	0.0243	30
	Garoua	Yaounde	0.1058	0.0044	939	0.1127	0.0047	200
	Garoua	Ndjamena	0.1142	0.0136	495	0.2306	0.0274	39
	Garoua	Maiduguri	0.0848	0.0137	425	0.1995	0.0323	20
	Garoua	Yola	0.1072	0.0141	167	0.6421	0.0844	33
	Yaounde	Libreville	0.2128	0.0296	933	0.2281	0.0317	2
Chad	Abeche	Ndjamena	0.0980	0.0068	753	0.1301	0.0090	95
	Moundou	Ndjamena	0.0796	0.0053	474	0.1680	0.0112	84
	Moundou	Sarh	0.0600	0.0150	305	0.1969	0.0493	18
	Ndjamena	Sarh	0.0700	0.0059	558	0.1255	0.0105	103
	Ndjamena	Maiduguri	0.0956	0.0136	260	0.3678	0.0525	52

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
C.d.I.	Abengourou	Abidjan	0.1216	0.0107	205	0.5932	0.0524	45
	Abengourou	Bouake	0.2114	0.0225	346	0.6108	0.0651	45
	Abengourou	Kumasi	0.1612	0.0146	266	0.6059	0.0551	45
	Abidjan	Bouake	0.1468	0.0127	351	0.4182	0.0362	50
	Abidjan	Daloa	0.0968	0.0128	385	0.2513	0.0331	51
	Abidjan	Sek.Tak.	0.1635	0.0274	321	0.5092	0.0852	19
	Bouake	Daloa	0.1068	0.0113	241	0.4432	0.0471	50
	Bouake	Sikasso	0.0607	0.0044	492	0.1234	0.0088	62
	Daloa	Man	0.0979	0.0137	188	0.5205	0.0731	52
	Man	Odienne	0.0799	0.0046	268	0.2982	0.0171	104
	Man	Nzerekore	0.2739	0.0497	205	1.3363	0.2423	4
	Man	Gbarnga	0.0946	0.0092	270	0.3505	0.0341	41
	Odienne	Kankan	0.1197	0.0107	301	0.3978	0.0355	39
	Odienne	Bamako	0.0914	0.0058	406	0.2251	0.0143	52
Gambia	Banjul	Kaolack	0.1662	0.0354	153	1.0864	0.2314	5
	Banjul	Ziguinchor	0.0875	0.0038	115	0.7612	0.0334	154
Ghana	Accra	Ho	0.1589	0.0307	156	1.0188	0.1966	31
	Accra	Kumasi	0.1309	0.0055	253	0.5175	0.0218	347
	Accra	Sek.Tak.	0.1692	0.0116	248	0.6824	0.0467	118
	Accra	Lome	0.2492	0.1001	192	1.2978	0.5212	5
	Bolgatanga	Tamale	0.1485	0.0541	172	0.8635	0.3144	2
	Bolgatanga	Wa	0.0485	0.0016	264	0.1839	0.0060	347
	Ho	Tamale	0.1826	0.0089	469	0.3893	0.0190	114
	Ho	Kara	0.1503	0.0263	462	0.3252	0.0569	4
	Ho	Lome	0.2800	0.0286	129	2.1704	0.2219	28
	Kumasi	Sek.Tak.	0.1084	0.0121	281	0.3858	0.0430	51
	Kumasi	Tamale	0.1256	0.0101	380	0.3305	0.0266	79
	Kumasi	Wa	0.0860	0.0045	446	0.1928	0.0102	222
	Tamale	Wa	0.1587	0.0287	303	0.5237	0.0946	2
	Tamale	Kara	0.1221	0.0058	258	0.4733	0.0226	260
Guinea	Conakry	Kankan	0.1724	0.0270	651	0.2648	0.0415	8
	Conakry	Labe	0.2316	0.0189	404	0.5733	0.0468	7
	Conakry	Nzerekore	0.1077	0.0220	845	0.1275	0.0260	3
	Conakry	Freetown	0.3976	0.0460	311	1.2786	0.1481	4
	Kankan	Labe	0.0882	0.0068	518	0.1703	0.0131	50
	Kankan	Nzerekore	0.2030	0.1054	450	0.4511	0.2343	2
	Kankan	Bamako	0.1596	0.0100	372	0.4291	0.0269	53
	Labe	Nzerekore	0.1482	0.0394	727	0.2039	0.0541	4
	Labe	Bissau	0.2681	0.0168	539	0.4974	0.0311	51
	Labe	Tambacounda	0.1789	0.0763	422	0.4240	0.1808	2
	Nzerekore	Gbarnga	0.3618	0.0372	168	2.1533	0.2214	6
G. Bissau	Bissau	Ziguinchor	1.0714	0.0736	145	7.3892	0.5076	46
Liberia	Gbarnga	Monrovia	0.0513	0.0060	196	0.2619	0.0307	33
	Monrovia	Bo	0.2382	0.0024	357	0.6671	0.0066	3

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Mali	Bamako	Kayes	0.0644	0.0023	613	0.1051	0.0037	264
	Bamako	Segou	0.0383	0.0015	236	0.1621	0.0065	192
	Bamako	Sikasso	0.0416	0.0061	364	0.1144	0.0168	28
	Bamako	AdelBagrou	0.1103	0.0070	431	0.2559	0.0161	82
	Bamako	Tintane	0.3943	0.0733	704	0.5601	0.1041	17
	Gao	Mopti	0.0435	0.0029	583	0.0747	0.0050	163
	Gao	Niamey	0.1270	0.0032	447	0.2842	0.0071	98
	Kayes	Tintane	0.3863	0.0759	563	0.6861	0.1349	17
	Kayes	Tambacounda	0.0878	0.0117	284	0.3092	0.0412	43
	Mopti	Segou	0.0506	0.0037	401	0.1263	0.0092	52
	Segou	Sikasso	0.0385	0.0044	291	0.1323	0.0151	33
Mauritania	AdelBagrou	Tintane	0.2659	0.0488	479	0.5552	0.1019	17
	Nouakchott	Tintane	0.1165	0.0277	747	0.1560	0.0370	4
	Nouakchott	SaintLouis	0.4857	0.0641	303	1.6029	0.2117	7
Niger	Agadez	Arlit	0.0532	0.0055	241	0.2207	0.0229	72
	Agadez	Tahoua	0.0546	0.0034	406	0.1344	0.0083	70
	Agadez	Zinder	0.0771	0.0024	446	0.1728	0.0053	193
	Diffa	Zinder	0.0703	0.0079	475	0.1479	0.0165	14
	Diffa	Maiduguri	0.0764	0.0048	220	0.3472	0.0216	32
	Maradi	Niamey	0.1763	0.0065	664	0.2654	0.0098	2
	Maradi	Tahoua	0.1108	0.0039	352	0.3148	0.0112	70
	Maradi	Zinder	0.0325	0.0095	238	0.1367	0.0397	11
	Maradi	Katsina	0.0902	0.0279	92	0.9803	0.3030	11
	Maradi	Sokoto	0.1053	0.0388	342	0.3080	0.1134	6
	Niamey	Tahoua	0.0356	0.0032	553	0.0643	0.0058	70
	Niamey	Sokoto	0.0666	0.0157	513	0.1298	0.0306	10
	Tahoua	Sokoto	0.0783	0.0051	230	0.3406	0.0223	36
	Zinder	Kano	0.0700	0.0230	240	0.2917	0.0960	8

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Nigeria	Abuja	Ilorin	0.1351	0.0727	453	0.2982	0.1604	2
	Abuja	Jos	0.0656	0.0024	275	0.2387	0.0089	288
	Abuja	Kaduna	0.1263	0.0259	211	0.5987	0.1229	8
	Abuja	Lokoja	0.0963	0.0062	202	0.4767	0.0305	144
	Abuja	Makurdi	0.1837	0.0716	283	0.6491	0.2531	4
	Akure	BeninCity	0.1252	0.0049	172	0.7282	0.0284	283
	Akure	Ibadan	0.0957	0.0030	178	0.5378	0.0171	282
	Akure	Ilorin	0.1327	0.0060	203	0.6539	0.0296	197
	BeninCity	Enugu	0.1244	0.0091	254	0.4899	0.0360	100
	BeninCity	Ibadan	0.1798	0.0054	282	0.6375	0.0190	278
	BeninCity	Lagos	0.1629	0.0660	326	0.4996	0.2025	13
	BeninCity	Lokoja	0.1561	0.0119	276	0.5657	0.0432	90
	BeninCity	PortHarcourt	0.1326	0.0061	332	0.3993	0.0182	287
	Calabar	Enugu	0.1540	0.0269	263	0.5857	0.1022	129
	Calabar	PortHarcourt	0.2567	0.0341	216	1.1886	0.1580	62
	Enugu	Makurdi	0.1455	0.0153	257	0.5662	0.0594	63
	Enugu	PortHarcourt	0.1679	0.0126	233	0.7204	0.0542	172
	Enugu	Yola	0.1830	0.0111	761	0.2404	0.0145	133
	Gombe	Jos	0.0859	0.0030	279	0.3080	0.0109	272
	Gombe	Maiduguri	0.1146	0.0457	319	0.3594	0.1431	3
	Gombe	Yola	0.0862	0.0092	250	0.3447	0.0368	96
	Ibadan	Ilorin	0.0703	0.0046	159	0.4420	0.0290	177
	Ibadan	Lagos	0.2131	0.0164	142	1.5005	0.1152	121
	Ilorin	Kaduna	0.0573	0.0056	492	0.1164	0.0113	127
	Ilorin	Lokoja	0.2157	0.0444	326	0.6617	0.1363	6
	Ilorin	Sokoto	0.0678	0.0024	682	0.0994	0.0035	276
	Jos	Kaduna	0.0605	0.0027	274	0.2208	0.0099	280
	Jos	Kano	0.0791	0.0030	392	0.2018	0.0075	284
	Jos	Maiduguri	0.1016	0.0206	587	0.1730	0.0350	4
	Jos	Makurdi	0.0874	0.0101	310	0.2818	0.0326	77
	Kaduna	Kano	0.0529	0.0026	233	0.2271	0.0112	288
	Kaduna	Sokoto	0.0588	0.0055	468	0.1255	0.0116	84
	Kano	Katsina	0.0614	0.0061	173	0.3547	0.0353	91
	Kano	Maiduguri	0.0748	0.0099	636	0.1176	0.0155	29
	Kano	Sokoto	0.0912	0.0297	540	0.1689	0.0551	7
	Maiduguri	Yola	0.1032	0.0167	406	0.2542	0.0411	62
	Makurdi	Yola	0.0811	0.0032	617	0.1314	0.0052	276

	Market 1	Market 2	τ_{mn}	Std. Error	Dist.	/t-km	Std. Error	Obs.
Senegal	Dakar	Kaolack	0.0778	0.0045	214	0.3636	0.0209	80
	Dakar	SaintLouis	0.0457	0.0022	245	0.1864	0.0090	152
	Dakar	Touba	0.0752	0.0027	181	0.4155	0.0151	135
	Kaolack	Tambacounda	0.0404	0.0033	375	0.1077	0.0087	73
	Kaolack	Touba	0.0366	0.0021	154	0.2379	0.0139	177
	SaintLouis	Touba	0.0940	0.0114	176	0.5341	0.0647	7
	Tambacounda	Ziguinchor	0.1128	0.0267	408	0.2765	0.0653	6
S. Leone	Bo	Freetown	0.0622	0.0076	237	0.2624	0.0321	25
	Bo	Kabala	0.0679	0.0153	253	0.2684	0.0603	18
	Freetown	Kabala	0.0667	0.0253	302	0.2209	0.0838	3
Togo	Kara	Lome	0.1858	0.0092	412	0.4510	0.0224	97

Table A.9: Estimated Port to World Market Trade Costs

	Market 1	Market 2	τ_{mn}	Std. Error	Observ.
Mozambique	Beira	Gulf	0.1084	0.0166	36
	Beira	Bangkok	0.2419	0.0160	61
	Maputo	Gulf	0.1838	0.0103	65
	Maputo	Bangkok	0.2092	0.0083	120
	Nacala	Gulf	0.0732	0.0096	28
	Nacala	Bangkok	0.2384	0.0144	26
Namibia	Swakopmund	Gulf	0.2751	0.0170	4
Angola	Luanda	Gulf	1.4519	0.0116	4
Congo	PointeNoire	Bangkok	0.6152	0.0649	10
D.R. Congo	Matadi	Gulf	0.3994	0.0239	55
	Matadi	Bangkok	0.7986	0.0492	57
Kenya	Mombasa	Gulf	0.1000	0.0070	64
Somalia	Bosaso	Gulf	0.3319	0.0142	184
	Kismayo	Gulf	0.1182	0.0112	55
	Mogadishu	Gulf	0.0764	0.0067	117
Tanzania	DaresSalaam	Gulf	0.1062	0.0117	33
	DaresSalaam	Bangkok	0.3191	0.0137	87
Djibouti	Djibouti	Gulf	0.0912	0.0032	112
	Djibouti	Bangkok	0.2737	0.0095	112
Eritrea	Massawa	Gulf	1.5038	0.0754	9
Sudan	PortSudan	Gulf	0.2723	0.0113	137
Benin	Cotonou	Gulf	0.2571	0.0182	53
	Cotonou	Bangkok	0.4291	0.0071	120
Cameroon	Douala	Gulf	0.3615	0.0072	100
	Douala	Bangkok	0.2482	0.0067	97
Côte d'Ivoire	Abidjan	Gulf	0.2730	0.0127	26
	Abidjan	Bangkok	0.2413	0.0178	25
Gabon	Libreville	Bangkok	0.5394	0.0119	74
Gambia	Banjul	Gulf	0.3193	0.0046	156
	Banjul	Bangkok	0.1151	0.0093	61
Ghana	Accra	Gulf	0.2816	0.0082	112
	Accra	Bangkok	0.4399	0.0315	73
Guinea	Conakry	Bangkok	0.5813	0.0478	9
Guinea Bissau	Bissau	Gulf	1.5468	0.1344	8
	Bissau	Bangkok	0.4296	0.0304	32
Liberia	Monrovia	Bangkok	0.1156	0.0117	39
Mauritania	Nouakchott	Gulf	0.6870	0.0536	11
	Nouakchott	Bangkok	0.1219	0.0048	48
Nigeria	Lagos	Gulf	0.4879	0.0309	47
	Lagos	Bangkok	0.5720	0.0337	41
	PortHarcourt	Gulf	0.4651	0.0096	147
	PortHarcourt	Bangkok	0.6436	0.0201	74
Senegal	Dakar	Gulf	0.2202	0.0062	88
	Dakar	Bangkok	0.0919	0.0280	8
Sierra Leone	Freetown	Bangkok	0.2129	0.0257	10
Togo	Lome	Gulf	0.3925	0.0366	14
	Lome	Bangkok	0.3816	0.0136	120

Table A.10: Correlation of Port to World Market Trade Costs with Port Characteristics

	(1)	(2)
Population $< 500,000$	0.184	0.169
	(0.151)	(0.142)
High volume	-0.0213	-0.0378
	(0.0990)	(0.124)
Corruption index	-0.0109	-0.0208*
	(0.0102)	(0.0121)
LPI customs index	0.184	0.241
	(0.237)	(0.209)
GDP per capita	5.07E-05	4.89E-05
	(3.21E-05)	(3.02E-05)
Import tariff		4.06E-04
		(0.00176)
Constant	0.203	0.404
	(0.430)	(0.354)
Observations	47	43
Clusters	25	23

Note: Robust standard errors in () clustered by country; * significant at 10%, ** at 5%, *** at 1%. Import tariff data was unavailable for Liberia and Somalia, so these 2 countries and their 4 ports are excluded from column (2).

A.8 Price Differences Elsewhere

In this section I assess whether my counterfactual trade costs of \$0.05/t-km for overland market links and \$50/tonne for port-to-world-market links are in line with observed price differences within the US and between the US and other major world markets. Importantly, I do not develop a full model of production, consumption, storage, and trade as I do for Africa, so I do not identify when and where trade occurs. The price differences I consider are therefore lower bounds on the actual trade costs, with the upper end of the range of price differences likely closest to actual trade costs.

I start by considering price series of maize (corn) for the 8 major US markets included in the USDA Feed Grains Database (Chicago, Kansas City, Memphis, Minneapolis, New Orleans, Omaha, St. Louis, and Toledo). As for my African network, I identify 11 transportation links along which direct trade between pairs of these markets is feasible. I then compute the price difference between each pair of markets for each of the 120 months corresponding to my African data (May 2003 – April 2013). The median price difference across all 1,320 observations is \$0.012/t-km with only 15 observations (1.1%) higher than \$0.05/t-km. Details for each link are shown in table A11. Given that the US is a major maize exporter through the Gulf ports near New Orleans, this evidence is highly suggestive that trade costs within the US rarely if ever exceed \$0.05/t-km.

Table A.11: Domestic US Price Differences

Market 1	Market 2	Avg. Difference	Distance (km)	Avg. /t-km	% > \$0.05
Chicago	Minneapolis	0.0115	657	0.0175	0%
Chicago	Omaha	0.0061	758	0.0081	0%
Chicago	St. Louis	0.0053	478	0.0110	0.83%
Chicago	Toledo	0.0036	394	0.0092	0%
Kansas City	Minneapolis	0.0097	702	0.0139	0%
Kansas City	Omaha	0.0035	303	0.0115	0%
Kansas City	St. Louis	0.0077	399	0.0193	2.50%
Memphis	New Orleans	0.0183	636	0.0287	6.67%
Memphis	St. Louis	0.0039	455	0.0085	1.67%
Minneapolis	Omaha	0.0075	615	0.0121	0%
Minneapolis	St. Louis	0.0134	900	0.0148	0.83%

I next consider prices at the major maize export ports for the US, Argentina, and Ukraine, which are the first, second, and fifth largest exporters of maize globally (Brazil and China are third and fourth). Pairing each of these three markets together and computing monthly price differences for my study period as above I find an average price difference of \$0.015 (\$15/tonne) with only 2.8% of observations higher than \$0.05 (\$50/tonne). Details for each pair are shown in table A12. Although these ports may not regularly trade with each other, this evidence suggests that trade costs between major global maize ports do not significantly exceed \$50/tonne, which is the average transport cost from the US Gulf to Durban, South Africa over the study period.

Table A.12: Price Differences Between Major Global Maize Ports

Market 1	Market 2	Avg. Difference	% > \$0.05
US Gulf	Argentina	0.0106	0%
US Gulf	Ukraine	0.0185	3.96%
Argentina	Ukraine	0.0170	4.95%

A.9 Comparison to Static Annual Model

To implement a static annual model, I remove storage S_{imt} and associated costs r_m and k_m from the model. There are now 10 time periods (years) instead of 120 (months). In each time period, traders must decide how much of the local harvest H_{imt} to trade with other markets (T_{imnt}) and to sell for local consumption (Q_{imt}). Equation 8 from the main text becomes:

$$Q_{imt} = H_{imt} - \sum_{n \neq m} T_{imnt}$$

While the spatial arbitrage conditions still hold, there are no temporal arbitrage conditions, so equilibrium for each time period (year) can be solved independently. I proceed to re-estimate trade costs τ_{mn} using the same iterative algorithm as before with the price series from my baseline estimated model as my price data. Trade cost estimates converge in 6 iterations.

Trade cost estimates are 23.4% lower on average using the static annual model. Of the 460 trade cost parameters (413 overland and 47 sea), the static annual model underestimates 12.2% by 50–97%, 25.2% by 25–50%, 33.0% by 10–25%, and 19.1% by 2–10%, while the percentage change for the remaining 10.4% of parameters is between –2% and +2%.

I next re-solve the model under counterfactual trade costs and compare equilibrium outcomes to those under the baseline (underestimated) trade costs. Given that the baseline trade costs are smaller than in the dynamic monthly model, it is not surprising that the effects of reducing trade costs are smaller. The overall welfare gain from lowering trade costs is 33.6% smaller than under the dynamic monthly model with storage. Of the 229 markets excluding Johannesburg, the welfare effects for 23.6% are underestimated by 50–98%, 30.1% by 25–50%, 23.6% by 10–25%, and 7.4% by 0.5–10%, while 7.4% of markets have a welfare effect that changes sign and 7.9% of markets have a welfare effect that is overestimated.

The intuition for the underestimation of trade costs and welfare effects is clear from the example in figure A1. For ease of illustration, I consider a case in which trade occurs between an African port and the world market. The left panel shows baseline maize price series in Accra, Ghana and the US Gulf, as well as the parity price for imports from the US Gulf to Accra under baseline trade costs. As is clear from the figure, Accra is an importer of maize. In keeping with Proposition 2, traders in Accra store maize first and import maize later, so that maize prices are significantly below import parity at harvest time and then increase to reach import parity as local stocks are consumed. Whereas my dynamic model estimates trade costs using price differences during the months when trade occurs at the end of the harvest cycle (i.e. from the peaks in the blue line to the black line), the static annual model using farm-gate prices estimates trade costs at the beginning of the harvest cycle (i.e. from the troughs in the blue line to the black line). The static annual model underestimates trade costs between the US Gulf and Accra by 22%. The right panel shows counterfactual maize price series in Accra (in red) as well as the parity price for imports from the US Gulf to Accra under counterfactual trade costs. The welfare effect of lowering trade costs depends on the change in prices, which for the dynamic monthly model is the difference between the blue and the red lines. In contrast, in the static annual model the change in prices is the difference between the troughs in the blue line and the dashed black line. This change in prices is always less than in the dynamic monthly model. The static annual model underestimates the welfare effect of lowering trade costs for Accra by 24%.

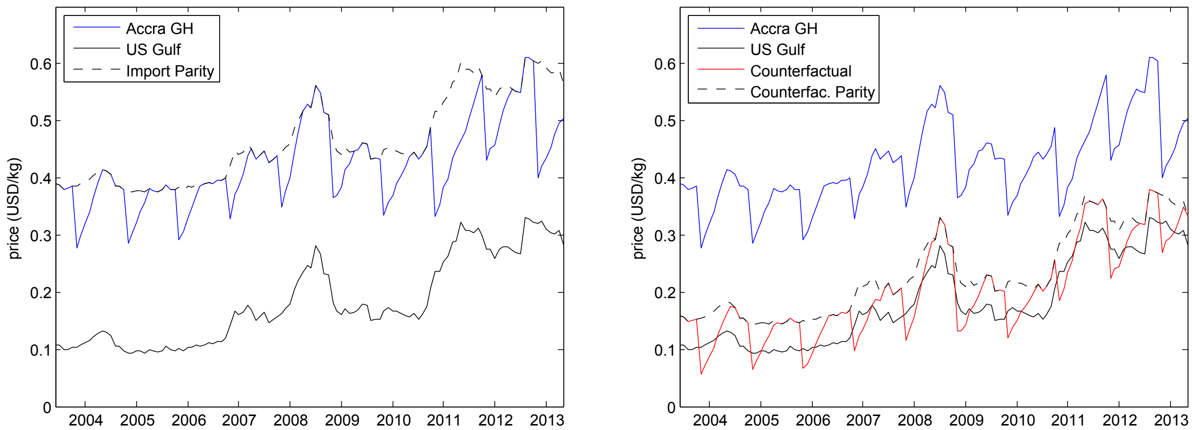

Figure A.1: Maize Price Series for Accra, Ghana and the US Gulf Under Baseline and Counterfactual Trade Costs, May 2003 – April 2013

For inland market pairs, the changes that take place under the counterfactual are less easily visualized as they depend on interactions between multiple markets. However, figure A2 illustrates the difference between the two models using baseline maize price series in Butembo, D.R. Congo and Mbarara, Uganda, as well as the parity price for imports from Mbarara to Butembo under baseline trade costs. These markets are both in the equatorial zone with two annual harvests. As in the previous case, traders in Butembo store maize first and import maize later, so that maize prices are significantly below import parity at harvest time and then increase to reach import parity as local stocks are consumed. Again, the dynamic model estimates trade costs using price differences during the months when trade occurs at the end of the harvest cycle (i.e. from the peaks in the blue line to the black line), while the static annual model using farm-gate prices estimates trade costs at the beginning of the harvest cycle (i.e. from the troughs in the blue line to the black line). The static annual model underestimates trade costs between Mbarara and Butembo by 58% and the welfare effect of lowering trade costs for Butembo by 37%.

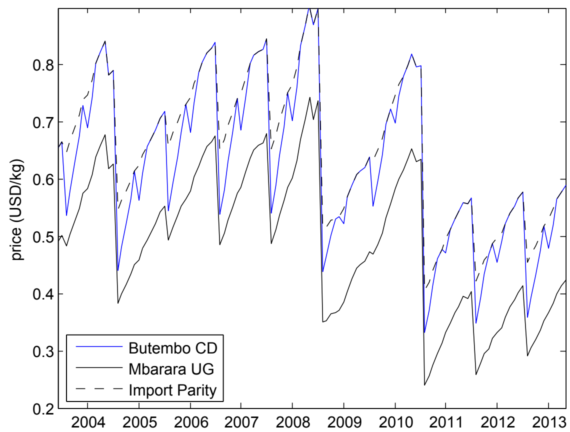

Figure A.2: Maize Price Series for Butembo, D.R. Congo and Mbarara, Uganda Under Baseline Trade Costs, May 2003 – April 2013

A.10 Corridor Selection Exercise

This section describes in greater detail the selection of overland links for targeted trade cost reduction in the trade corridor extension in the main text. To select links, I first compared the absolute difference in equilibrium welfare between the "just sea scenario" in which only port to world market costs are reduced and the main counterfactual in which all trade costs are reduced. Table A13 shows these differences for the 34 markets with a welfare difference of over \$500 million equivalent variation, which together account for 65.5% of the total difference in welfare. These 34 markets come from only 9 countries, with 28 of them coming from only 4 countries (Nigeria, South Sudan, Sudan, and Ethiopia). I then identified 30 critical links for closing the welfare gap by looking at equilibrium trade flows to and from these 34 markets.

Table A14 shows the 24 markets in 14 countries which have a welfare gap of over \$300 million equivalent variation after my initial reduction of trade costs along the 30 critical links. I proceeded to identify an additional 45 links (for a total of 75) important for closing the welfare gap for these markets. 87.5% of the welfare gains from reducing trade costs everywhere can be achieved by lowering trade costs on the 75 links in tables A13 and A14 along with port to world market trade costs. A map of the 75 targeted links is included in figure A3.

My corridor selection exercise suggests that certain types of trade corridors may be particularly beneficial. First, reducing trade costs all the way from the world market to "dry ports" in densely-populated inland areas can achieve significant welfare gains even if trade costs from the dry ports to areas further inland remain high. Table A15 shows the welfare effects of reducing trade costs along a single link between the port of Matadi in the Democratic Republic of Congo and the capital city Kinshasa. The table compares the potential gains from full trade cost reduction on all links with the gains achieved by reducing trade costs on this single link, reporting results for Kinshasa as well as for seven other inland markets in the western D.R. Congo which are either directly linked to Kinshasa or have only a single market in between. Reducing trade costs for this one of the 11 links that connect these markets results in 53.7% of the welfare gain achievable by reducing trade costs on all 11 links (\$1.03 of \$2.22 billion equivalent variation). This is due both to the large population in the Kinshasa market catchment, which accounts for 39.5% of the potential welfare gains for the eight markets, as well as the secondary effects on the other seven markets, which achieve 26.9% of their potential welfare gains as lower prices in Kinshasa translate into lower prices everywhere despite continued high trade costs further inland.

Second, reducing trade costs along major inland corridors with significant imbalances or fluctuations in production and consumption can lead to major gains. My second, 75-link corridor counterfactual includes trade cost reduction along the complete east-west trans-Sahelian highway from Dakar, Senegal to Port Sudan, Sudan (22 links). This route traverses 7 countries (including 4 land-locked countries) which are major producers of millet and sorghum and include 6 of the 8 countries with the highest per-capita grain demand as measured by my estimated A_m parameters. The Sahel is also subject to significant local harvest fluctuations due to its arid climate with erratic rainfall. Out of a total possible welfare gain of \$65.2 billion equivalent variation from reducing trade costs on all 413 overland links, the 23 markets on the trans-Sahelian highway gain \$9.1 billion (14.0%) in my 75-link corridor counterfactual. This figure increases to \$15.2 billion (23.3%) when the 35 markets with direct connections to one of the 23 markets on the trans-Sahelian highway are included.

Finally, targeting those inland areas isolated by extremely large trade costs can lead to very large welfare improvements. The five markets of South Sudan are perhaps the continent's most isolated grain deficit areas. These five markets account for \$10.5 billion (16.1%) of the total possible welfare gain from reducing trade costs on all 413 overland links, and my second, 75-link corridor counterfactual achieves all of this welfare gain.

Table A.13: Initial Targeting of 30 Overland Links

Country	Market	Welfare Diff.	Targeted Links
Nigeria/	Enugu	3187	Enugu–Makurdi
Niger	BeninCity	2969	BeninCity–Enugu
	Ibadan	2542	Ibadan–Ilorin
	PortHarcourt	1776	PortHarcourt–Enugu
	Kano	1547	Kano–Katsina
	Lagos	1386	Lagos–BeninCity
	Akure	1294	Lagos–Ibadan
	Calabar	931	PortHarcourt–Calabar
	Tahoua	668	Katsina–Maradi
	Maiduguri	658	Kaduna–Kano
	Makurdi	593	Makurdi–Jos
	Ilorin	575	Ilorin–Kaduna
	Lokoja	569	Jos–Kano
	Gombe	523	
	Maradi	520	
South Sudan/	Wau	2527	Rumbek–Wau
Sudan/	Rumbek	2473	Juba–Rumbek
Uganda	Juba	2071	Gulu–Juba
	Malakal	1723	Kosti–Malakal
	Bor	1718	Juba–Bor
	Nyala	1620	Kosti–ElObeid
	AlFashir	1098	ElObeid–AlFashir
	ElGeneina	869	AlFashir–ElGeneina
	Kosti	611	Khartoum–Kosti
	Mbarara	573	Kampala–Mbarara
			Kampala–Gulu
Ethiopia	Awasa	1176	AddisAbaba–Awasa
	Dessie	1003	Djibouti–Dessie
	BahirDar	977	AddisAbaba–BahirDar
	AddisAbaba	852	Djibouti–AddisAbaba
	Yabelo	711	
	Mekele	658	
Mali	Bamako	912	
D.R. Congo	Kinshasa	876	Matadi–Kinshasa
Ghana	Kumasi	560	Accra–Kumasi

Table A.14: Targeting of 45 Additional Overland Links

Country	Market	Welfare Diff.	Additional Targeted Links
Nigeria/	Maiduguri	915	Kano–Maiduguri
Niger/	Akure	610	Ibadan–Akure
Chad	Zinder	586	Maradi–Zinder
	Lokoja	491	BeninCity–Lokoja
	Gombe	468	Jos–Gombe
	Ndjamena	451	Maiduguri–Ndjamena
	Tahoua	405	Maradi–Tahoua
			Maradi–Niamey
			Ndjamena–Abeche
South Sudan/	Wau	1578	Kadugli–Wau
Sudan/	Juba	966	ElObeid–Kadugli
Uganda	Bor	910	Malakal–Bor
	Kampala	875	Jinja–Kampala
	Rumbek	767	Abeche–ElGeneina
	Nyala	679	AlFashir–Nyala
	Mbarara	404	Kigali–Mbarara
			Mombasa–Nairobi
			Nairobi–Nakuru
			Nakuru–Eldoret
			Eldoret–Jinja
			PortSudan–Kassala
			Kassala–AlQadarif
			AlQadarif–Kosti
Ethiopia/	Yabelo	353	Awasa–Yabelo
Eritrea	Asmara	349	Massawa–Asmara
	Gambela	311	Gambela–Malakal
			Nekemte–Gambela
			AddisAbaba–Nekemte
Mali	Bamako	807	Bamako–Kayes
			Kayes–Tambacounda
			Tambacounda–Kaolack
			Kaolack–Dakar
			Sikasso–Bamako
			BoboDioulasso–Sikasso
			Ouagadougou–BoboDioulasso
			FadaNgourma–Ouagadougou
			Niamey–FadaNgourma
Ghana	Bolgatanga	371	Ouagadougou–Bolgatanga
			Bolgatanga–Tamale
			Tamale–Kumasi

Country	Market	Welfare Diff.	Additional Targeted Links
D.R. Congo	Kisangani	342	Gulu–Bunia
	Lubumbashi	303	Kitwe–Lubumbashi
Guinea	Labe	333	Conakry–Labe
Zambia	Chipata	326	Chipata–Lilongwe
Cameroon	Yaounde	302	Douala–Yaounde

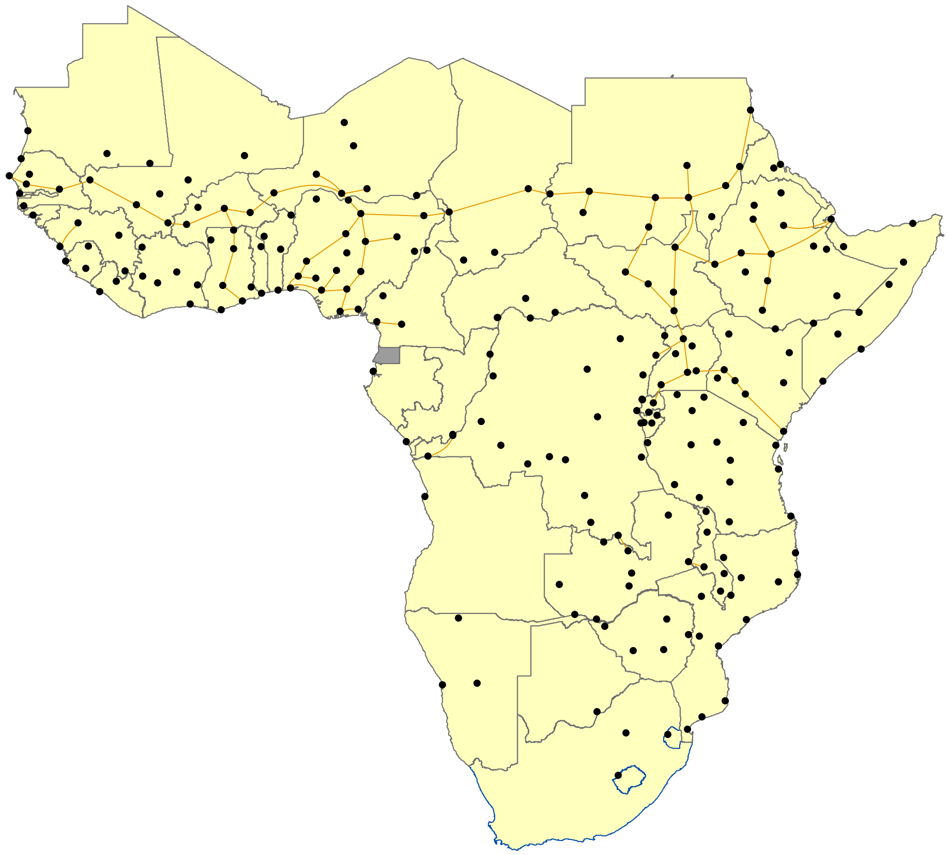

Figure A.3: Map of 75 Targeted Links

Table A.15: Welfare Effects of Trade Cost Reduction for Single Link (Matadi-Kinshasa, D.R. Congo)

	Potential Gains	Achieved Gains	Percent Achieved
Kinshasa	876.4	831.2	94.8%
Bandundu	93.3	32.6	34.9%
Gbadolite	191.5	4.9	2.6%
Kisangani	461.7	119.8	25.9%
Kikwit	154	44.5	28.9%
Mbandaka	207.3	100.4	48.4%
Tshikapa	83.2	8.3	10.0%
Zongo	153.4	50.8	33.1%
Total	2220.8	1192.5	53.7%

A.11 Partial Technology Adoption

In the main text I report results from counterfactuals in which I double African agricultural production to mimic the effects of technology adoption. In this section, I consider counterfactuals in which African agricultural production increases by less than 100% under existing high trade costs. This could reflect a scenario in which all farmers adopt a technology that increases yields by less than 100%, or it could reflect partial technology adoption with only a certain percentage of farmers adopting yield-doubling technology.

Table A16 reports the results from these counterfactuals and compares them to the results of doubling agricultural production from the main text (bottom row). The effects have the same sign for all indicators and all levels of technology adoption, with increasing levels of technology adoption leading to increasing magnitudes.

Table A.16: Effects of Partial Technology Adoption

Level	Grain Price Index	Net Ag Revenues	Net Grain Exports	Welfare
+10%	–12.6%	–14.1%	+51.0 mill t	+0.6%
+20%	–22.8%	–26.3%	+93.2 mill t	+1.0%
+30%	–31.3%	–37.1%	+127.3 mill t	+1.4%
+40%	–38.0%	–45.8%	+154.1 mill t	+1.7%
+50%	–43.5%	–53.1%	+176.8 mill t	+1.9%
+60%	–48.1%	–59.5%	+195.9 mill t	+2.1%
+70%	–51.7%	–64.2%	+212.6 mill t	+2.2%
+80%	–54.4%	–67.4%	+227.1 mill t	+2.4%
+90%	–56.5%	–69.5%	+240.5 mill t	+2.5%
+100%	–58.6%	–71.4%	+254.1 mill t	+2.6%