Food Loss in Agricultural Value Chains*

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November 1, 2024

Abstract

Food loss is endemic in agricultural supply chains in developing countries. Reductions in food loss can be attained through two methods: decreasing the perishability of crops through investments in storage technologies or decreasing the length of time it takes farmers to find buyers for their harvest. However, the lack of data and a robust theoretical framework limit our understanding of how the feedback between storage and search and matching frictions affects food loss. The goals of this paper are threefold. First, I conduct a survey and document patterns in crop disposition, storage practices, and food loss among farmers in Ghana. Second, I develop a model of agricultural trade that incorporates storage and frictional wholesale markets. Third, I estimate the model to analyze the counterfactual welfare effects of implementing agricultural policy at scale. To reduce food loss in Ghana to the level of the United States, storage technology would need to be improved by 70%.

*I thank my advisors Erik Hurst, David Lagakos, Chang-Tai Hsieh, and Esteban Rossi-Hansberg for their advice and support. I also thank Chris Moser, Thibaut Lamadon, Emma Zhang, Vishan Nigam, Jordan Rosenthal-Kay, Robert Townsend, Rob Shimer, Masao Fukui, Ryungha Oh, Niclas Moneke, Olivia Bordeu, Elena Aguilar, Jeanne Sorin, Josh Morris-Levenson, Marcos Sora, Aleksei Oskolkov, Krishna Kamepalli, Kristina Manysheva, Tommaso Porzio, Greg Kaplan, Mike Waugh, and Rachel Glennester for helpful comments. I am particularly thankful to all the non-University of Chicago faculty who took the time to help advise this project and to the MIT Department of Economics and Columbia Business School for hosting me during the project's development. This project would not have been possible without the support of Henry Telli and James Dzansi at IGC Ghana and Sedzro Mensah at DataPlas. This project was funded by the Becker Friedman Institute, the International Growth Centre, the Structural Transformation and Economic Growth Initiative, and the National Science Foundation Graduate Research Fellowship. All errors are my own, but are the ultimate responsibility of my advisors who should have trained me better.

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1 Introduction

Food loss – the phenomenon of crops perishing before reaching retailers or consumers – is a global problem but is of particular concern in agricultural supply chains in developing countries.[1] Estimates of crop losses before reaching consumer markets in developing economies range from 20% to 30% and can be as high as 40% to 50% for fruits and vegetables. Moreover, over 50% of crops perish before even leaving the farm (National Academies of Sciences, 2019). In other words, farmers grow their crops but are unable to find buyers before the crops go bad. In the case of red peppers in Ghana, which are key staple in Ghanaian soups and stews, farmers lose on average 10% of their harvest.

The high levels of food loss are a pressing issue for local policymakers. Food loss has several economic implications: It reduces farmer welfare by decreasing profits and increasing risk, and it reduces consumer welfare by reducing food access and increasing prices. Furthermore, the fraction of food lost is greater in developing than developed countries. Figure 1 plots the percent of food that perishes before reaching retailers or consumers by country. Food loss is decreasing in GDP per capita: for every 1% increase in GDP per capita, the fraction of food loss decreases by 1%.

Why do farmers lose their harvest before selling it? Farmer food loss is generated by the interaction of two properties of agricultural wholesale markets: crops are perishable and finding a buyer takes time. Consider an end-point scenario where trade is instantaneous: food loss is no longer a concern because farmers will always sell to traders before their harvest spoils. Similarly, when crops are durable, food loss is no longer a concern. Regardless of the time it takes to find a buyer, crops will remain perfectly preserved.

Farmer food loss can therefore be reduced via two methods: decreasing the perishability of crops or decreasing the time it takes to find a buyer. Farmers can decrease the perishability of crops by investing in storage technologies. Common methods of storage include storing crops on the farm, in sacks or bins, or on the floor of one's house. Crops stored using these methods are prone to high losses from mold, rot, or pests. Investments in more sophisticated storage technologies, such as metal silos or cold storage facilities, can mitigate losses. Losses can also be reduced by improving the process of finding a buyer. One common method of finding a buyer is bringing crops to the farmgate (the roadside) and flagging down passing trucks. Another common method involves transporting the crops to local markets and hoping that enough traders show up to meet local supply. Although cell phones have improved coordination between farmers and traders, calling a trader is not a guarantee of

[1] Crops can perish throughout the entire supply chain. Generally, food loss refers to crop that perish before reaching retail markets, while food waste refers to crops that perish once reaching retailers or consumers.

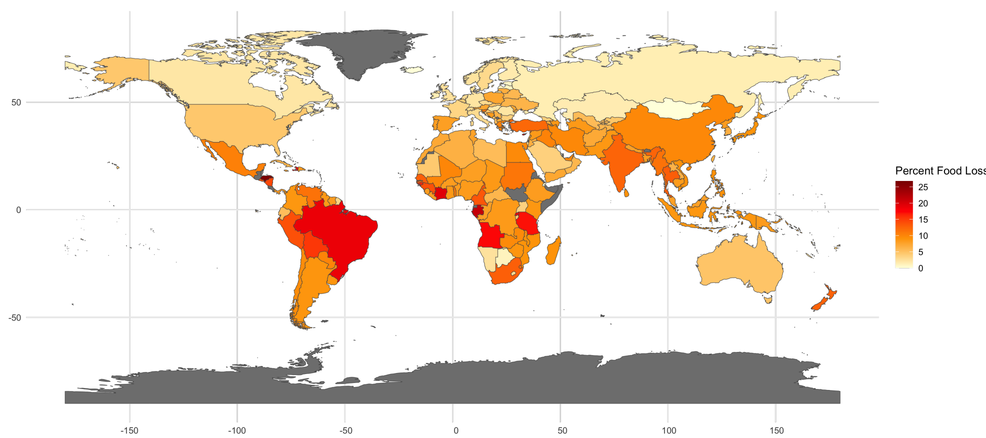


Figure 1: Global Food Loss

Notes. Map of the average percent of food loss in 2015 in fruit supply chains by country. Data is from the United Nations Food and Agriculture Organization. Food loss is imputed from food balance sheets and includes losses from the farming stage up-to transportation and distribution, but does not include losses during retail and consumption. Outliers are dropped.

a successful sale if they are operating on the opposite side of the country or already have a full truck. By decreasing the length of time between the harvest and sale of crops, less food loss occurs.

Despite the availability of better storage and communication technologies, high losses persist. How much of food loss is due to low investment in storage technologies or challenges in finding a buyer? And how much do we stand to gain by decreasing the perishability of food or improving the process through which farmers find buyers?

The challenge of answering these questions is twofold. The first challenge is the lack of data. Micro-level evidence is necessary to understand the causes and equilibrium mechanisms that generate food loss. However, most agricultural surveys are ill-equipped to tackle this question. Traditional agricultural surveys primarily focus on collecting data on inputs, yields, and on-farm productivity, such as the mechanization of production, and abstract away from crop disposition beyond asking for sale prices and quantities. The second challenge is the lack of a theoretical framework through which to evaluate policy. Neoclassical models of trade assume that goods are perfectly durable and that the exchange of goods is instantaneous. While, for the most part, these may be innocuous assumptions, neoclassical trade models are unable to capture the phenomenon of food loss. Understanding food loss thus requires a departure from models of neoclassical trade.

To overcome the first challenge, I conduct a novel survey of search and matching frictions in Ghana's agricultural wholesale markets. I survey 1800 farmers and 500 traders in Ghana's fruit and vegetable supply chain on their crop disposition, storage, and purchasing practices. The survey covers all major agricultural regions of Ghana and all major fruits and vegetables grown and sold by Ghanaian farmers. Using the survey, I document 6 key features of Ghana's agricultural wholesale markets. First, farmers believe that most food loss is caused by events such as rain or pests that are inherently unpredictable. Second, farmers who struggle to find buyers experience more food loss. Third, farmers who struggle to find buyers are more likely to invest in storage technologies. Fourth, farmers who experience more food loss also invest more in storage technologies that can preserve their crops for longer. Fifth, the majority of farmers sell their harvest by calling traders directly. Sixth, traders sort through crops at the point of sale, observe the quality of the harvest, and reject low-quality crops.

Motivated by the facts documented in the survey, I develop a model of agricultural trade with incomplete asset markets and frictional wholesale markets. Unlike models of neoclassical trade, my model incorporates a process through which farmers search and match with buyers. Risk-averse farmers and risk-neutral traders meet in a directed search environment. First, traders pay a fixed cost to enter the market. They then post a price at which they wish to purchase crops and are segmented into sub-markets by their posted price. Next, farmers observe each posted prices and choose which sub-market to search in. Within each sub-market, farmers and traders come together through a matching technology that is constant returns to scale in the measure of farmers and traders. Finally, once matched, traders observe the quality of the crops, and can choose to reject purchasing the harvest if the quality is too low.

Not all farmers will match with a trader. And some of the farmers who match with traders will be rejected due to the low quality of their harvest. Unmatched or rejected farmers run the risk of losing their crops. However, if they do not lose their harvest, farmers can again attempt to search for a buyer. To reduce the depreciation rate and extend their crops' shelf life, farmers invest in storage technologies. By investing in storage technologies and thus decreasing the perishability of their harvest, farmers increase the number of opportunities to make a successful sale.

I find that the decentralized economy is inefficient. Two features give rise to the inefficiency. First, incomplete asset markets and farmer risk-aversion generate an inefficiency in equilibrium. Risk-averse farmers wish to equalize consumption across states, but cannot transfer consumption through time. They are therefore willing to sell their crops at lower prices but with higher probability to maximize their chances of a successful sale. In contrast, the social planner would set higher prices and a lower probability of a sale. Second, traders have limited commitment and can reject purchases with low quality. When prices are high, traders are more sensitive to quality and reject crops more often. Farmers must therefore under-price their crops to ensure a successful sale. The equilibrium is inefficient because even when the total surplus of a purchase is positive, traders reject a purchase when their private surplus is negative.

A key insight of the theory developed in this work is that welfare and food loss do not necessarily move one-to-one. This is because (1) investment in storage technology is inefficiently low (and thus crop depreciation is inefficiently high) and (2) the probability of matching is inefficiently high. I show that food loss depends on the ratio of crop depreciation to the probability of a sale; both of these terms are inefficiently high in the decentralized economy, implying that food loss can be either *too low* or *too high* in equilibrium. Moreover, improvements in storage technology increase storage investment, which decreases crop depreciation and the match rate, leading to an ambiguous effect on food loss. The effect on food loss is ultimately a quantitative question that depends on the relative elasticities of crop depreciation and match rate to the price of storage.

With the survey in hand, I estimate the model parameters. I calculate several parameters directly from the survey data and calibrate the remaining parameters to best fit the survey data using the simulated method of moments. I test the model's external validity by qualitatively reproducing patterns in food loss among farmers in Ghana and find that the model can replicate key dimensions of heterogeneity in the data. I finally quantify the potential welfare gains from reducing food loss. I find that although contract enforcement increases welfare by only 2%, the maximum welfare gain in an economy with no search frictions is 300% greater than in the baseline. However, a government or social planner may not have the tools to reduce search frictions. Instead, I examine a popular policy tool: improvements in storage technology. I find that to reduce food loss from Ghana's average of 10% to the US average of 4%, storage technology would need to be improved by 70% in general equilibrium and 55% in partial equilibrium. In partial equilibrium, farmers make consumption and investment decisions, but no adjustments in the search market. In general equilibrium, farmers reduce their search intensity when investment in storage is higher, resulting in more food loss. Thus the improvement in storage needs to be higher in general equilibrium.

This project contributes to several strands of literature. First, it adds to the literature on food loss and storage. This literature primarily focuses on the partial-equilibrium effects of storage technologies. Contributions to this literature include Delavallade and Godlonton (2023) who study grain warrantage in Burkina Faso, Omotilewa et al. (2018) and Aker et al. (2023) who study the effects of new storage bags on Maize losses in Uganda and Niger respectively, and Aggarwal et al. (2018) who study a grain savings club intervention in Kenya. Affognon et al. (2015) and Stathers et al. (2020) provide a meta-analysis of the literature and document that over 80% of studies focus on the role of tangible technologies and that studies of storage technologies account for over 40% of all interventions.[2] Jensen (2007) is a notable exception in that it studies the role of information frictions in generating food loss. This is the first paper, to my knowledge, that studies the aggregate welfare effects of food loss. In doing so, I focus on a novel food loss-generating channel: coordination frictions between farmers and traders. By incorporating this channel into a model that allows for feedback between output market frictions and storage technologies, I can perform a general equilibrium analysis of popular agricultural interventions.

Second, this project contributes to the literature on agricultural productivity and structural transformation. Low aggregate agricultural productivity remains a persistent problem for sub-Saharan Africa (see Caselli, 2005; Restuccia et al., 2008; Gollin et al., 2014; Lagakos and Waugh, 2013); food loss contributes to the issue by depressing profits throughout the entire supply chain. This project differs from existing approaches studying the agricultural productivity gap by endogenizing output market frictions, and advancing a nascent literature on the structural transformation of the agricultural value chain (e.g., Reardon, 2015; Bar-

[2]A secondary motive for investing in storage is smoothing price fluctuations across time. See Cardell and Michelson (2023) and Burke et al. (2019) for recent work on the topic.

rett et al., 2022). Both the misallocation approach (e.g., Adamopoulos and Restuccia, 2014; Adamopoulos et al., 2022; Gollin and Udry, 2021), which attributes low agricultural productivity to input misallocation, or the spatial approach (e.g., Atkin and Donaldson, 2015; Porteous, 2019; Sotelo, 2020), which attributes low agricultural productivity to domestic spatial costs, take wedges and trade costs as given. This hampers a nuanced evaluation of policy. In contrast, coordination frictions depend on agent choices and adjust in response to agricultural interventions. Closet to this paper are Donovan (2021) and Bergquist et al. (2022) who study the macroeconomic effects of scaling up agricultural interventions.

Finally, the project builds on the literature on directed search. Seminal papers in this literature include Montgomery (1991), Shimer (1996), and Moen (1997) (see Wright et al. (2021) for an overview). Closest to this paper are Acemoglu and Shimer (1999) and Golosov et al. (2013), who study a labor market with directed search and risk-averse workers. As in both papers, incomplete asset markets distort the equilibrium so that it is inefficient. Farmers prefer to match more often and receive lower prices than in the first-best, because they wish to smooth consumption over time. Relative to these papers, my innovation is two-fold. First, I adapt their models to study agricultural goods trade. This is the first model that studies agricultural markets in a directed search environment[3]. Second, I introduce a novel self-insurance mechanism: storage technology. In my model, storage technology plays a similar role to unemployment insurance in Acemoglu and Shimer (1999); storage lowers the risk of crop depreciation and thus reduces the inefficiency due to incomplete asset markets.

The paper proceeds as follows: In Section 2, I describe the data. In Section 3, I present motivating evidence. In Section 4, I lay out the model and discuss the theoretical implications. In Section 5, I combine the survey and structural model to estimate the model and discipline model parameters. In Section 6, I quantify the welfare and food loss effects of introducing agricultural policy at scale.

2 Survey Data

Data on food loss is sparse and its causes are poorly understood. I bridge this gap by conducting a survey tailored to study how search and matching frictions affect the crop disposition and marketing practices of farmers and traders in the domestic fruit and vegetable supply chain in Ghana. The survey covers 1800 farmers and 500 traders and was implemented nationwide, drawing from 13 districts in four of Ghana's major agricultural zones.[4] To

[3]Nyarko and Pellegrina (2022) features agricultural markets with random search and no food loss. Their focus is on how search frictions affect which markets farmers choose to sell in.

[4]Although the country is divided into five major zones (North, South, East, West, and Central), the Central zone was omitted from the study due to not being a major producer of fruits and vegetables.

capture the diversity and variability in farming and trading practices nationwide, districts with higher agricultural activities and trade volumes were selected for the study in each region. Stratified sampling ensured comprehensive coverage and proportional representation from each district. I report additional details of the survey construction, including details on pre-testing and power calculations, in appendix B.3.

Participants were included in the survey according to the following criteria. Farmers must have 1) been adults, 2) farmed fruits or vegetables in the last farming season, 3) participated in the market (grew crops for sale rather than own-consumption), and 4) farmed less than 50 acres in the last farming season. Similarly, traders must have 1) been adults, 2) bought directly from farmers or aggregators, and 3) traded fruits or vegetables in the last farming season. The survey participation criteria are not highly selective. The Food and Agricultural Organization of the United Nations (FAO) estimates that over 85% of farms in Ghana are less than 5 acres with an average size of 4 acres. The only farmers excluded based on size are those with large commercial operations. Importantly, limiting the food loss survey sample to farmers who sell their crops does not seem like an egregious restriction; as of 2012, almost 80% of farmers participate in the market.[5] Farmer participation in the market is likely to be higher in 2024. Finally, the survey focuses on fruit and vegetable supply chains because food loss is highest in these markets.

The farmer survey is composed of five modules. The first module covers farmer demographics and general farming information, including age, family size, crops grown and sold, plot sizes, and harvest amounts. The second module covers crop disposition practices - where farmers sell (e.g., farmgate or market), how often farmers sell at each location, the probability of successfully finding a buyer, the distance from the farm to each location, the price received per unit of crop, etc. The third module covers uses of storage technology and causes of loss. This includes properties of the storage technology, such as the maximum amount of time a farmer can store their crops using the storage technology without losing crops and the average amount of time the farmer stores their crops. The fourth module covers how farmers search for buyers - do they call buyers directly or do they bring their crops to the roadside and flag down passing trucks? Do farmers negotiate with traders over prices or are prices publicly available? Finally, the fifth module covers coordination between farmers. For instance, does coordinating with other farmers help find buyers or offset fixed costs? And what are the barriers to greater cooperation?

The trader survey is composed of six modules. The first module similarly asks about

[5] To determine the representativeness of my survey, I analyze the 2012 round of the Ghana Statistical Agency's National Transport Survey. I provide a more detailed analysis of the National Transport Survey in Appendix Table 9.

trader demographics and an overview of their business, such as age, family size, location of their residence, years in the horticulture trading business, crops traded, etc. The second module concerns sourcing practices - where do traders buy, what prices they pay per unit, how many units do they purchase per trip, the number of trips they make, etc. The third module asks about coordination with other traders - do traders coordinate and if yes, how? The fourth module covers trader selling practice and includes topics such as the usual location where traders sell, the price at which traders sell, and the average number of customers they sell to. The fifth module studies trader storage practices and losses due to storage, transportation, and other factors. The sixth and final module estimates operational costs, both fixed and variable.

Data was gathered using computer-assisted personal interviews. A team of 20 enumerators was trained to conduct the survey and sent into the field to meet with farmers and traders. Enumerators used electronic tablets, pre-loaded with the survey, to administer the survey and record responses. Survey responses were finally collated across enumerators to construct the final data set.

3 Motivating Evidence

In this section, I use the survey to document 6 facts about agricultural wholesale markets in Ghana. The average fruit and vegetable quantity loss among farmers in Ghana is 10%. However, these averages mask large heterogeneity among farmers: the standard deviation of quantity loss is 15%. Farmers differ along many dimensions, including which crops they grow, their locations and distances from wholesale markets, age, education, farm size, etc[6]. In the cross-section, it is difficult to know which factors matter and why. I proceed by studying crops one at a time. Inference across crops is complicated because both storage and crop disposition practices vary across crops. For instance, tomatoes are more fragile than peppers and spoil quicker. Moreover, many farmers preserve peppers through drying, whereas no comparable practice exists for tomatoes. In the main text, I focus exclusively on pepper farmers and I provide heterogeneity analysis in the appendix. Peppers are a staple of Ghanaian cuisine, forming the base of many soups and stews. One third of all farmers in my sample grow peppers.

Fact 1. ***Farmers believe the causes of food loss are unpredictable.*** In the survey, I delineate food loss into 4 reported causes: rain and mold, pests, disease, or other (which

[6]I plot food loss by farmer characteristics in the appendix. Appendix figure 14 plots food loss by crop type and figure 15 plots food loss by region.

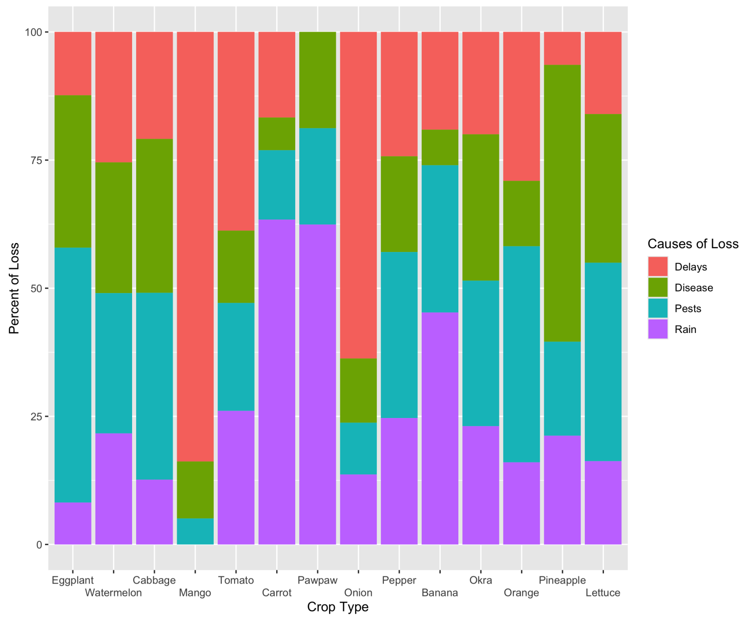


Figure 2: Reported Causes of Food Loss by Crop

Notes. Percent of losses farmers attribute to each cause: pests, rain/mold, disease, and other. Each column is a different crop and sums to 100.

captures losses that don't occur due to a specific event). For instance, when crops are stored outside uncovered, rain can causes crops to spoil. Farmers are asked what share of the food loss they experience is caused by each cause. I plot in Figure 2 the average share of food loss generated by each of the 4 causes by crop. Chili pepper farmers report that the majority of food loss is due the rain and mold, pests, or disease. The pattern is robust to all other farmers, with the exception of mango and onion farmers. Rain, pests, and disease are inherently unpredictable. Farmers cannot predict whether there will be rain tomorrow or whether their farms will be affected by pests. Although economists normally model depreciation as a gradual and continuous process with respect to time, the results in Figure 2 motivate me to model food loss as a stochastic process. Modeling loss as a stochastic process yields a unique expression for food loss as a function of time. This expression has an empirical counterpart in the data, providing a test of the model's fit. I find that modeling food loss as a stochastic process reasonably describes food loss among chili pepper farmers.

Fact 2. ***Farmers who struggle to find buyers experience more food loss.*** Do farmers who struggle to find buyers experience more food loss? In the survey, I ask farmers whether they "Strongly Agree", "Agree", "Neutral", "Disagree", or "Strongly Disagree" with

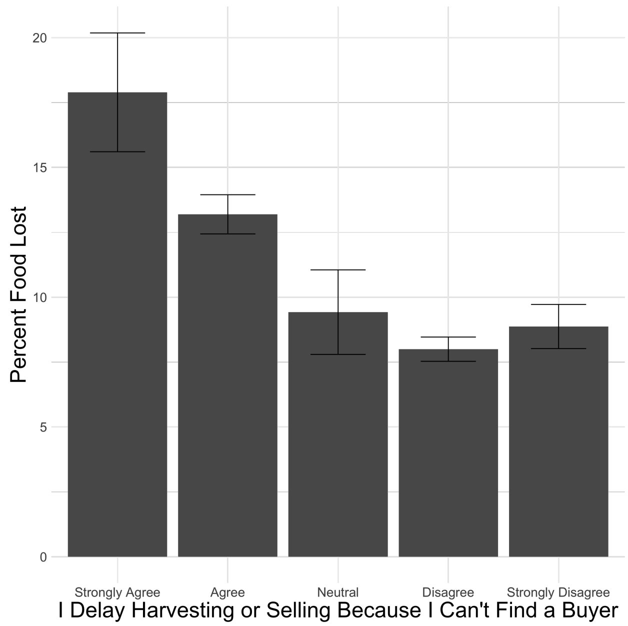


Figure 3: Food Loss by Market Tightness

Notes. Do farmers who struggle to find buyers report higher levels of food loss? This figure is a bar chart of the percent of food lost by chili pepper farmers' reports about whether they delay harvesting or selling crops because they can't find buyers. Farmers are asked whether they strongly agree, agree, are neutral, disagree, or strongly disagree with the following statement: "I delay harvesting or selling crops because I can't find a buyer." Each bar is the average food loss for each category of respondents to the previous question.

the following statement: "I delay harvesting or selling crops because I can't find a buyer".[7] Approximately 25% of farmers strongly agree or agree with the statement that they delay harvest or selling crops because they can't find a buyer and 30% of farmers believe that their crops perish while waiting for a buyer.[8] I then plot the average food loss for each category of respondents in Figure 3. Farmers who report having to delay harvesting or selling crops due to an inability to find a buyer lose on average almost double the share of crops than farmers who don't.[9] I quantify the effects of market tightness more precisely in Figure 4, where I plot a binscatter of the percent of food loss by chili pepper farmer against the probability of a successful sale. I show that farmers who report a lower probability of successfully selling to a buyer have a higher average food loss. The pattern in both plots is robust to other crops. Motivated by figures 3 and 4, I include search and matching frictions in the model of

[7]Delaying harvesting often serves as a method of extending a crops shelf life; once crops are picked, the speed at which they spoil increases.

[8]I report farmers beliefs about the search market in Appendix Table 8.

[9]Similarly, in Figure 17, farmers who believe it is hard or very hard to find a buyer have an average food loss 0.5 times higher than those who don't.

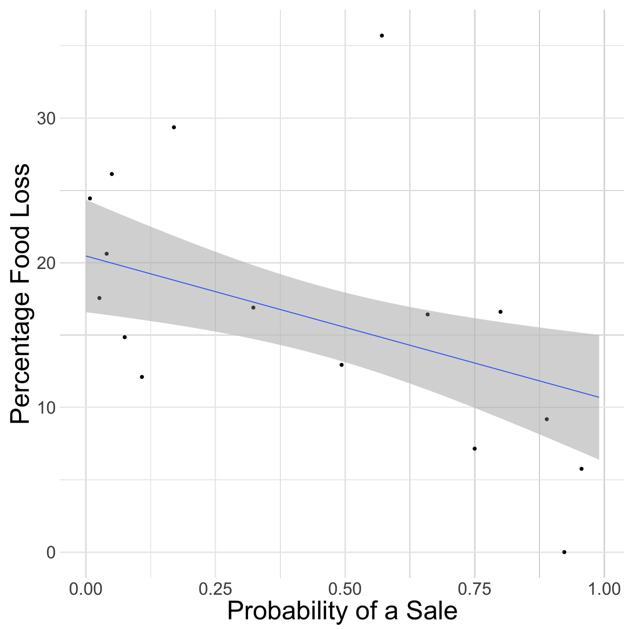


Figure 4: Food Loss vs Probability of Selling Crops

Notes. Binscatter of the percent of chili pepper food loss against the probability of making a successful sale. Food loss is measured as the share of peppers that go bad before sale to a buyer. Data is from the survey of Ghanaian farmers.

agricultural wholesale markets. Farmers search for trades but are not guaranteed to succeed with each search attempt. Farmers who are unlucky and do not find a buyer experience more food loss.

Fact 3. ***Farmers who struggle to find buyers are more likely to invest in storage technologies.*** One way to reduce the effect of output market frictions is to invest in storage.[10] Storage technologies allow farmers to store crops for longer. If farmers search for a buyer but cannot find one, storage provides the farmer with additional time to search again. Farmers are smart and forward-looking - I show in Figure 5 that farmers who are more likely to successfully find a buyer for their crops invest less in storage technologies on the extensive margin. In other words, when finding a buyer is easy, farmers store their peppers directly on the farm using no advanced storage technologies. And when the probability of finding a buyer is low, farmers invest in storage technologies in order to gain additional time to search for a buyer. The result is robust to other crops. Motivated by fact 3, I allow

[10]Another possible mechanism to reduce food loss is through cooperation with other farmers. However, I find in Table 8 that only 20% of farmers cooperate with each other and that cooperation does not help find buyers. The majority of farmers do not cooperate for two reasons. First, farmers are located far apart. And second, crops on different farms are ready to harvest at different times making it difficult to coordinate in advance.

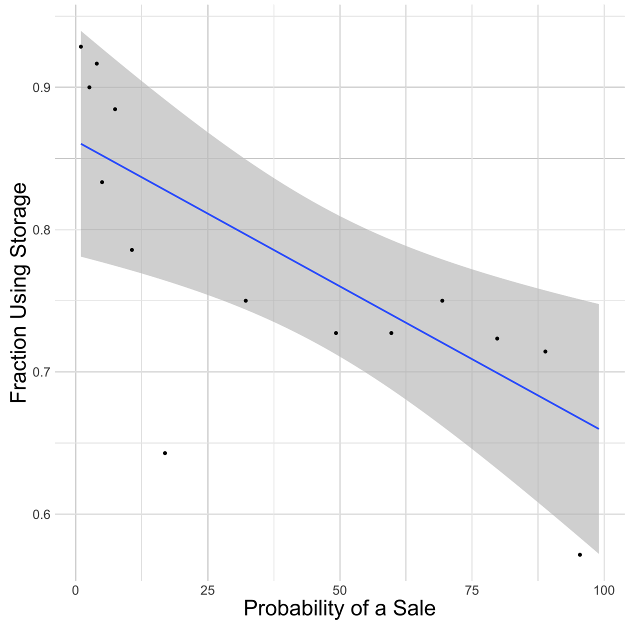


Figure 5: Storage Usage vs Probability of a Sucessful Sale

Notes. Do farmers that are less likely to find a buyer store their crops using advanced storage technologies? A bin-scatter of the fraction of farmers using any storage technology against the probability of a successful sale to a trader. Data is from the survey of Ghanaian farmers.

farmers to invest in storage technologies in the model. Storage technologies extend the shelf life of a crop, allowing farmers more opportunities to find a buyer.

Fact 4. ***Farmers who lose a larger fraction of crops are more likely to invest in better storage technologies.*** There are a few methods to store peppers. Farmers can store peppers in fridges; they can store peppers by drying them; they can store peppers in their home; they can store peppers using plastic sacks or bins; or they can store peppers directly on the farm in piles using no advanced technology.[11] These technologies differ in how well they preserve crops. I capture these technological differences by asking farmers what is the maximum amount of time they can store their crops given the technology they use. I call this a technology's maximum shelf life. I plot in Figure 6 the percent of food loss (black line) and the maximum shelf life (red bars) by the storage technology used.[12] Surprisingly, the largest losses of 13%, 11%, and 10% are among farmers who use the most sophisticated

[11]Drying entails a multi-day process during which the peppers are placed on plastic tarps and left out in the sun, exposing the peppers to rain and animals. For a visual example, see Figure 18 in the appendix.

[12]I specifically look at food loss among pepper farmers, rather than averaging across crops. Not all storage technologies are used for each crop (e.g. metal/wooden silos aren't used for storing peppers) and the effectiveness of a storage technology varies by crop. An average across crops suggests that there is no effect of storage technology on food loss.

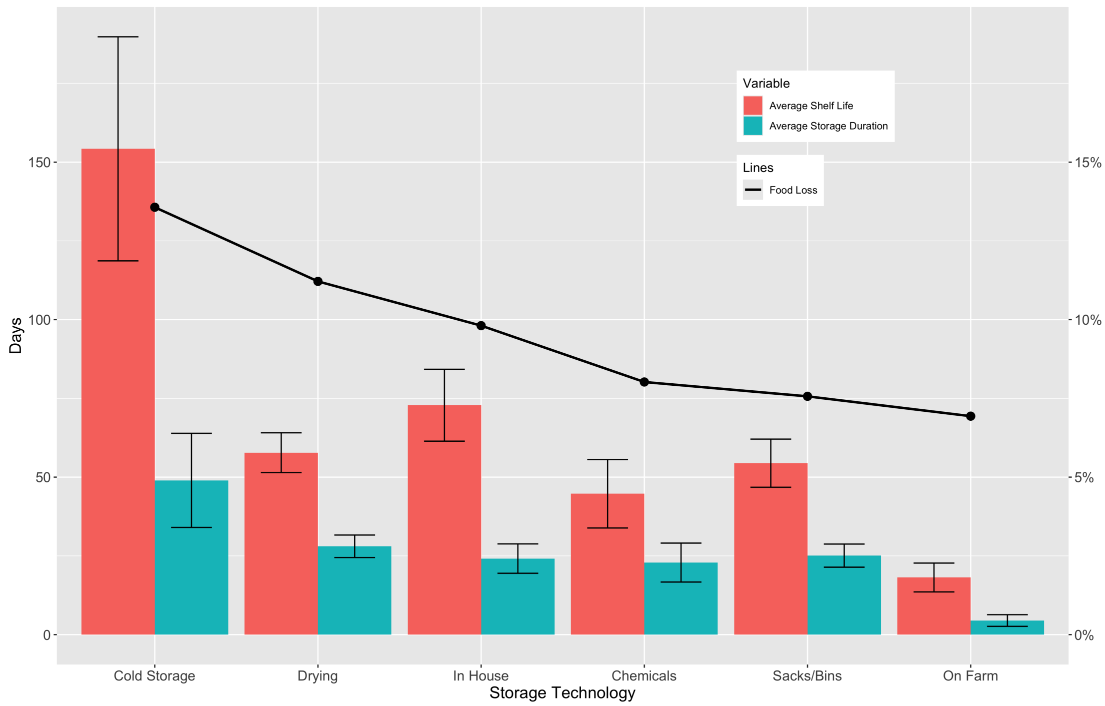


Figure 6: Effects of Pepper Storage Technology

Notes. The red bars plot the average shelf life (in days) of peppers by storage technology. The teal bars plot the average duration (in days) farmers store peppers by storage technology. The black points plot the percent of quantity pepper food loss by storage technology. Data is from the Ghanaian survey of farmers.

storage technologies (with the highest maximum shelf life), cold storage, drying, and in-house storage respectively. Why does better storage technology not reduce loss? The most likely hypothesis is that farmers who invest in storage technologies also store their crops for longer. This is indeed the case: I plot in Figure 6 (teal bars) the average amount of time that farmers store their crops by storage technology. I show that farmers using storage technologies with a higher maximum shelf life also store their crops for longer.[13]

Fact 5. ***The majority of farmers sell their crops by calling traders directly.*** Who are farmers' primary buyers and how do farmers find them? Farmers have four potential buyers: consumers, exporters, food processors, and traders. Farmers can also choose to search for buyers through a variety of means: they can call the buyer directly, call an aggregator who will find a buyer for them, bring the crops to the farmgate/road side and flag down passing trucks, bring the crops to a local market, or wait for a buyer to call them.

[13]Another hypothesis that while drying does extend the shelf life, food loss occurs before the peppers are fully dry. This argument would not apply, however, for cold storage, which is not a time-intensive or high-effort process.

Table 1: Percent of Farmers by Buyer and Sale Method

Search Method	Primary Buyer				
	Consumer	Exporter	Food Processor	Trader	Total
Bring to Farmgate	0.2	0.1	0.0	9.6	9.9
Bring to Market	1.3	0.0	0.0	25.4	26.6
Buyer Calls	0.2	0.00	0.1	3.0	3.2
Call Aggregator	0.0	0.1	0.2	8.4	8.6
Call Buyer	0.1	0.4	1.6	49.6	51.7
Total	1.7	0.6	1.9	95.9	100

Notes. Summary Statistics about the share of farmers by method of searching for a buyer and primary buyer. Each entry is the percentage of farmers in that category. Numbers may not sum to 100 due to rounding.

I break down the percentage of farmers using each option in Table 1 and show that over 95% of farmers sell to traders. Furthermore, over 50% of farmers call buyers directly. The second most popular option of finding buyers utilized by 26% of farmers is bringing crops to the local market. The results in Table 1 suggest that farmer search practices are more consistent with a model of directed rather than random search. In a model of random search, there is a single market in which all farmers and traders search. In a model of directed search, farmers and traders have multiple markets they can choose to search in. And although not all of the assumptions of the directed search environment are met (such as perfectly observable prices), the majority of farmers direct their search efforts toward specific markets.[14]

Fact 6. ***Traders sort through the harvest at the point of sale and reject low-quality crops.*** The quality of a harvest is unobservable to the trader until they meet with a farmer. Once a meeting takes place, the trader will sort through the harvest and discard any crops that show obvious signs of bruising. Why do traders discard crops rather than re-negotiating on price? Transportation from where traders buy crops to where traders sell crops takes time and crops that are already bruised will spoil before reaching downstream customers. The degree of acceptable bruising may depend on the trader - traders who sell locally may care less than traders who sell in major cities and must transport their crops for longer. I plot in Figure 7 a histogram of the share of crops bruised when traders meet farmers. The average share of bruised of bruised crops is 10%. The lack of information about crop quality until farmers and trader meet motivates the inclusion of a limited commitment mechanism in the model, where traders can reject farmers upon observing the harvest quality.

[14] I further document in Figures 16a and 16b that these markets differ in both market tightness and the fraction of food lost.

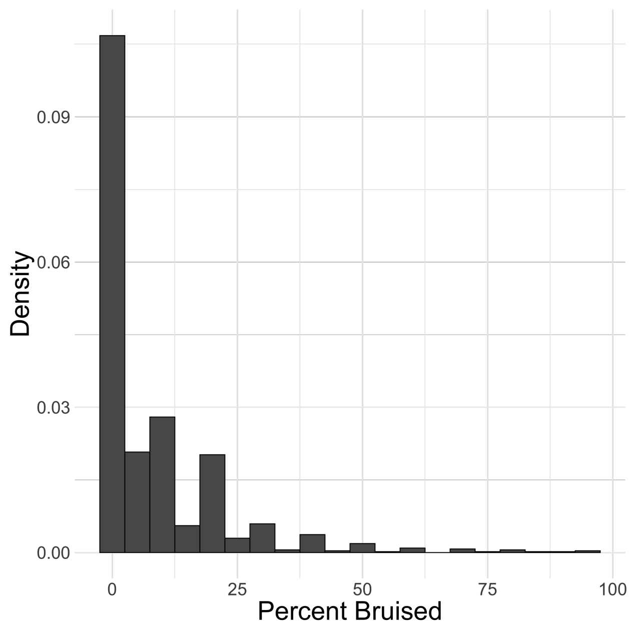


Figure 7: Histogram of the Percent of Bruised Crops at the Point of Sale

Notes. A histogram of the percent of bruised chili peppers at the point of sale for farmers. Data is from the Ghanaian survey of farmers.

4 Baseline Model

Motivated by the facts documented in the previous section, I exposit a stylized model of directed search within agricultural wholesale markets. The goal of the model is to 1) decompose food loss as a function of storage and search and matching, and 2) provide a framework through which welfare gains from policy can be evaluated. The model's simplicity will be illustrative of key mechanisms, while still retaining enough flexibility to match key moments in the data.

4.1 Environment

Time is continuous and indexed by t. The economy is populated by a unit mass of homogeneous farmers and an endogenous mass of homogeneous traders. Farmers and traders meet in frictional output markets, where farmers sell and traders buy crops. Crops depreciate over time, so farmers who are unable to meet with traders can lose their harvest. Investments in storage technology can slow the rate of depreciation.

Preferences. Farmers and traders discount the future at rate ρ. Farmers have von Neumann–Morgenstern utility function $u(c)$ over a consumption stream c, where u is twice continuously differentiable, strictly increasing, and weakly concave. In the baseline model, I assume that preferences are given by $u(c) = \log(c - \bar{c})$ where $\bar{c}$ is a subsistence parameter. Risk-neutral traders maximize profits, $\pi(p)$, where they purchase quantity x of crops at purchase cost p and sell at retail price p_A[15]. I assume that traders are price takers in the retail market and take p_A as given[16].

Farmer Technology. A farmer's consumption flow depends on being in one of three states: harvested and searching for a trader (s), matched to a trader (m), or having lost their harvest (l). When harvested and searching for a trader, farmers can allocate up to M units of endowment between consumption and investments in storage technology. Investment in storage technology decreases the depreciation rate. Unmatched farmers lose their crops at Poisson rate $\delta(i)$, where i is investment in storage, $\delta'(i) < 0$ and $\delta''(i) > 0$. That is, both the depreciation rate and the marginal depreciation rate are decreasing in the amount invested. I assume that $\delta(i) = \delta_0(1+i)^{-\beta}$, which satisfies the above conditions. The first term, δ_0, can be interpreted as a crop's baseline depreciation rate when investment in storage is zero. For more perishable crops, such as tomatoes, the baseline perishability is higher than for more durable crops, such as peppers. Finally, β captures the elasticity of storage to investment. When matched, farmers sell x quantity of crops at price p and receive a continuation value from consuming the proceeds of the sale[17]. Farmers who lose their harvest or match with a trader will subsequently "die".

Search Frictions. Unmatched farmers and traders search among segmented sub-markets indexed by price p. Within each sub-market, farmers and traders come together through a constant returns to scale matching technology. Let $\mathcal{U}(p)$ be the measure of unmatched farmers, $\mathcal{V}(p)$ be the measure of unmatched traders, and market tightness $\theta(p) := \mathcal{V}(p)/\mathcal{U}(p)$ be the relative measure of traders to farmers in sub-market p. Assume that the matching technology is given by a Cobb-Douglas matching function with constant returns to scale, which produces a flow of $s(p) = \mathcal{U}(p)^\alpha \mathcal{V}(p)^{1-\alpha}$ matches and where α is the elasticity of matches to the unmatched farmers.[18] Given market tightness $\theta(p)$, farmers' match rate is

[15] In the baseline model, I assume that that traders are risk-neutral and preferences are linear in profit. This assumption is not necessary for the model derivations or key results. In practice, traders have small operations and are likely to be risk-averse. I relax this assumptions in the model appendix.

[16] Similarly, the assumption that traders are price takers in the retail market is not necessary for the model derivations or key results.

[17] Farmers produce crops using a fixed amount of land: $x = L$. This can be relaxed to include capital and labor inputs: $x = k^\zeta \ell^\nu L^{1-\zeta-\nu}$ where $\zeta + \nu < 1$.

[18] Search and matching frictions exist for multiple reasons including imperfect information about prices, locations of sellers and buyers, or buyer and seller quality. Rather than modeling these frictions directly, following Mortensen and Pissarides (1994), I model search frictions in a reduced form way.

$f(\theta(p)) = s(p)/\mathcal{U}(p) = \theta(p)^{1-\alpha}$ and traders match rate is $q(\theta(p)) = s(p)/\mathcal{V}(p) = \theta(p)^{-\alpha}$.[19]

Once farmers and traders match, traders draw a match quality, ξ. The match quality of a harvest affects trader profits by scaling revenue:

$$\pi(p, \xi) = (p_A \xi - p)x$$

Assume that the match shock is an i.i.d. draw from a Beta distribution with parameters ϕ and ω, where $\omega, \phi > 0$. Given their observation of ξ, traders can choose to either follow through with the purchase or reject the harvest and keep searching. Let $\Omega(p)$ be the probability that a trader accepts a harvest[20].

The search process proceeds in several steps. First, traders observe the market tightness and probability of accepting a harvest for each sub-market p and choose which sub-market to search in. To enter a sub-market, they pay fixed cost κ where $\kappa > 0$.[21][22] Next, farmers similarly observe the market tightness and probability of a trader accepting a harvest in each sub-market and choose one to search in. Finally, once a trader and a farmer are matched, the trader observes the match shock and decides whether or not to proceed with the purchase.

Agent Choices. Farmers make two decisions. First, farmers choose which sub-market (p) to sell in. Second, farmers invest in storage technology, which lowers the crop depreciation rate. Traders similarly make two decision - they choose which sub-market (p) to buy from and whether to accept or reject a harvest once they observe the match specific shock.

4.2 Defining an Equilibrium

The directed search environment admits a block recursive equilibrium, allowing us to consider the problems of the farmers and the trader without keeping track of the aggregate state

[19] More generally, I only need to assume that the Poisson rate with which a farmer matches to a trader in sub-market p be given by $f(\theta(p))$, where $f : [0, \infty) \to [0, \infty)$ is continuously differentiable and increasing. Similarly, let the Poisson rate with which a trader matches to a farmer in sub-market p be given by $q(\theta(p))$ where $q : [0, \infty) \to [0, \infty)$ is continuously differentiable and decreasing. Finally, the following boundary conditions must hold: $f(0) = q(\infty) = 0$ and $f(\infty) = q(0) = \infty$.

[20] An important question is why don't farmers and traders re-negotiate once traders observe the match quality? In practice, re-negotiations are costly and it is often easier to re-search for the trader. Furthermore, even through buying locations vary, traders usually sell in pre-fixed locations. Some crops, while still edible, may not be fit for long distance transport and including them will lead to spoilage of the other crops. In this case, traders will sort through the harvest and discard a portion of the crops rather than re-negotiate on price.

[21] The fixed cost captures barriers to entry, such as the cost of buying a vehicle, transportation costs, language differences, or a 'market queen' extracting rents from traders for buying in a particular location. Although barriers to entry may be high, they are not insurmountable. Over 85% of traders report that they choose where to buy crops independently of any other trader.

[22] The fixed cost is constant across sub-markets.

variables[23].

Farmers. Consider first the farmer. Let V^s be the value of a farmer has harvested and is searching for a trader, V^l be the continuation value of a farmer who has lost their harvest, and let $V^m(p)$ be the continuation value of a matched farmer who sells x quantity of crops at price p. The problem of a farmer who has harvested and searching for a buyer is characterized by the Hamilton-Jacobi-Bellman (HJB) equation,

$$\begin{aligned} \rho V^s = & \max_{c,i} \left\{ u(c) + \delta(i)[V^l - V^s] + \max_p \{ f(\theta(p))\Omega(p)[V^m(p) - V^s]\} \right\} \\ & \text{s.t} \quad c + p_i i \leq M \end{aligned} \tag{1}$$

with optimal search strategy p^*, optimal consumption strategy c^*, and optimal storage investment strategy i^*. Farmers' choose how much to invest in storage, how much to consume, and which sub-market to sell in. Equation 1 captures that the flow value of an unmatched farmer is equal to the flow of consumption minus the expected value of losing the harvest and plus the expected value from matching. The continuation value from matching is given by $V^m(p)$ where $V^m(\cdot) > 0, V^{m\prime}(\cdot) < 0$ is an increasing and concave function in p. I assume $V^m(p) = u(px)$. Furthermore, I assume the continuation value of a farmer who last their harvest is zero: $V^l = 0$[24]. Equation 1 fully characterizes the farmer problem.

Traders. Consider now the trader. Let $J^s(p)$ be the value of a trader who is searching in sub-market (p) and let $J^m(p, \xi)$ be the value of a trader who has matched in sub-market (p) with a farmer with match shock ξ. The problem of a trader who is searching in sub-market (p) is characterized by the Hamilton-Jacobi-Bellman (HJB) equation,

$$\rho J^s(p) = q(\theta(p)) E_\xi[\max\{J^m(p, \xi) - J^s(p), 0\}] \tag{2}$$

where $q(\theta(p))$ is the trader match rate; $J^m(p, \xi) - J^s(p)$ is the traders value from a successful match; the max operator allows a trader to accept or reject a match if the value of a match is negative; and the expectation is taken over the match quality.

[23] For a proof, see Menzio and Shi (2011), who show that a model of directed search can be written as a block recursive equilibrium that does not depend on aggregate state variables such as the distribution of prices or the measure of farmers in each state.

[24] The key assumption is that V^l is constant and does not depend on the quantity of crops lost. In practice, this assumption may be violated if farmers make ex-ante investments out of wealth that they carry across states. I abstract away from this issue here.

The continuation value of a trader matching at price p and match quality ξ is given by

$$J^m(p, \xi) = \pi(p, \xi) + J^s(p) \tag{3}$$

where I assume that traders consume the profits from selling the crops and immediately begin to search again for the next farmer. Free entry requires that

$$\min\{\kappa - J^s(p), \theta(p)\} = 0 \tag{4}$$

The condition in equation 4 implies that if a sub-market is open, traders will have zero utility, and if a sub-market is closed, then traders must have non-positive utility.

With the farmer and trader problems in hand, I now turn to defining an equilibrium.

Definition 1. An equilibrium consists of a set of value functions V^s, V^m, V^l, J^s, J^m, a market tightness function $\theta(p)$, and the unmatched farmers' search strategy function p^*, storage investment strategy function i^*, and consumption strategy c^*, such that:

1) Given $V^m(p), V^l$ and $\theta(p)$, V^s solves (1) with optimal storage strategy i^*, optimal search strategy p^*, and optimal consumption strategy c^*.

2) $J^s(p)$ solves (2).

3) $J^m(p)$ solves (3).

4) Given $J^s(p)$, market tightness $\theta(p)$ satisfies free entry condition (4).

Part (1) of the definition of an equilibrium captures the farmer's problem. In particular, part 1 requires that farmers make optimal search and investment decisions given the information available. Parts (2) and (3) of the definition capture the trader problem and require that the trader make optimal decisions to accept or reject a harvest. Finally, part (4) requires trader free entry.

4.3 Equilibrium Characterization

In this section, I characterize the properties of equilibrium. I first simplify the trader and farmers problems.

Lemma 1. For each sub-market (p), there exists a unique cut-off value $\bar{\xi}(p)$ such that traders accept harvests when $\xi \geq \bar{\xi}(p)$ and reject harvests when $\xi < \bar{\xi}(p)$. This value is given by

$$\bar{\xi}(p) = p/p_A.$$

Furthermore, the probability of a trader accepting a harvest in sub-market (p) is

$$\Omega(p) = 1 - F(p/p_A; \omega, \phi)$$

where $F(\cdot)$ is the cdf of a Beta distribution with parameters ω, ϕ. The HJB of a trader searching in sub-market (p) can be re-written as

$$\rho J^s(p) = \underbrace{q(\theta(p))}_{\text{Flow of Matches}} \underbrace{\Omega(p)}_{\text{Probability of Accepting}} \underbrace{(p_A E[\xi|\xi \geq p/p_A] - p)}_{\text{Expected Profit per Match}}. \tag{5}$$

where

$$E[\xi|\xi \geq p/p_A] = \frac{\omega}{\omega + \phi} \times \frac{1 - F(p/p_A; \omega + 1, \phi)}{1 - F(p/p_A; \omega, \phi)}$$

Proof. See appendix A.1.

Intuitively, traders will reject a harvest when the profit is negative. This is more likely when the purchase price p is close to the sale price p_A. When p is small, traders have positive profits even when ξ is small. This is no longer true when p is large. I can then derive the probability of accepting or rejecting a harvest using the properties of the Beta distribution. The trader's flow value of searching is then given by equation 5, where the first term is as before the rate of matching; the second term is the probability of accepting a harvest conditional on matching; and the third term is the expected profit of match conditional on proceeding with the purchase. The expected profit is equal to the cost times a markup.

I next show that an equilibrium exists and is unique.

Lemma 2. There exists a unique equilibrium.

Proof: See Appendix A.2.

An equilibrium maximizes farmer welfare subject to traders earning zero profits. I now turn to characterizing the properties of equilibrium.

Lemma 3. An equilibrium has the following properties:

1) Define the joint match surplus as

$$S(p) = \underbrace{(V^m(p) - V^s)}_{\textit{Farmer Surplus}} + \underbrace{E[\max\{(J^m(p,\xi) - J^s), 0\}]}_{\textit{Trader Surplus}} \tag{6}$$

and let the share of the surplus captured by the farmer be given by

$$\eta(p) = (V^m(p) - V^s)/S(p)$$

2) The competitive crop price, $p^* = \arg\max_p f(\theta(p))\Omega(p)(V^m(p) - V^s)$, exists and is unique. Moreover, it solves

$$p^* = \arg\max_p \left\{(V^m(p) - V^s)^\alpha (E[\max\{(J^m(p,\xi) - J^s), 0\}])^{1-\alpha}\Omega(p)^\alpha\right\} \tag{7}$$

$$= \arg\max_p \left\{\eta(p)^\alpha [1 - \eta(p)]^{1-\alpha} S(p)\Omega(p)^\alpha\right\}, \tag{8}$$

and has a unique solution characterized by the following optimality condition:

$$\underbrace{\eta'(p^*)\left(\frac{\alpha}{\eta(p^*)} - \frac{1-\alpha}{1-\eta(p^*)}\right)}_{\textit{Share Channel}} = -\underbrace{\frac{S'(p^*)}{S(p^*)}}_{\textit{Risk Aversion}} - \underbrace{\alpha\frac{\Omega'(p^*)}{\Omega(p^*)}}_{\textit{Limited Commitment}} \tag{9}$$

3) The equilibrium match finding rate for farmers and the opportunity cost of a match are:

$$\theta(p^*) = \left[\frac{E[\max\{J^m(p^*,\xi) - J^s], 0\}}{\kappa}\right]^{\frac{1}{\alpha}} \tag{10}$$

$$f(\theta(p^*)) = \left[\frac{E[\max\{J^m(p^*,\xi) - J^s], 0\}}{\kappa}\right]^{\frac{1-\alpha}{\alpha}} \tag{11}$$

$$\rho V^s = u(M - p_i i) - \delta(i)V^s + f(\theta(p^*))\Omega(p^*)(V^m(p^*) - V^s) \tag{12}$$

4) Optimal storage strategy i^* exists and is unique. Moreover, it solves

$$i^* = \arg\max_i V^s(i) \tag{13}$$

with optimality condition

$$p_i u'(M - p_i i) = -\delta'(i)\, V^s \tag{14}$$

Proof: see Appendix A.3.

Lemma 3 has several implications. Part (1) of Lemma 3 is straightforward: the joint match surplus is the sum of the match value for farmers plus the match value for traders. The first term captures the farmer surplus while the second term captures the trader surplus.

The second part of Lemma 3 solves for the competitive crop price, p^*. The optimal price equalizes the value of a worker gaining an additional share of the surplus (the share channel) against the change in the surplus (the risk aversion channel) and a change in the probability of traders rejecting the harvest (the limmited commitment channel). The share channel is composed of two parts. The first term is the share of the surplus received by the worker. The second term is the probability of matching. The form of the share channel is isomorphic to a random search model where matched farmers and traders engage in Nash Bargaining and the farmer's bargaining weight is α. Farmers trade-off receiving an increase in the share of the surplus against a lower probability of matching.

Part (3) of Lemma 3 is again straightforward and derives market tightness and the flow value of a farmer searching for a buyer as a function of the surplus value and the competitive crop price. Due to free entry, the market tightness is proportional to the value of the firm. The remaining equations directly follow through the substitution of terms.

Part (4) of Lemma 3 solves for the optimal investment strategy. The optimal level of consumption and investment balances the marginal cost of consuming less today against the marginal value of preserving crops for longer.

Finally, Lemma 3 suggests a straightforward algorithm for computing the equilibrium. The block recursive structure reduces the problem to a value function, where one does not need to keep track of the aggregate state variables, such as the measure of farmers or traders. The problem can then be solved as a fixed point of (p, c), iterating on the choice of c and p. See appendix A.5 for additional details.

I now define the key variable of interest: food loss.

Lemma 4. Let δ^* be a farmer's equilibrium rate of deprecation and $\hat{f}(\theta^*) = f(\theta^*)\Omega(p^*)$ be a farmer's equilibrium rate of matching with a trader. Then the expected fraction of food loss, the expected storage duration, and the expected shelf life are given by:

$$E[\text{Fraction Food Lost}] = \frac{\delta^*}{\delta^* + \hat{f}(\theta^*)} \tag{15}$$

$$E[\text{Storage Duration}] = \frac{1}{\delta^* + \hat{f}(\theta^*)} \tag{16}$$

$$E[\text{Shelf Life}] = \frac{1}{\delta^*} \tag{17}$$

Proof. I leave a full proof for Appendix A.4 but provide the intuition here. The key assumption underlying these results is that matches with traders and depreciation events have Poisson rates of arrival. This implies that the wait time until an event occurs is distributed exponentially. The results directly follow. The lemma shows that a farmer's expected food loss is solely a function of two equilibrium moments: the depreciation rate and the match rate. Parameters, functional forms, or agent choices affect the equilibrium rates of depreciation and matching, but do not affect the relationship between the fraction of food loss, the depreciation rate, and the farmer match rate.

Lemma 5. The decentralized equilibrium is bilaterally inefficient.

Proof: The inefficiency result follows directly from part 2 of Lemma 3. The decentralized economy is bilaterally efficient when the relationship between the share of the surplus captured by farmers and the probability of matching satisfies the Hosios (1990) condition: the match probability is equal to the surplus share. The condition can be summarized as

$$\eta'\left(p^*\right)\left(\frac{\alpha}{\eta\left(p^*\right)}-\frac{1-\alpha}{1-\eta\left(p^*\right)}\right)=0$$

and implies that $\eta(p^*) = \alpha$. A sufficient condition in my model for efficiency is when the risk-aversion channel is zero ($S'(p^*) = 0$) and the limited commitment channel is zero ($\Omega'(p^*) = 0$).

The presence of risk-aversion in the model generates an inefficiency. Intuitively, risk-averse farmers wish to equalize consumption across all states. However, due to incomplete asset markets, they are unable to do so. They instead minimize risk by choosing sub-markets with lower prices but higher probabilities of matching with traders. The joint match surplus would be higher if the price increased and the probability of a farmer matching decreased. The derivative of the joint match surplus with respect to price is only zero when the marginal value of an extra dollar to the farmer is equal to the marginal cost of paying an extra dollar to the trader. When farmers are risk averse, this is not the case.

Note that although decreasing the perishability of crops decreases the inefficiency, it does not eliminate it. When crops are perfectly durable ($\delta = 0$), the risk of losing one's crop is eliminated but the risk of not finding a buyer remains. Risk-averse farmers will still wish to equalize consumption between states and will search for traders in markets with lower prices and higher match probabilities relative to the first-best.

Limited commitment - the ability of farmers to reject a harvest - generates an additional externality. Because traders have the option to reject harvests when the match quality is low, they reject harvest where the private surplus is negative but the joint surplus is positive. In other words, society would benefit when traders purchase crops regardless of the match quality, even if it is not the best interest of the trader themselves. In order to avoid rejection by traders farmers must under price their goods. This compounds the effects of the risk-aversion.

4.4 Model Validity

I now validate the model against data.

Estimating Equation. The starting point of my validation strategy is a model-derived relationship between food loss, the expected storage duration, and the expected shelf life of a crop. An immediate corollary of Lemma 5, is that we can relate the expected shelf life and and expected storage duration to the expected fraction of food lost through the following equation:

$$\text{E[Fraction Food Loss]} = \frac{E[\text{Storage Duration}]}{E[\text{Shelf Life}]} \equiv \text{Relative Storage Duration} \tag{18}$$

In particular, the expected fraction of food loss can be expressed as the ratio of the average storage duration divided by the average shelf life. Both the average fraction of food loss, the average storage duration, and the average shelf life of a crop are observed in the survey, so I can test the model specification by regressing the fraction of food lost on the relative storage duration. I therefore estimate

$$\text{Food Loss}_i = \Gamma \times \text{Relative Storage Duration}_i + \varepsilon_i \tag{19}$$

where i indexes the farmer. If the model is correctly specified, the coefficient on the relative storage duration should be one[25]. Importantly, this is not a test of whether the model can correctly predict the expected storage duration or the expected shelf life. Instead, this is a test of the Poisson process - if the arrival rates of matches and depreciation is Poisson, then the above relationship will hold.

[25] An alternative specification would be to estimate

$$\log(\text{Food Loss})_i = \Gamma_1 \log(\text{Storage Duration})_i + \Gamma_2 \log(\text{Shelf Life})_i + \varepsilon_i$$

and test whether $\Gamma_1 = -\Gamma_2$. I instrument for the average storage duration and average shelf life using distance to the market and harvest size. I fail to reject that $\hat{\Gamma}_1 = -\hat{\Gamma}_2$.

Identification. There are two concerns with estimating Γ via ordinary least squares. The first concern is that the regression suffers from simultaneity: farmers' choice of storage technology and market affect the fraction of food lost, but farmer expectation of food loss affects their choice of storage technology and market. This simultaneity confounds estimation. The second concern is measurement error. In the model, the relationship between food loss and relative storage duration holds exactly. In practice, relative storage duration may be reported with measurement error. For instance, the estimator will be downward biased given classical measurement error.

I overcome these identification challenges through an instrumental variables approach. The choice of instrumental variable is closely linked to the model, which suggests that the cost to a trader of accessing a market only affects food loss through δ and $f(\theta)$. In the model, the trader fixed cost κ does not in and of itself generate food loss; rather, it affects trader profits which then affects market tightness and farmer choice of storage technology[26]. Furthermore, significant land market frictions prevent the buying and selling or renting of land. Farm and plot locations are fixed over time, implying that the distance from the farm to the market is exogenous from the perspective of the farmer. The exclusion restriction will hold under these assumptions. I proxy for the fixed cost using the distance from the farmgate to the market.

Estimates of $\hat{\Gamma}$. I report the results for pepper farmers in Table 2. For the OLS estimates, I find that the ordinary least squares estimates of $\hat{\Gamma}$ range from 0.1 to 0.3. While they are all positive and statistically significant from zero, they are also statistically different from 1 at the 1% level. I then instrument the relative storage duration using the distance from the farmgate to the market and have a strong first stage with an F-statistic of 25. Consistent with classical measurement error, I find that the IV estimates are higher than the OLS estimates. For the IV estimates, I find that $\hat{\Gamma}$ ranges from 0.5 to 0.9. In my preferred specification where I control for farmer characteristics such as age, family size, and plot size (column 4), I cannot reject the null hypothesis that the coefficient is equal to one. This suggests that modeling pepper depreciation as a Poisson process is a reasonable assumption.

[26] In practice, farmers sometimes bring crops directly to the market and traders sometimes commute to the farmgate. The latter is more prevalent with over 70% farmers selling at the farmgate. Regardless of who pays the fixed cost of bringing crops to the point of sale, the effect on food loss is the same.

Table 2: Effect of Relative Storage Duration on Food Loss - Peppers

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Relative Storage Duration	0.31***	0.17***	0.50***	0.89***
	(0.03)	(0.03)	(0.04)	(0.23)
Observations	501	501	439	439
Controls		✓		✓
R^2	0.23	0.31	0.16	−0.30
Adjusted R^2	0.23	0.31	0.16	−0.32
Residual Std. Error	0.13	0.13	0.15	0.18
F Statistic	150.64***	55.97***		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for pepper farmers. Coefficients in columns (3) and (4) are estimated via two-stage least squares for pepper farmers, where average storage duration is instrumented by distance to the market. *p<0.1; **p<0.05; ***p<0.01

5 Model Quantification

The goal of this section is to discipline the model parameters and quantify the model, in order to perform policy counterfactuals and to develop a deeper understanding of model mechanics.

5.1 Internal Validity

The equilibrium is a function of 10 parameters:

$$\{\rho, \delta_0, \beta, p_i, M, \kappa, \alpha, p_A, \phi, \omega\}.$$

My estimation strategy consists of three components. First, I take well-known parameters directly from the literature. Second, I normalize parameters where possible. Third, I estimate the remaining parameters using the survey data. I discuss each of these in turn. I summarize the parameter values and estimation strategy in Table 3.

External calibration. I take one parameter from the literature: the discount rate (ρ). It is generally estimated in the context of developed countries, and unfortunately, good estimates do not exist for developing economies. I assume the discount rate does not vary much with GDP. I normalize one additional parameter: the price of storage (p_i). I normalize

Table 3: Calibrated Parameter Values

Parameter	Description	Value	Source
ρ	Discount rate	0.03	Literature
p_i	Storage price	1	Normalized
δ_0	Storage baseline	20	Data
p_A	Retail price	770	Data
ω	Beta Distribution	1.3	GMM
ϕ	Beta Distribution	0.2	GMM
α	Match elasticity	0.79	SMM
β	Storage elasticity	1.8	SMM
M	Farmer endowment	3.6	SMM
κ	Trader Fixed Cost	47	SMM

the price of storage because it is jointly identified with farmer endowment, M. Both the price and the endowment are unobserved in the survey and thus modeled in a reduced form way.[27]

Calibration from survey data. I discipline the remaining parameters using the survey data. I estimate the storage baseline (δ_0) as the inverse of the average storage duration for farmers who use no storage technology. As Lemma 5 shows, $1/\delta^* = E[\text{Equilibrium Shelf Life}]$. This implies that $1/\delta_0 = E[\text{Shelf Life When } i = 0]$. I also estimate the retail price (p_A) directly from the trader survey. In the survey, the average retail price of peppers is $\hat{p}_A = 770$ per unit. Finally, to estimate ω and ϕ, I fit a beta distribution to the distribution of bruised crops in the wholesale market using the general method of moments. The key assumption is that the distribution of bruised crops is independent of either storage technology or storage duration. I find that $\omega = 1.3$ and $\phi = 0.2$.

Simulated Method of Moments. I am finally left with four parameters: farmer endowment (M), trader fixed cost (κ), the elasticity of matches to the measure of unmatched farmers (α), and the elasticity of depreciation to storage investment (β). Disciplining these parameters is key to evaluating the benefits of policy. In particular, the effectiveness of storage subsidies will primarily depend on β, whereas the effectiveness of trader subsidies will primarily depend on α. I calibrate M, κ, α, and β using simulated method of moments. I target four moments: the average rate of depreciation in the economy, the average match rate (which together with the depreciation rate implies an average food loss of 10%), the

[27] The price of storage is unobserved because farmers generally do not keep track of fixed costs of storage such as purchasing plastic bins. In many cases, such as storing crops at home or drying, the cost of storage is time and effort rather than monetary.

average own-consumption of harvest, and the average percent of crops rejected by traders.

The depreciation rate and match rate are unobservable, but can be estimated using the structure of the model. To estimate the depreciation rate, I revisit Lemma 5 and express the fraction of food loss as a function of the average storage duration and the depreciation rate:

$$\text{E[Fraction Food Loss]} = \delta^* \times E[\text{Storage Duration}] \tag{20}$$

I can then estimate δ^* by regressing average food loss on average storage duration:

$$\text{Average Food Loss}_i = \delta^* \times \text{Average Storage Duration}_i + \varepsilon_i$$

where i indexes the farmer. Estimation using ordinary least squares runs into the same identification challenges as before: simultaneity and measurement error. I similarly instrument the average storage duration using the distance to the market.

I can now estimate δ^*, the equilibrium rate of crop depreciation. I report the results for pepper farmers in Table 4. The first stage of the instrumental variables has strong predictive power with an F-statistic of 15. Consistent with classical measurement error, the OLS estimates are an order of magnitude lower than the IV estimates. The OLS estimates are approximately 0.3, whereas the IV estimates are approximately 2. The larger coefficients are more reasonable than the smaller ones. The interpretation of $\hat{\delta}$ is that $1/\hat{\delta}$ is the average shelf life of a crop. A coefficient of 0.3 implies that the average shelf life of a farmer's harvest is 40 months, whereas a coefficient of 2 implies that the average shelf life is 6 months, which is more in line with farmers' own estimates of their crops' perishability. Given the percent of food lost, the depreciation rate maps one-to-one to the match rate. When the arrival rate of depreciation is 2 and the percent of food loss is 10%, the arrival rate of matches is 18. This implies that on average it takes a farmer 20 days to find a trader and that the average storage duration is 18 days. As a robustness check, I extend the analysis to include farmer characteristics such as age, education, farm size, and location fixed effects. The results are consistent across all specifications.

Using the regression results as an input, I discipline the remaining model parameters using simulated method of moments. I target an equilibrium depreciation rate of 2, a match rate of 18, consumption levels of 1.1 units, and an acceptance rate by traders of 90% (or equivalently a rejection rate of 10%). I report the results from the simulated method of moments in Table 5. I find that the match elasticity is $\alpha = 0.35$, the storage elasticity is $\beta = 0.7$, the farmer endowment is 3.6, and the trader fixed cost is 47. The calibration does well, hitting each of the target moments. Moreover, the calibration is not sensitive to initial guesses of the parameters.

Table 4: Effect of Storage Duration on Food Loss - Peppers

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Average Storage Duration	0.3***	0.2***	1.8***	1.8***
	(0.1)	(0.1)	(0.2)	(0.5)
Implied Shelf Life (Months)	40	60	6	6
Observations	569	569	569	569
Controls		✓		✓
R^2	0.1	0.2	−1.1	−1.1
Adjusted R^2	0.1	0.2	−1.1	−1.1
Residual Std. Error	0.2	0.2	0.3	0.3
F Statistic	39.0***	42.1***		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. The sample includes only pepper farmers. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for pepper farmers. Coefficients in columns (3) and (4) are estimated via two stage least squares, where average storage duration is instrumented by distance from the farmgate to the market. *p<0.1; **p<0.05; ***p<0.01

Table 5: Simulated Method of Moments

Parameter	Parameter Value	Target Moment	Data Value	Model Value
β	1.8	Depreciation rate $\delta(i)$	2.0	2.1
α	0.79	Match rate $f(\theta)$	22.0	22.1
M	3.6	Consumption c	1.1	1.2
κ	47	Acceptance Rate $\Omega(p)$	0.9	0.9

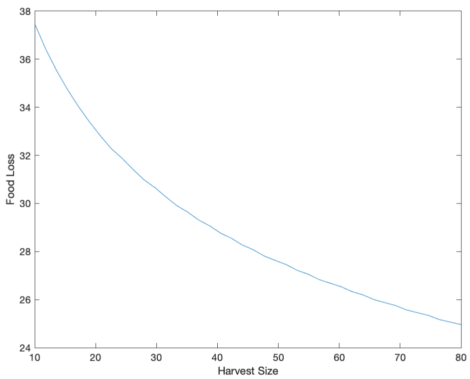
5.2 External Validity

In the model, there is a single representative farmer and trader. I therefore discipline the model parameters using averages: average depreciation rate, average match rate, average trader fixed cost, average price, etc. How well does the model speak to the heterogeneity in the data? I consider three dimensions of heterogeneity: harvest size (x), baseline perishability of a crop (δ_0), and the trader fixed cost (κ). I compare the model simulations and data along two dimensions: the fraction of food lost and equilibrium match rate.

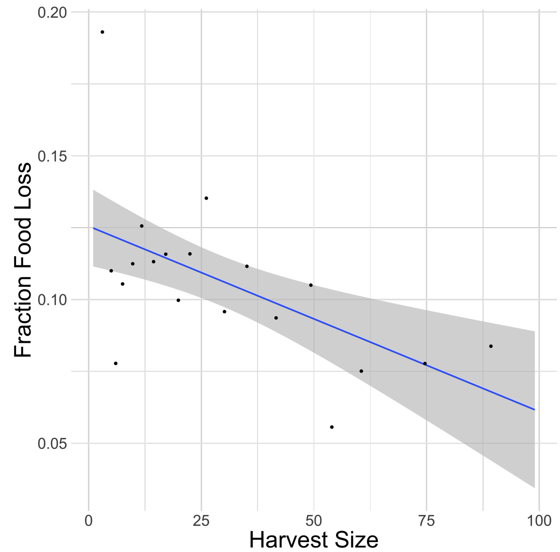
I first map the model variables to the data. Of the two outcome variables I only observe food loss directly. However, while I do not observe $f(\theta^*)$ directly, I observe the search intensity of the farmer - the number of days per month that the farmer attempts to sell their harvest - and the probability of a successful sale per search. By combining the two, I can construct an estimate of $f(\theta^*)$. Finally, I do not directly observe κ or δ_0. As in the previous section, I proxy for κ using distance from the the farm to the market. And I can impute δ_0 by observing the average shelf life of farmers who do not use any storage.

Harvest Size. I show in Figure 8 that in both the model and the data, increasing harvest size (or equivalently farm size in the model) decreases food loss (Figures 8a and 8b) and increases the match rate (Figures 8c and 8d). In the model, a larger harvest heightens the amount of risk to the farmer by increasing the difference in consumption between states. To reduce that risk, farmers will 1) invest more in storage to lower the rate of depreciation, and 2) accept lower prices at higher probabilities of matching with a trader. A secondary mechanism also works in the farmers' favor: a bigger harvest boosts trader revenue. Since there is free entry for traders, the measure of traders also increases. This further tightens the market. The effect of harvest is consistent in both the model and the data.

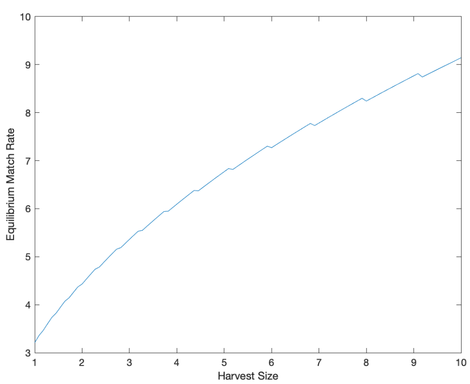
Although the effect of farm size parallels the results from much of the misallocation literature, the mechanisms differ. Similar to the findings of Restuccia and Santaeulalia-Llopis (2017), Foster and Rosenzweig (2022), or Chen et al. (2023), increasing farm size increases input investment and welfare. The mechanism, however, contrasts. In Foster and Rosenzweig (2022), for instance, larger farms can afford to pay the fixed costs associated with hiring labor and buying capital and thus reap the benefits from more productive technologies. In other words, a reduction in land market frictions relaxes the constraints on other inputs. In this paper, however, a larger farm size does not relax any constraints. Instead, it increases the amount of risk born by the farmer, forcing the farmer to increase storage investment and decrease the price. The result is a decrease in the short-term flow of consumption but an increase in the long-term.



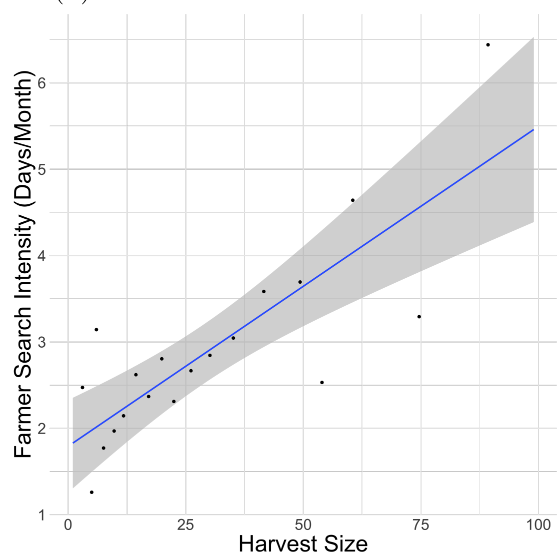
(a) Model: Harvest Size vs Food Loss



(b) Data: Harvest Size vs Food Loss



(c) Model: Harvest Size vs Match Rate

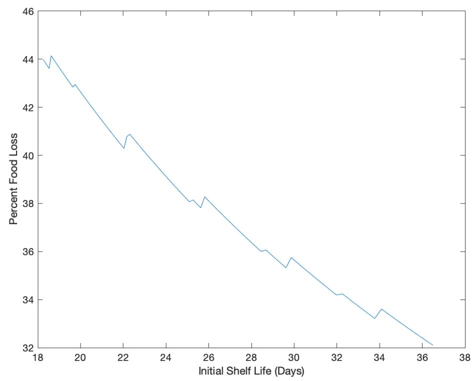


(d) Data: Harvest Size vs Match Rate

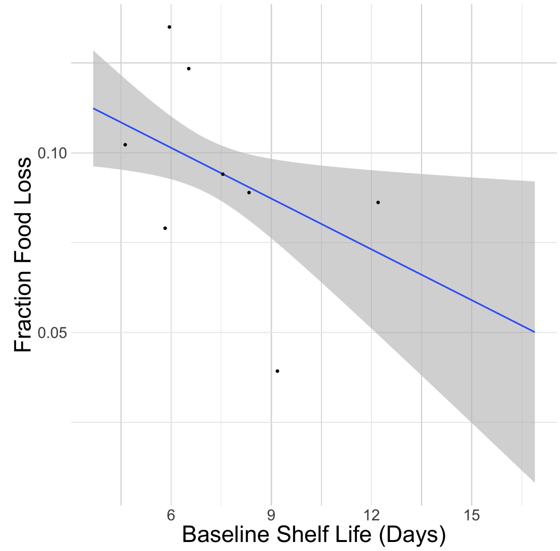
Figure 8: Effect of Harvest Size (x)

Notes. Comparison of the effect of harvest size in the model and the data. Plots (b) and (d) are binscatters of harvest size against the fraction of food loss (in plot b) and farmer search intensity (plot d) among pepper farmers. Plots (a) and (c) plot the effect of harvest size in the model. Farmer search intensity is measured as the number of days per month a farmer attempts to sell their crops. Harvest size is measured as the number of bags of peppers farmers grow.

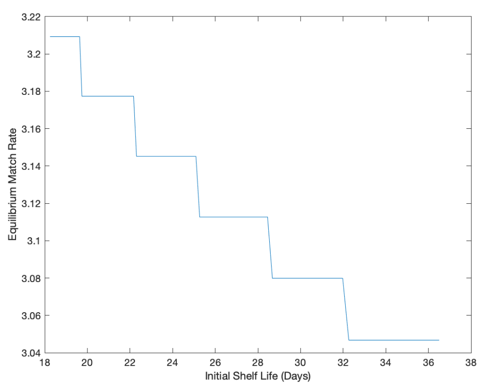
Baseline Depreciation. I show in Figure 9 that the qualitative effect of baseline depreciation rate on the fraction of food lost and the match rate is consistent in both the model and data. In both the model and the data, food loss is higher for a higher baseline depreciation rate (Figures 9a and 9b) and the match rate is similarly greater a higher baseline deprecia-



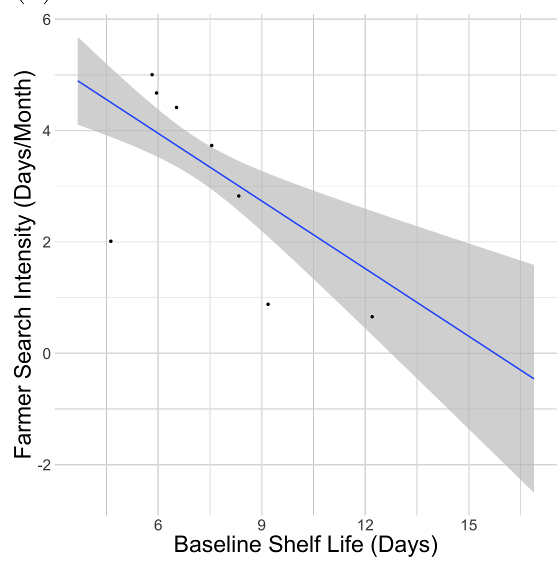
(a) Model: Baseline Shelf Life vs Food Loss



(b) Data: Baseline Shelf Life vs Food Loss



(c) Model: Baseline Shelf Life vs Match Rate

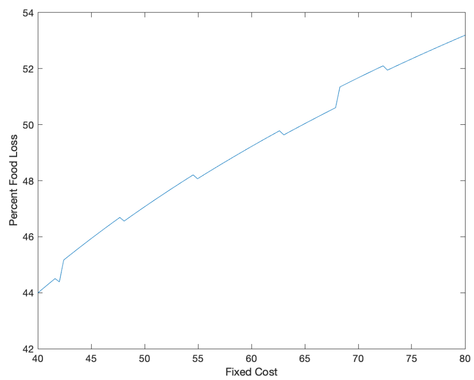


(d) Data: Baseline Shelf Life vs Match Rate

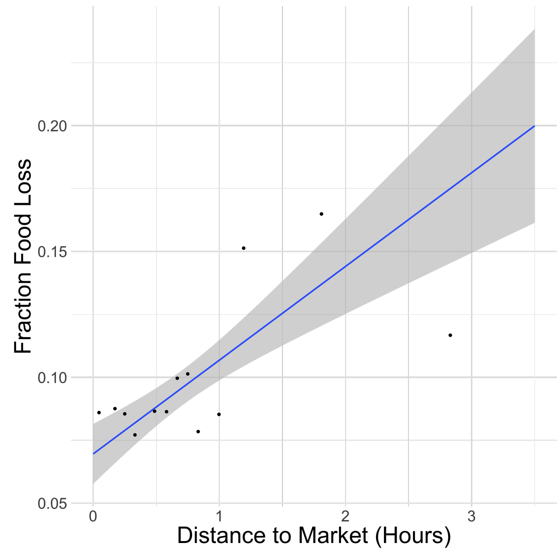
Figure 9: Effect of Baseline Shelf Life (δ_0)

Notes. Comparison of the effect of the baseline shelf life in the model and the data. Plots (b) and (d) are binscatters of baseline shelf life against the fraction of food loss (in plot b) and farmer search intensity (plot d) among pepper farmers. Plots (a) and (c) plot the effect of baseline shelf life in the model. Baseline shelf life is measured as the maximum number of days a farmer can store their crops without using storage. Farmer search intensity is measured as the number of days per month a farmer attempts to sell their crops.

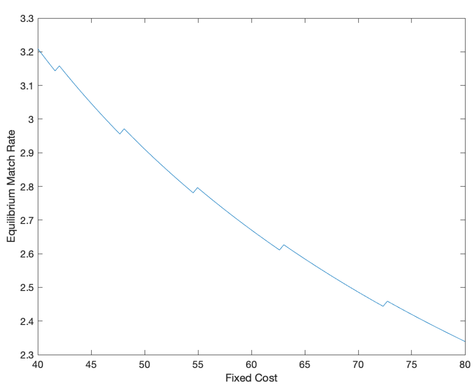
tion rate (Figures 9c and 9d). Intuitively, when farmers grow more perishable crops, the risk of losing one's harvest before matching with a trader increases. Farmers compensate for this increase in risk in two ways. First, they invest more in storage. Second, they increase the match probability. However, holding all other parameters constant, the increase in storage investment doesn't fully compensate for the increase in perishability. Food loss increases as a result.



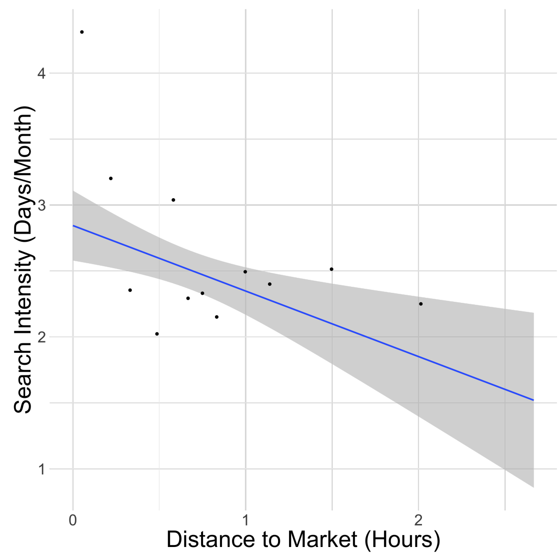
(a) Model: Fixed Cost vs Food Loss



(b) Data: Fixed Cost vs Food Loss



(c) Model: Fixed Cost vs Match Rate



(d) Data: Fixed cost vs Match Rate

Figure 10: Effect of Trader Fixed Cost (κ)

Notes. Comparison of the effect of the trader fixed cost in the model and the data. Plots (b) and (d) are binscatters of distance to the market against the fraction of food loss (in plot b) and farmer search intensity (plot d) among pepper farmers. Plots (a) and (c) plot the effect of trader fixed cost in the model. Farmer search intensity is measured as the number of days per month a farmer attempts to sell their crops.

Trader Fixed Cost. As with the harvest size and the depreciation rate, the effect of a chance in the fixed cost of entry generates qualitatively similar results in both the model and the data. I show in figures 10a and 10b that as the fixed cost increases, so does food loss in the model and the data. I plot the effect of the fixed cost on the match rate in the model and data in figures 10c and 9d respectively. The match rate is decreasing in the fixed cost in both plots. When traders have to pay a higher cost to enter a market, fewer traders enter the market. This lowers market tightness and decreases the farmer match rate. To compensate for the decrease in market tightness, farmers invest more in storage. However, the increase in storage investment doesn't fully offset the decrease in the match probability. Food loss ultimately increases.

6 Implications for Welfare and Food Loss

Having quantified the model, I now turn to discussing the implications for welfare and food loss.

6.1 Relaxing Market Frictions

What does Ghana stand to gain by removing search frictions or through better enforcement of contracts? I consider three counterfactual economies. In the first economy, the government enforces contracts so that traders cannot reject harvests if the quality is too low.[28] In the second economy, there are no search frictions.[29] And in the the third economy, there is both contract enforcement and no search frictions.

I report the effects on welfare and food loss in Table 6. In the baseline, the percent of food lost is 9.2% and I normalize consumption-equivalent welfare to 1. Contract enforcement has a small positive effect on welfare, increasing welfare by 1.01 times, and a reduces food loss by 0.3%. Why is the effect so small when 10% of matches are rejected in the baseline? Contract enforcement has opposite effects on farmers and traders. Holding constant the measure of traders, farmer probability of matching increases. However, contract enforcement lowers trader expected profits and reduces the number of traders in the market. To compensate traders for lower profits, farmers decrease the price at which they sell, which lowers welfare. In contrast, reducing search frictions benefits both farmers and traders because both farmers

[28] Expected quality is then given by the expectation of the Beta distribution with parameters ω and ϕ. This equal to $\omega/(\omega+\phi)$.

[29] I model the no search friction scenario by letting the flow of matches be equal to $m(p) = \max\{T(p), F(p)\}$. When this is the case, θ cannot be determined in equilibrium. I estimate the no search friction scenario by taking the limit as $\alpha \to 0$ since $T > F$.

and traders match more quickly. The resulting welfare is 3.3 times (or 230%) higher than in the baseline and food loss is 30 times lower at 0.3%. Finally, in the economy with neither friction, welfare is 4.3 times (or 315%) higher than in the baseline and only 0.2% of food is lost. The effect of reducing both search and contract frictions is greater than the sum of reducing each individually because the frictions build on each other - when the rejection rate is high, it becomes even harder for the farmer to match successfully with a farmer (and vice-versa). In other words, the two frictions have the same effect on farmers - increasing the risk of not matching with a trader.

Table 6: Welfare Gains in Frictionless Economies

	Welfare (Relative to baseline)	Food Loss (%)
Baseline	1	9.2
No rejection	1.01	8.9
No search	3.3	0.3
No rejection or search	4.3	0.2

Notes. Change in consumption equivalent welfare and the percent of food lost for three counterfactual economies: no rejection of farmer harvests once traders and farmers match (contract enforcement), no search frictions, and no rejection and no search frictions. Relative welfare is the ratio of consumption equivalent welfare in each counterfactual economy relative to the baseline.

6.2 Improvements in Storage Technology

The previous section documents the potential welfare gains from removing search and matching and contracting frictions. However, the government may not have the tools to enforce contracts or improve the matching process. One of the most popular methods to reduce food loss is to improve storage technologies. If the Ghanaian government wished to reduce food loss from 10% to the US average of 4%, by how much would it need to improve storage technology? And what would be the welfare gains?[30] I conduct two experiments. In the first experiment, I allow the farmer to choose optimal storage and consumption but assume there are no adjustments in the search market. That is, I evaluate the effects of an improvement in storage in partial equilibrium. In the second experiment, I allow search markets to adjust as well, accounting for a general equilibrium feedback between the choice of storage technology and the search and matching process. I report the results in Table 7.

To reduce food loss in Ghana to the same average level as in the US, storage technology would need to be improved by 55% in partial equilibrium and 70% in general equilibrium.

[30] An important caveat is that I can only evaluate the potential welfare gains from a storage subsidy, but not its cost. In equilibrium, the government budget constraint must balance and the funds for the subsidy must be raised through taxes. The current set-up is equivalent to receiving a grant from the World Bank with no expectation of repayment.

The improvement is greater in general equilibrium because farmers can make adjustments in the search market. As investment in storage increases, farmers want to match to traders at higher prices and with lower probabilities. Thus they reduce their search intensity, leading to greater losses in general than in partial equilibrium. The improvement needs to be greater in general equilibrium to have the same level of loss as in partial equilibrium. Welfare is also higher in general equilibrium because farmers have an extra margin of adjustment through the search market. Welfare in general equilibrium can never be lower than in partial equilibrium.

Why are welfare gains due to improvements in storage technology so much smaller than the potential welfare gains from relaxing search frictions? Although relaxing search frictions and improving storage has the similar effect of reducing food loss, they accomplish this in two different ways. Storage improvements reduce the probability of a bad event; improvements in search increase the probability of a good event. Farmer welfare can increase even when crops are perfectly durable, because they wish to spend less time searching.

Table 7: Gains from Storage Subsidies

	Storage Improvement (%)	Welfare (Relative to baseline)
Partial Equilibrium	55	1.5
General Equilibrium	70	1.8

Notes. The first column is the percent improvement in the effectiveness of storage technology required to reduce food loss in Ghana from 10% to the same level as the US average at 4%. The second column is the relative gain from welfare from the subsidy, where relative welfare is the ratio of consumption-equivalent welfare in each counterfactual economy relative to the baseline.

7 Conclusion

In this paper, I provide the first macroeconomic analysis of food loss. By gathering a novel survey of search and matching frictions in Ghana's fruit and vegetable supply chain, I document a tight link between food loss, storage, and market tightness. I show that food loss is decreasing in market tightness and increasing in the quality of storage technology. To explain these results, I develop a model through which I investigate the interaction between storage technology and search frictions. I find that food loss can be expressed solely as a function of the market friction and the rate of depreciation. Finally, I quantify the model and explore the effects of counterfactual policy. I find that to reduce food loss to US levels, storage technology in Ghana would need to be improved by 70%.

Further research into the macroeconomics of food loss is essential to perform more nuanced policy evaluations. Future work can build on this paper in several direction. First, additional data is needed on the scope and properties of food loss. Accurately measuring food loss is costly and challenging methodologically, especially in gauging quality food loss and tracking crops throughout the entire agricultural value chain. This has resulted in a significant gap in data, where food loss estimates are imputed via extrapolations across crops, time, and space. Furthermore, while the structure of search and matching in agricultural output markets has recently received increased attention, the area has been historically understudied, and much remains unknown about the nature of search frictions in these markets and how they contribute to food loss.

Finally, progress can be made using structural general equilibrium models to understand the impact of agricultural policy on food loss and agricultural productivity more broadly. Given the high scale of food loss, incorporating this dimension into models of agricultural productivity may lead to an increased understanding of the agricultural productivity gap between developed and developing nations. A particularly promising direction for further research is the structural transformation of agricultural value chains. The structure of upstream markets can have downstream consequences and a more formal treatment and exploration of the cross-market and cross-agent interactions is required.

References

Acemoglu, Daron and Robert Shimer (1999), 'Efficient unemployment insurance', *Journal of Political Economy* **107**(5), 893–928.

Adamopoulos, Tasso and Diego Restuccia (2014), 'The Size Distribution of Farms and International Productivity Differences', *American Economic Review* **104**(6), 1667–97.

Adamopoulos, Tasso and Diego Restuccia (2020), 'Land Reform and Productivity: A Quantitative Analysis with Micro Data', *American Economic Journal: Macroeconomics* **12**(3), 1–39.

Adamopoulos, Tasso, Loren Brandt, Jessica Leight and Diego Restuccia (2022), 'Misallocation, Selection, and Productivity: A Quantitative Analysis With Panel Data From China', *Econometrica* **90**(3), 1261–1282.

Affognon, Hippolyte, Christopher Mutungi, Pascal Sanginga and Christian Borgemeister (2015), 'Unpacking postharvest losses in sub-Saharan Africa: A Meta-Analysis', *World Development* **66**, 49–68.

Aggarwal, Shilpa, Eilin Francis and Jonathan Robinson (2018), 'Grain today, gain tomorrow: Evidence from a storage experiment with savings clubs in Kenya', *Journal of Development Economics* **134**, 1–15.

Aker, Jenny C., Brian Dillon and C. Jamilah Welch (2023), 'Demand, supply and long-term adoption: Evidence from a storage technology in West Africa', *Journal of Development Economics* **165**, 103129.

Allen, Treb (2014), 'Information Frictions in Trade', *Econometrica* **82**(6), 2041–2083.

Allen, Treb and David Atkin (2022), 'Volatility and the Gains From Trade', *Econometrica* **90**(5), 2053–2092.

Antràs, Pol and Arnaud Costinot (2011), 'Intermediated Trade', *The Quarterly Journal of Economics* **126**(3), 1319–1374.

Atkin, David and Dave Donaldson (2015), 'Who's Getting Globalized? The Size and Implications of Intra-national Trade Costs', *NBER Working Paper* **21439**.

Bardhan, Pranab, Dilip Mookherjee and Masatoshi Tsumagari (2013), 'Middlemen Margins and Globalization', *American Economic Journal: Microeconomics* **5**(4), 81–119.

Barrett, Christopher B., Thomas Reardon, Johan Swinnen and David Zilberman (2022), 'Agri-food Value Chain Revolutions in Low- and Middle-Income Countries', *Journal of Economic Literature* **60**(4), 1316–77.

Bergquist, Lauren, Benjamin Faber, Thibault Fally, Matthias Hoelzlein, Edward Miguel and Andrés Rodríguez-Clare (2022), 'Scaling Agricultural Policy Interventions'.

Burdett, Kenneth, Shouyong Shi and Randall Wright (2001), 'Pricing and Matching with Frictions', *Journal of Political Economy* **109**(5), 1060–1085.

Burke, Marshall, Lauren Falcao Bergquist and Edward Miguel (2019), 'Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets', *The Quarterly Journal of Economics* **134**(2), 785–842.

Cardell, Lila and Hope Michelson (2023), 'Price risk and small farmer maize storage in Sub-Saharan Africa: New insights into a long-standing puzzle', *American Journal of Agricultural Economics* **105**(3), 737–759.

Caselli, Francesco (2005), ' Accounting for Cross-Country Income Differences', *Handbook of Economic Growth* **1**, 679–741.

Chatterjee, Shoumitro (2023), 'Market Power and Spatial Competition in Rural India', *The Quarterly Journal of Economics* .

Chen, Chaoran (2017), 'Untitled Land, Occupational Choice, and Agricultural Productivity', *American Economic Journal: Macroeconomics* **9**(4), 91–121.

Chen, Chaoran, Diego Restuccia and Raül Santaeulàlia-Llopis (2023), 'Land Misallocation and Productivity', *American Economic Journal: Macroeconomics* **15**(2), 441–65.

Delavallade, Clara and Susan Godlonton (2023), 'Locking crops to unlock investment: Experimental evidence on warrantage in Burkina Faso', *Journal of Development Economics* **160**, 102959.

Delgado, Luciana, Monica Schuster and Maximo Torero (2017), 'The Reality of Food Losses: A New Measurement Methodology', *IFPRI Discussion Paper* **01686**.

Dhingra, Swati and Silvana Tenreyro (2023), 'The Rise Of Agribusinesses And Its Distributional Consequences'.

Donovan, Kevin (2021), 'The Equilibrium Impact of Agricultural Risk on Intermediate Inputs and Aggregate Productivity', *Review of Economic Studies* **88**, 2275–2307.

Foster, Andrew D. and Mark R. Rosenzweig (2022), 'Are There Too Many Farms in the World? Labor Market Transaction Costs, Machine Capacities, and Optimal Farm Size', *Journal of Political Economy* **130**(3), 636–680.

Gollin, Douglas and Christopher Udry (2021), 'Heterogeneity, Measurement Error, and Misallocation: Evidence from African Agriculture', *Journal of Political Economy* **129**(1), 1–80.

Gollin, Douglas, David Lagakos and Michael E. Waugh (2014), 'The Agricultural Productivity Gap', *The Quarterly Journal of Economics* **129**(2), 939–993.

Golosov, Mikhail, Pricila Maziero and Guido Menzio (2013), 'Taxation and Redistribution of Residual Income Inequality', *Journal of Political Economy* **121**(6).

Grant, Matthew and Meredith Startz (2024), 'Cutting Out the Middleman: The Structure of Chains of Intermediation'.

Hosios, Arthur J. (1990), 'On The Efficiency of Matching and Related Models of Search and Unemployment', *The Review of Economic Studies* **57**(2), 279–298.

Jensen, Robert (2007), 'The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector', *The Quarterly Journal of Economics* **122**(3), 879–924.

Lagakos, David and Michael E. Waugh (2013), 'Selection, Agriculture, and Cross-Country Productivity Differences', *American Economic Review* **103**(2), 948–80.

Menzio, Guido and Shouyong Shi (2011), 'Efficient Search on the Job and the Business Cycle', *Journal of Political Economy* **119**(3).

Moen, Espen R. (1997), 'Competitive search equilibrium', *Journal of Political Economy* **105**(2), 385–411.

Montgomery, James D. (1991), 'Equilibrium Wage Dispersion and Interindustry Wage Differentials', *The Quarterly Journal of Economics* **106**(1), 163–179.

Mortensen, Dale T. and Christopher A. Pissarides (1994), 'Job creation and job destruction in the theory of unemployment', *Review of Economic Studies* **61**(3), 397–415.

National Academies of Sciences (2019), *Reducing Impacts of Food Loss and Waste: Proceedings of a Workshop*, The National Academies Press, Washington, DC.

Nyarko, Yaw and Heitor S. Pellegrina (2022), ‘From bilateral trade to centralized markets: A search model for commodity exchanges in Africa’, *Journal of Development Economics* **157**.

Omotilewa, Oluwatoba J., Jacob Ricker-Gilbert, John Herbert Ainembabazi and Gerald E. Shively (2018), ‘Does improved storage technology promote modern input use and food security? Evidence from a randomized trial in Uganda’, *Journal of Development Economics* **135**, 176–198.

Porteous, Obie (2019), ‘High Trade Costs and Their Consequences: An Estimated Dynamic Model of African Agricultural Storage and Trade’, *American Economic Journal: Applied Economics* **11**(4), 327–66.

Reardon, Thomas (2015), ‘The hidden middle: the quiet revolution in the midstream of agrifood value chains in developing countries’, *Oxford Review of Economic Policy* **31**(1), 45–63.

Restuccia, Diego, Dennis Tao Yang and Xiaodong Zhu (2008), ‘Agriculture and aggregate productivity: A quantitative cross-country analysis’, *Journal of Monetary Economics* **55**(2), 234–250.

Restuccia, Diego and Raul Santaeulalia-Llopis (2017), Land Misallocation and Productivity.

Shimer, Robert (1996), Contracts in a Frictional Labor Market.

Sotelo, Sebastian (2020), ‘Domestic Trade Frictions and Agriculture’, *Journal of Political Economy* **128**(7), 2690–2738.

Stathers, Tanya, Deirdre Holcroft, Lisa Kitinoja, Brighton M. Mvumi, Alicia English, Oluwatoba Omotilewa, Megan Kocher, Jessica Ault and Maximo Torero (2020), ‘A scoping review of interventions for crop postharvest loss reduction in sub-Saharan Africa and South Asia’, *Nature Sustainability* **3**(10), 821–835.

Wright, Randall, Philipp Kircher, Benoît Julien and Veronica Guerrieri (2021), ‘Directed Search and Competitive Search Equilibrium: A Guided Tour’, *Journal of Economic Literature* **59**(1), 90–148.

A Model

A.1 Lemma 1

Assume that once farmers and traders match, farmers draw a match shock ξ which is drawn from a Beta distribution with shape parameters ϕ, ω. Let profit be given by:

$$\pi(p, x, \xi) = (p_A \xi - p)x$$

For every sub-market p, traders will have a cutoff value of $\bar{\xi}(p)$ below which they will reject any offer. This cutoff will be given by when profit is non-positive:

$$\bar{\xi} = p/p_A$$

Then the traders HJB is

$$\begin{aligned} J^s(p) &= q(\theta(p))E[\max\{J^m(\xi, p) - J^s, 0\}] \\ &= q(\theta(p))E[\max\{(p_A\xi - p)x, 0\}] \\ &= q(\theta(p))\Omega(p)\left[(p_A E[\xi|\xi \geq p/p_A] - p)\, x\right] \end{aligned}$$

where the probability of a trader accepting a harvest in sub-market (p) is

$$\Omega(p) = 1 - F(p/p_A; \omega, \phi)$$

where $F(\cdot)$ is the cdf of a Beta distribution with parameters ω, ϕ. Furthermore, using the properties of the Beta distribution:

$$E[\xi|\xi \geq p/p_A] = \frac{\omega}{\omega + \phi} \times \frac{1 - F(p/p_A; \omega + 1, \phi)}{1 - F(p/p_A; \omega, \phi)}$$

A.2 Lemma 2

The block recursive equilibrium is the solution to the following constrained optimization problem: If $\{p, \theta, c, i\}$ are an equilibrium then they solve:

$$\rho V^s = \max_{c,i} \left\{ u(c) + \delta(i)[V^l - V^s] + \max_p \{ f(\theta(p))\Omega(p)[V^m(p) - V^s]\} \right\} \tag{21}$$

$$\text{s.t} \quad c + p_i i = M \tag{22}$$

$$q(\theta)J^s(p) - \kappa = 0 \tag{23}$$

The solution exists and is unique if the dynamic programming problem is well-defined and satisfies the sufficient conditions in Stokey, Lucas, and Prescott (1989). Specifically,

- The state space of i is $[0, M/p_i]$ which is convex subsets of $\mathcal{R}$. The state space of p is $[0, p_A]$ which is convex subsets of $\mathcal{R}$.
- The feasible set for i_{t+1} is non-empty and compact and is again given by $[0, M/p_i]$. The feasible set of p_{t+1} is non-empty and compact and is again given by $[0, p_A]$.
- The period return function $u(i)$ is continuous and bounded on the feasible set.
- The discount factor is between 0 and 1.

Blackwell's theorem then implies existence and uniqueness.

A.3 Lemma 3

Proof:

1) Part 1 follows directly from the definition of the surplus and the surplus share.

2) The first step relies on the free entry condition of traders. When free entry is satisfied:

$$\theta = q\left(\frac{\kappa}{J^s(p)}\right)^{-1}$$

To see the existence and uniqueness of the solution we can use the following transformation:

$$\begin{aligned} p^* &= \arg\max_p \left\{(V^m(p) - V^s)^\alpha (J^m(p) - J^s)^{1-\alpha}\right\} \\ &= \arg\max_p \left\{\alpha \log(V^m(p) - V^s) + (1-\alpha)\log(J^m(p) - J^s)\right\} \end{aligned}$$

with optimality condition

$$\frac{\alpha}{1-\alpha}\frac{V^{m\prime}(p^*)}{V^m(p^*) - V^s} = \frac{J^{m\prime}(p^*)}{J^m(p) - J^s}$$

Since $u'(\cdot) > 0$, the right-hand side is increasing in p. Furthermore, the left hand side is decreasing in p when $p < p_A$. Thus for p_A large enough, a solution exists and is unique.

3) This follows directly from the definitions of $\theta, f(\theta)$ and $\hat{h}$.

4) Take FOC and re-arrange:

$$p_i u'(M - p_i i) = \delta'(i) V^s$$

The left hand side is decreasing in c and the right hand side is increasing in c, so a solution exists and is unique.

A.4 Lemma 4

Proof: For part 1 of the lemma, since farmers lose their entire harvest, the aggregate fraction of food lost is equal to the fraction of farmers whose goods depreciate before they are matched with a trader. Since farmers are homogeneous, this in turn is equal to the probability of a single farmer losing their entire harvest. Let A be the event that the crops depreciate and let B be the event that a farmer sells to a trader. The two events are independent and distributed exponentially with parameters $\delta, f(\theta)$ respectively. Then the probability that A occurs before B is

$$\begin{aligned} P(A < B) &= \int_0^\infty \int_0^b p(a,b) da db \\ &= \int_0^\infty f(\theta) e^{-f(\theta)b} \int_0^b \delta e^{-\delta a} da db \\ &= \int_0^\infty f(\theta) e^{-f(\theta)b} \left(1 - e^{-\delta b}\right) db \\ &= \frac{\delta}{\delta + f(\theta)} \end{aligned}$$

To derive the expected storage duration and expected shelf life, I again rely on the properties of the exponential distribution. Note the arrival time of storage is distributed exponentially with parameter δ and the arrival rate of matches is distributed exponentially with parameter $f(\theta)$. The expected storage time is equal to the time it takes until either the crops depreciate or the crops are sold. The arrival rate of either storage or crop loss is distributed exponentially with parameter $\delta + f(\theta)$ since the two events are independent and the expected storage duration is $1/(\delta + f(\theta))$. Similarly, the average shelf life is $1/\delta$.

For the second half of the lemma, the first equation directly follows from the definition of expected food loss and expected storage duration. The second equation can be derived as follows:

$$
\begin{aligned}
\text{Fraction Food Loss} &= \frac{\delta^*}{\delta^* + f(\theta^*)} = \frac{\frac{1}{\delta^*+f(\theta^*)}}{\frac{1}{\delta^*}} \\
&= \frac{E[\text{Storage Duration}]}{E[\text{Shelf Life}]} \\
&= \frac{\text{Average Storage Duration}}{\text{Average Shelf Life}} \\
&\equiv \text{Relative Storage Duration}
\end{aligned}
$$

A.5 Algorithm

Since I can write the model as block recursive equilibria, the model can be solved without keeping track of the aggregate distribution. The equilibrium is the solution to the representative agent problem with the appropriate constraints. I therefore solve for the equilibrium using a fixed point strategy akin to value function iteration:

1) Guess V^s.

2) Given V^s,solve for p^*:

$$
p^* = \arg\max_p \left\{ (V^m(p) - V^s)^{\alpha} (J^m(p) - J^s)^{1-\alpha} \right\}
$$

by taking the maximum over a discrete grid of prices $p \in (0, p_A)$.

3) Given p^*, update c':

$$
c^* = \arg\max_c \hat{h}(c)
$$

by taking the maximum over a discrete grid of storage investment strategies $c \in (0, M)$.

3) Update $V^{s\prime}$.

4) If $D(V^s, V^{s\prime}) < \epsilon$ for some $\epsilon > 0$ terminate the algorithm, otherwise repeat steps 2-.4

A.6 Normative Implications

Can the social planner improve welfare by subsidizing storage? I next turn to the problem of the constrained social planner.

Lemma. Assume the social planner takes the search technology, contracting frictions, and the incomplete markets as given. If the social planner cannot make transfers across farmer states, the decentralized equilibrium is constrained efficient.

Proof. See appendix A.4. The intuition for this result stems from the missing asset market. Farmers wish to equalize consumption *across* states, which within-state taxes and transfers can't accomplish. In other words, to improve welfare, storage subsidies need to be financed through state-contingent transfers. If the social planner cannot observe farmer states, is it possible to make state-contingent transfers? Surprisingly, yes. This result relies on two observations. First, farmers only need storage when they are searching for a buyer. And second, when a trader sells to consumers, they must have purchased crops from a farmer. The social planner can therefore implement state-contingent transfers by taxing trader revenue and subsidizing storage. This will reduce farmer consumption once they have matched and will increase consumption while they are searching.

Proof: Assume the social planner can subsidize storage by $1-\tau$ which is financed through a lump sum transfer T out of endowment M such that $T = \tau p_i i$. The first order condition of the farmer with respect to investment is

$$(1-\tau)p_i u'(M - p_i i) = \delta'(i)\, V^s$$

where

$$c + (1-\tau)p_i i \leq M - T$$

The social planner problem is then:

$$\begin{aligned}
\max_{i,p,\tau} \quad & V^s = \frac{1}{\rho + \delta(i) + f(p)}\left(u(M - p_i i) + f(p)u(px)\right) \\
\text{s.t} \quad & (1-\tau)p_i u'(M - p_i i) = \delta'(i)\, V^s \\
& f(p) = \left(\frac{(p_A - p)x}{\kappa}\right)^{\frac{1-\alpha}{\alpha}} \\
& (\rho + \delta(i))[f'(p)u(px)] + (\rho + \delta(i) + f(p))xu'(px)f(p) = 0
\end{aligned}$$

The first order conditions are:

$$
\begin{aligned}
[i]: \quad & \frac{-(\rho+\delta(i)+f(p))p_i u'(M-p_i i)-(u(M-p_i i)+f(p)u(px))\delta'(i)}{(\rho+\delta(i)+f(p))^2} \\
& +\lambda[-p_i u''(M-p_i i)+\delta''(i)p_i(1-\tau)V^s] \\
& +\mu[\delta'(i)f'(p)u(px)+\delta'(i)xu'(px)f(p)]=0 \\
[\lambda]: \quad & p_i(1-\tau)u'(M-p_i i)=-\delta'(i)V^s \\
[\tau]: \quad & -\lambda p_i u'(M-p_i i)=0 \\
[p]: \quad & \frac{(\rho+\delta(i)+f(p))[f'(p)u(px)+xu'(px)f(p)]-f'(p)(f(p)u(px)}{(\rho+\delta(i)+f(\theta(p)))^2} \\
& +\mu((\rho+\delta(i))[f''(p)u(px)+f'(p)u'(px)x]+f'(p)xu'(px)f(p) \\
& +(\rho+\delta(i)+f(p))x[u''(px)xf(p)+u'(px)f'(p)])=0 \\
[\mu]: \quad & (\rho+\delta(i))[f'(p)u(px)]+(\rho+\delta(i)+f(p))xu'(px)f(p)=0
\end{aligned}
$$

The FOC for $[\tau]$ implies that $\lambda=0$. Further substituting the FOC for $[\mu]$ into $[p]$ we have:

$$
\begin{aligned}
[i]: \quad & \frac{-(\rho+\delta(i)+f(p))p_i u'(M-p_i i)-(u(M-p_i i)+f(p)u(px))\delta'(i)}{(\rho+\delta(i)+f(p))^2} \\
& +\mu[\delta'(i)f'(p)u(px)+\delta'(i)xu'(px)f(p)]=0 \\
[\lambda]: \quad & p_i(1-\tau)u'(M-p_i i)=-\delta'(i)V^s \\
[p]: \quad & \mu((\rho+\delta(i))[f''(p)u(px)+f'(p)u'(px)x]+f'(p)xu'(px)f(p) \\
& +(\rho+\delta(i)+f(p))x[u''(px)xf(p)+u'(px)f'(p)])=0
\end{aligned}
$$

which implies $\mu=0$. Then social planner FOC collapse to the same FOC as the farmer.

A.7 Model Extensions.

While the simplicity of the model is illustrative of the role of key mechanisms, the model can be extended along several dimensions.

Search process. The search process can be extended along several dimensions. First, the baseline model does not model quality loss. Although quality loss is hard to measure, one way to measure it is through the fraction of crops that are bruised at the point of sale. Second, the matching function has constant returns to scale. The model can be extended to include matching functions that encompass both decreasing and increasing returns to scale.

Traders. In the model, traders make only two decisions: which sub-market p to enter and whether to accept or reject a harvest. But in practice, traders make ex-ante investments into the type and quality of vehicles and choose the quantity of goods to purchase. Furthermore, traders are often individual enterprises and are thus also risk-averse.

Farmers. In the model, farmers make two choices: storage investment and which market to search in. The model can be extended to include the choice of capital and labor inputs. Endogenizing the quantity produced will generate feedback between the quantity produced, the storage investment, and the coordination frictions. This will act as a source of misallocation because risk-averse farmers will reduce output to minimize their market exposure. Moreover, the model's treatment of farmer consumption, home production, and investment endowment is superficial. Farmers often consume a portion of the crops they grow and sell the rest.

Price Dynamics. One motive for storage not considered in this paper is the incentive to wait for higher prices. Harvest times are often correlated across farmers, generating large shocks to supply with no shocks to demand. This results in price fluctuations - when many farmers harvest prices are low, and when few farmers harvest prices are high. Farmers who invest in better storage can wait to sell until prices increase.

B Data

B.1 Aggregate data

Cross-country food loss data is available annually from 2011 to 2021 through the Food and Agriculture Organization of the United Nations (FAO), which constructs food balance sheets tracking food supply and utilization by crop and country. The food balance sheets include measures of agricultural yields (tonnes per hectare of area cultivated), food availability for consumption (grams per person per day), food supply variability (the standard deviation in annual per capita food supply), and food loss (percent of domestic supply lost from harvest up to retail).

Cross-country food loss estimates should be interpreted with caution. Yearly measurements of food loss by country, crop, and stage of the value chain are generally not available, so losses are often imputed via a small number of case studies extrapolated across time and space. Moreover, food loss encompasses the degradation in both quantity and quality of food. But due to the difficulty in measuring quality, cross-country estimates primarily incorporate changes in quantity. A series of follow-up surveys from the International Food Policy Research Institute (IFPRI) attempts to overcome both the extrapolation and measurement issue by surveying a small subset of countries and crops[31]. They conclude that FAO statistics overestimate physical loss and underestimate quality loss.

I incorporate additional data on country-level agricultural productivity from the World Bank and the International Labour Organization.

B.2 Cross Country Patterns

I first document cross-country patterns in food loss in the FAO data. Food loss is a worldwide phenomenon (see Figure 1 for a map of food loss by country). However, food loss is of particular concern for developing economies, since the share of food loss is decreasing with GDP[32]. Figure 11 documents a strong negative relationship between the share of food lost in the fruit supply chain and GDP - for every 1% increase in GDP per capita, the fraction of food loss decreases by 1%[33]. Yet with cross-country evidence alone, it is difficult to attribute food loss to a specific set of mechanisms. Variation in GDP is correlated with multiple factors that may affect food loss, such as farm size[34] and road density[35]. To make progress, I document specific features in Ghana's fruit and vegetable wholesale markets that affect food loss.

B.3 Survey Construction

The sample size was determined to achieve a 95% confidence level with a 5% margin of error, accounting for the total population sizes of farmers and traders. The formula used to

[31]IFPRI's survey studies food loss in the potato, maize, beans, teff, and wheat value chains of Ecuador, Peru, Guatemala, Honduras, Ethiopia, and China.

[32]Food loss is doubly a concern because agriculture accounts for a larger share of GDP in developing economics. In Figure 12, I reproduce a well-known result: lower-income countries also have a higher share of employment in agriculture, which amplifies the welfare consequences of food loss

[33]Food loss has two first-order economic effects. First, food loss decreases farmer welfare. Farmers who lose crops miss out on potential income. Figure 13a shows that food loss is negatively correlated with per-capita value added in agriculture, suggesting that food loss may contribute to the agricultural productivity gap. Second, food loss decreases consumer welfare. Food loss decreases the availability of perishable crops necessary for a healthy diet. Figure 13b shows that food loss is positively correlated with food insecurity. The cross-country food loss patterns suggest that understanding the sources of food loss and potential policy remedies may be crucial to improving welfare in developing economies and resolving the agricultural productivity gap.

[34]A negative effect of farm size on food loss is consistent with a misallocation story. Foster and Rosenzweig (2022) argue that small farm size contributes to the low levels of mechanization in developing countries.

[35]See figures 13c and 13d respectively in the appendix.

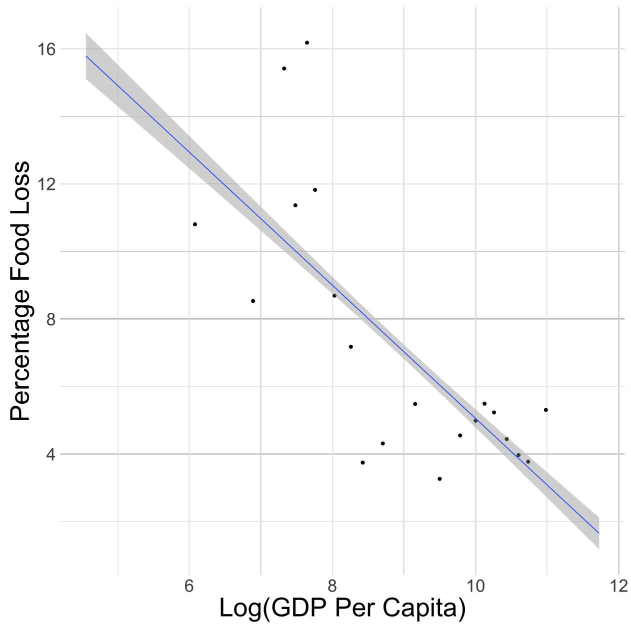


Figure 11: Food Loss vs GDP Per Capita

Notes. Binscatter of the percent of food lost in fruit supply chains in 2015 by log of GDP per capita. Each observation is the percent of food loss by country. Data is from the FAO. Food loss is imputed from food balance sheets and includes losses from the farming stage up-to transportation and distribution. Outliers are dropped.

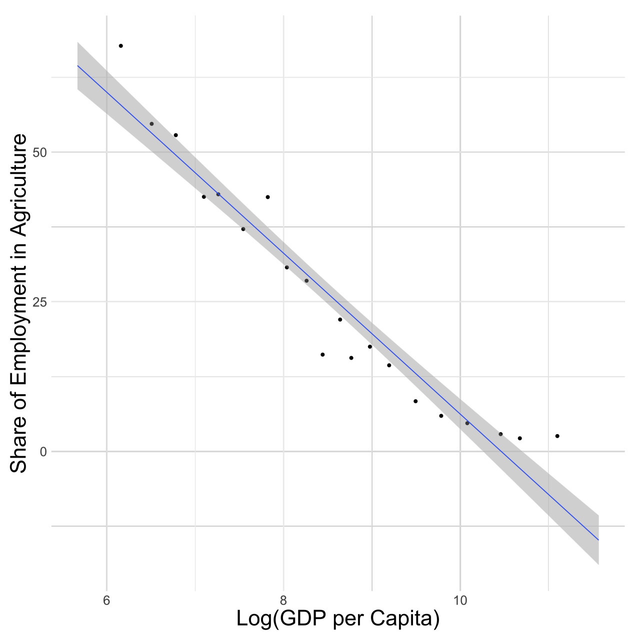
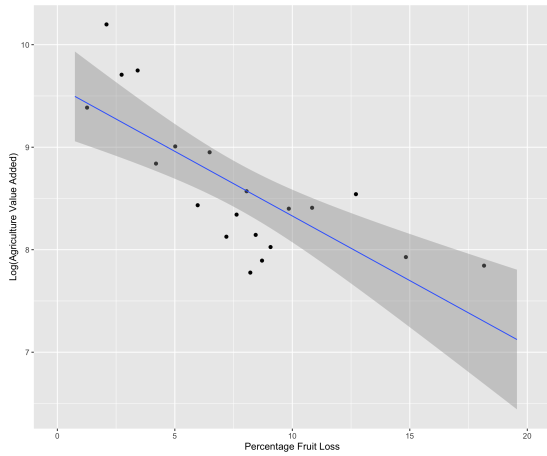
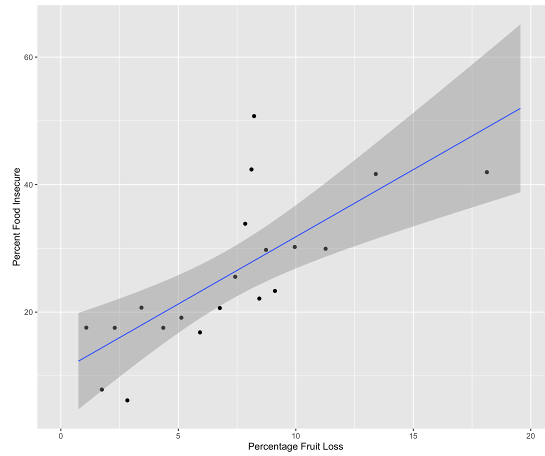


Figure 12: Food Loss vs Agricultural Employment Share

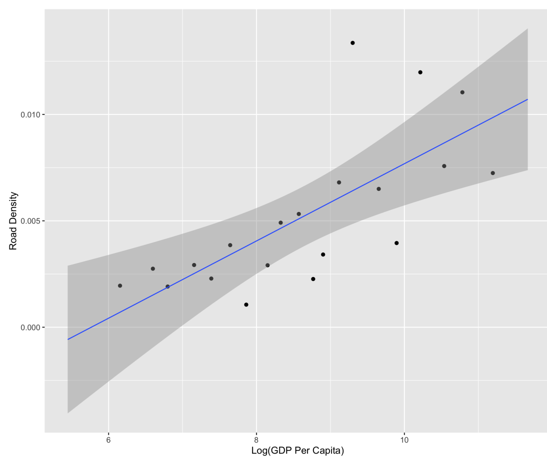
Notes. Binscatter of the agricultural employment share by log of GDP per capita in 2015. Each observation is the employment share by country. Data is from the FAO. Outliers are dropped.



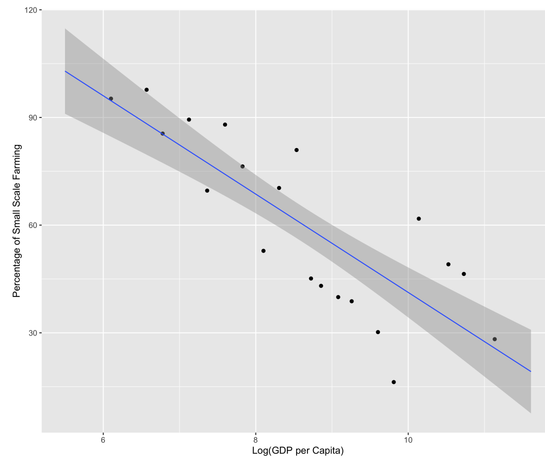
(a) Agricultural Value Added vs Food Loss



(b) Food Insecurity vs Food Loss



(c) GDP vs Road Density



(d) GDP vs Farm Size

Figure 13: Cross Country Food Loss Patterns

Notes. Binscatters of agricultural value added, food insecurity, road density, and percentage of small scale farming plotted against GDP per capita and the percent of food loss. Each observation is a country in 2015. Data is from the FAO.

estimate the population size is

$$n = \frac{z^2 \rho(1-\rho)}{E^2}$$

where n is the sample size, z is the desired confidence level, E is the margin of error, and ρ is the estimated proportion of the population that is a farmer or trader respectively. For farmers, we let $\rho = 0.32$, which is the fraction of the population in Ghana engaged in agriculture according to recent estimates from the Ghana Statistical Service. This yields a sample size of $n = 352$ per region. The fraction of the population engaged in trading is not reported, but trading and storage account for approximately 5% of Ghana's GDP, so we let

$\rho = 0.05$, which yields a sample size of $n = 76$ per region.

I increased the sample size to 450 farmers and 100 traders per region for several reasons. First, increased precision: a larger sample size reduces the margin of error and increases the precision of survey results. Second, sub-group analysis: a large sample size enables detailed analysis within sub-groups, such as analysis of food loss within different districts or across crop types and farm sizes. Third, diversity and variability: a larger sample size captures a wider diversity and variability in farming and trading practices. Fourth, non-response and attrition: a larger sample size accounts for potential non-response and attrition rates. Finally, policy relevance: a larger sample size provides more robust data to inform decision-making processes.

B.4 Food Loss in Ghana

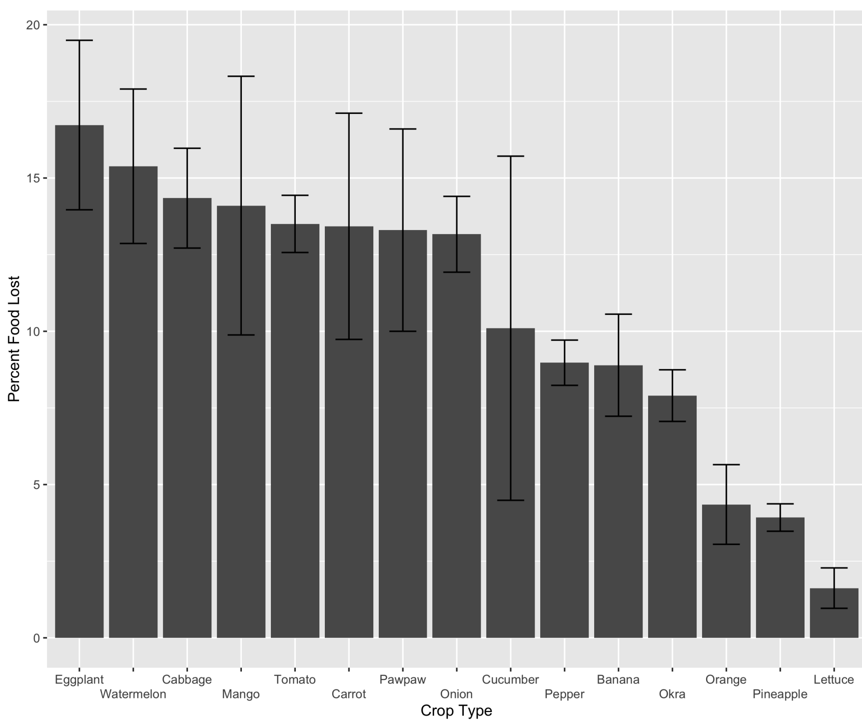


Figure 14: Percentage Food Loss by Crop

Notes. Average food loss and standard deviation by crop among farmers. Data is from the Ghana farmer survey. Outliers are dropped.

B.5 National Transportation Survey

In Table 9, I show summary statistics from the 2007 and 2012 National Transport survey from the Ghana Statistical Agency. In both surveys, the majority of farmers sell at either

Table 8: Farmer Beliefs About Market Conditions

	Farmer Beliefs				
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Panel A. Market Conditions					
Easy to find buyers	0.05	0.12	0.06	0.56	0.20
Delay harvesting or selling to find buyers	0.19	0.49	0.09	0.20	0.04
Crops perish while finding buyers	0.18	0.45	0.08	0.24	0.05
Traders prefer larger quantities	0.13	0.36	0.10	0.27	0.13
Traders pay more for larger quantities	0.18	0.53	0.10	0.13	0.04
Traders prefer farms closer to markets	0.12	0.32	0.13	0.33	0.08
Traders pay more when farms are closer to markets	0.16	0.46	0.14	0.19	0.03
Traders prefer less storage time	0.07	0.23	0.13	0.40	0.18
Traders pay more for less storage time	0.10	0.37	0.14	0.27	0.11
Panel B. Difficulty Cooperating with other farmers					
Farms are far away	0.08	0.23	0.11	0.42	0.15
Can't agree on price	0.10	0.31	0.11	0.36	0.13
Can't settle disagreements	0.17	0.41	0.19	0.19	0.05
Crops aren't ready at the same time	0.08	0.29	0.15	0.37	0.11

Notes. Summary Statistics about farmer beliefs on food loss and market conditions. Farmers were asked to rate on a Likert scale whether they agreed or disagreed with a particular statement. Rows may not sum to 1 due to rounding.

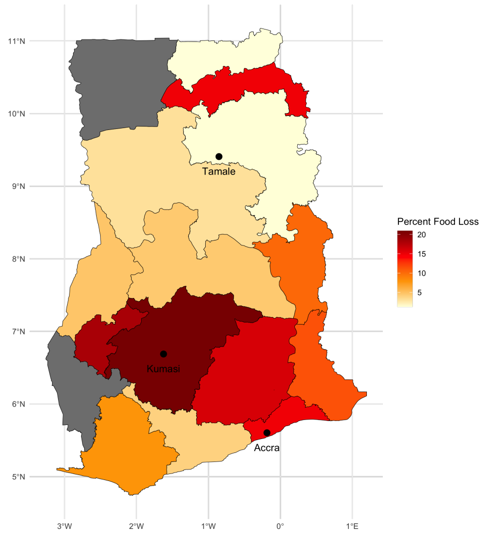


Figure 15: Map of Food Loss in Ghana

Notes. Average food loss by region in Ghana. Data is from the Ghana farmer survey. Longitude and latitude from interviews with farmers are mapped to regions and then averaged.

the farm gate or at the local market, have a market within 3km, and have a road that is not accessible during the rain. Similarly, in both surveys, approximately one-third of respondents report difficulty in selling their crops. Importantly, limiting the food loss survey sample to farmers who sell their crops does not seem like an egregious restriction; in the 2012 round of the National Transport Survey, almost 80% of farmers participated in the market.

B.6 Model Consistent Estimation

I extend the analysis by estimating δ^* for all crops, only tomatoes, and only okra. I report the results in appendix tables 10, 11, and 12, respectively. As with the pepper farmers, the OLS estimates are a magnitude lower than the IV estimates. The IV estimates of δ^* for all crops farmers are higher than the full sample and imply an average shelf life of 4 months as opposed to 6 months. When I subset to only tomato or okra farmers, I lack the power to estimate δ^* when I control for farmer characteristics. However, in the baseline specification, I find an implied equilibrium shelf life of 0.25 months for tomatoes and 1.5 months for okra.

As a robustness check, I extend the regression of food loss on relative storage duration to all crops, tomatoes, and okra. I report the results in appendix Tables 13, 14, and 15, respectively. Although the coefficients are statistically different than 0 and the regressions have a large R^2, I reject the hypothesis that estimates are equivalent to one. The lack of an exact fit is likely the result of two factors. First, measurement error. Farmers are asked to estimate the average amount of time they store their crops. However, this is not a statistic

Table 9: Summary Statistics of Farmer Transportation and Marketing Practices

	2007 Survey	2012 Survey
# Observations	3232	3913
Frac Farmers Selling Crops	0.77	0.69
Frac Selling in Local Mkt	0.62	0.37
Fraction Selling in Distant Mkt	0.25	0.44
Fraction Selling at Farmgate	0.11	0.17
Fraction with market < 3km	0.65	0.59
Fraction difficulty marketing	0.33	0.23
Fraction with road < 3km	0.73	0.75
Fraction with road that is unmotorable during rainy season	0.76	0.82
Fraction with road that is unmotorable during dry season	0.52	0.65
Fraction with daily transport during harvest	0.32	0.3
Fraction with weekly transport during harvest	0.54	0.57
Fraction with daily transport during lean season	0.21	0.25
Fraction with weekly transport during lean season	0.53	0.49

Notes. Data is from the 2007 and 2012 National Transport Survey run by the Ghana Statistical Agency.

Table 10: Effect of Storage Duration on Food Loss - All Crops

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Average Storage Duration	0.39***	0.15***	4.21***	2.90***
	(0.05)	(0.04)	(0.42)	(0.72)
Implied Shelf Life (Months)	30	80	3	4
Observations	1,813	1,813	1,813	1,813
Controls		✓		✓
R^2	0.03	0.28	−3.34	−1.34
Adjusted R^2	0.03	0.28	−3.34	−1.34
Residual Std. Error	0.18	0.15	0.38	0.28
F Statistic	65.68***	177.03***		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. The sample includes all farmers. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for all crops. Coefficients in columns (3) and (4) are estimated via two-stage least squares for all crops, where average storage duration is instrumented by distance to the market. *p<0.1; **p<0.05; ***p<0.01

Table 11: Effect of Storage Duration on Food Loss - Tomatoes

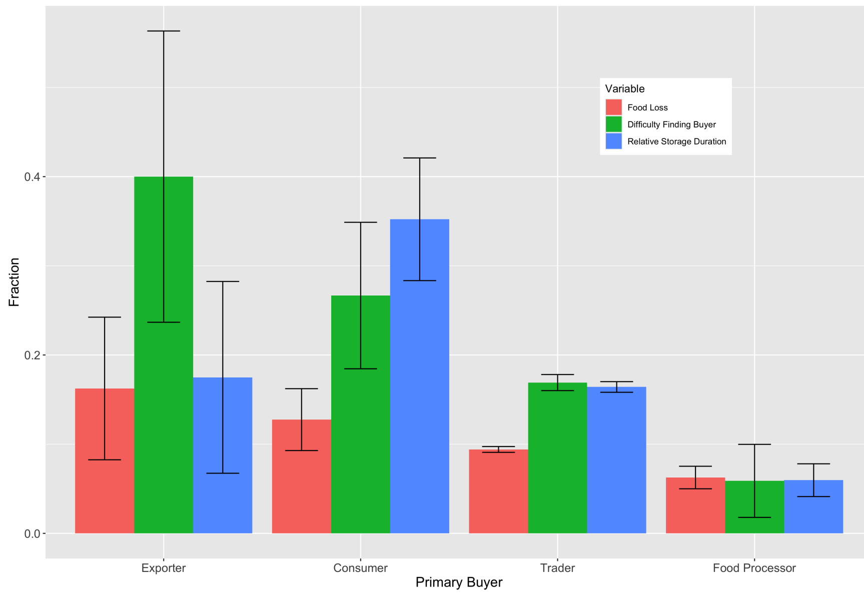
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Average Storage Duration	3.9***	1.2	48.6***	26.4
	(1.1)	(0.9)	(12.7)	(21.6)
Implied Shelf Life (Months)	3	10	0.25	0.5
Observations	321	321	321	321
Controls		✓		✓
R^2	0.04	0.4	−5.0	−1.1
Adjusted R^2	0.04	0.4	−5.1	−1.2
Residual Std. Error	0.2	0.2	0.5	0.3
F Statistic	13.2***	52.0***		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. The sample includes only tomato farmers. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for all crops. Coefficients in columns (3) and (4) are estimated via two-stage least squares, where average storage duration is instrumented by distance to the market. *p<0.1; **p<0.05; ***p<0.01

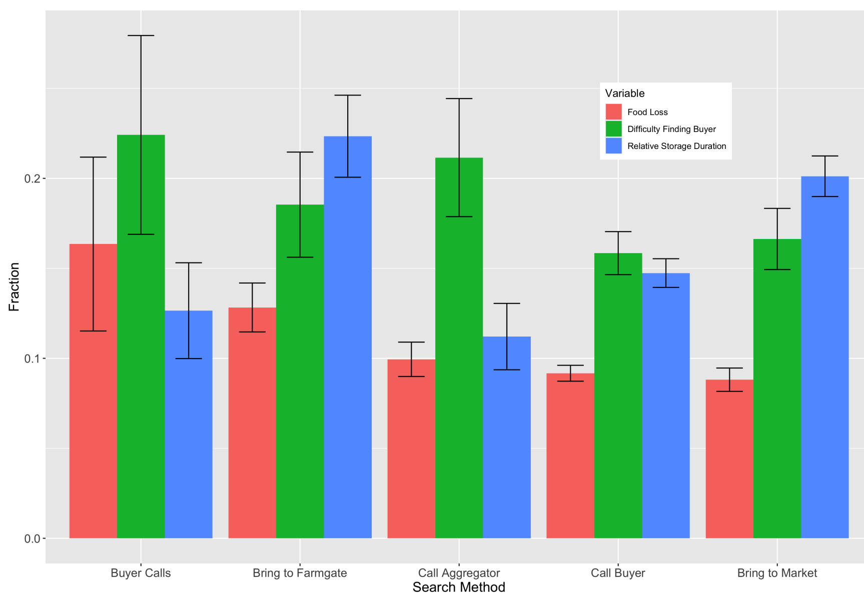
Table 12: Effect of Storage Duration on Food Loss - Okra

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Average Storage Duration	0.7**	0.1	7.7***	−2.1
	(0.3)	(0.3)	(2.3)	(5.2)
Implied Shelf Life (Months)	17	120	1.5	
Observations	213	213	213	213
Controls		✓		✓
R^2	0.02	0.3	−1.9	0.1
Adjusted R^2	0.02	0.3	−2.0	0.1
Residual Std. Error	0.1	0.1	0.3	0.1
F Statistic	4.9**	20.3***		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. The sample includes only Okra farmers. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for all crops. Coefficients in columns (3) and (4) are estimated via two-stage least squares, where average storage duration is instrumented by distance to the market. *p<0.1; **p<0.05; ***p<0.01



(a) Food Loss by Primary Customer



(b) Food Loss by Search Method

Figure 16: Food Loss by Market

Notes. Average fraction of food loss, fraction of farmers who report difficulty in finding a buyer, and the relative storage duration (average duration divided by maximum shelf life) by primary buyer and search method. Data is from the Ghana farmer survey.

they generally track. Furthermore, if they can sell their crops, they do not observe their crops' full shelf life. The reported value is their best guess at how long their crops could last. Second, model misspecification. The Poisson process used to model the depreciation process is memoryless; this may not be the case in practice and the depreciation rate can

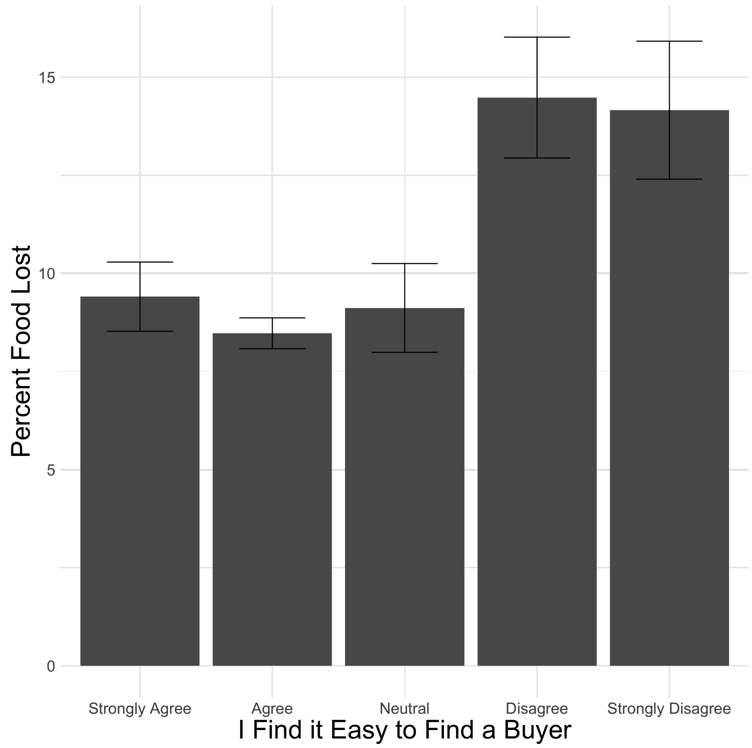


Figure 17: Food loss by ease of finding a buyer

depend on the contemporaneous quality of the crop. Crops also depreciate gradually, which the model abstracts away from.

Table 13: Effect of Relative Storage Duration on Food Loss - All Crops

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Relative Storage Duration	0.35^{***}	0.11^{***}	0.60^{***}	0.51^{***}
	(0.02)	(0.02)	(0.03)	(0.15)
Observations	1,637	1,637	1,272	1,272
Controls		✓		✓
R^2	0.17	0.31	0.11	0.19
Adjusted R^2	0.17	0.31	0.10	0.18
Residual Std. Error	0.15	0.14	0.16	0.15
F Statistic	337.97^{***}	185.35^{***}		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. The sample includes all farmers. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for all crops. Coefficients in columns (3) and (4) are estimated via two-stage least squares for all crops, where average storage duration is instrumented by distance to the market. *p<0.1; **p<0.05; ***p<0.01

Table 14: Effect of Relative Storage Duration on Food Loss - Tomatoes

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Relative Storage Duration	0.46***	0.02	0.68***	−0.31
	(0.07)	(0.07)	(0.10)	(0.45)
Observations	303	303	219	219
Controls		✓		✓
R^2	0.14	0.39	0.19	0.26
Adjusted R^2	0.14	0.39	0.18	0.25
Residual Std. Error	0.19	0.16	0.17	0.16
F Statistic	50.30***	48.68***		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. The sample only includes Tomato farmers. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for all crops. Coefficients in columns (3) and (4) are estimated via two-stage least squares, where average storage duration is instrumented by distance to the market. *p<0.1; **p<0.05; ***p<0.01

Table 15: Effect of Relative Storage Duration on Food Loss - Okra

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Relative Storage Duration	0.29***	0.13**	0.37***	0.13
	(0.04)	(0.05)	(0.06)	(0.27)
Observations	179	179	161	161
Controls		✓		✓
R^2	0.21	0.30	0.25	0.34
Adjusted R^2	0.21	0.28	0.24	0.32
Residual Std. Error	0.13	0.12	0.12	0.11
F Statistic	48.25***	18.48***		

Notes. The dependent variable is the fraction of food lost and the independent variable is the average storage duration measured in years. The sample only includes Okra farmers. Controls include farmer age, the number of family members, and plot size. Coefficients in columns (1) and (2) are estimated through ordinary least squares for all crops. Coefficients in columns (3) and (4) are estimated via two-stage least squares, where average storage duration is instrumented by distance to the market. *p<0.1; **p<0.05; ***p<0.01

B.7 Example of Pepper Drying

Figure 18: Pepper Drying Operation

Notes. A photo of pepper drying in Ghana's Volta region near Ayitepa. Peppers are placed on plastic tarps and exposed to the sun for multiple days. Rain or pests can cause large losses. Once dried, the peppers are then often boiled and ground into a powder.