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PhD thesis

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Essays on risk management of natural resources in developing countries

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Contents

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Summary (English)

This thesis consists of 4 self-contained papers, all examining how production risk from natural shocks affects decisions regarding the management of natural resources and agriculture in a developing country context. This challenge is addressed empirically using different rigorous microeconometric approaches. Three of the chapters investigate households' risk-management strategies in resource-based activities, while a fourth chapter focuses on market functioning at the face of climate shocks. The first chapter is developed on the basis of a unique census data from artisanal fisheries in Chile. The objective is to examine the mechanisms by which revenues are distributed to labor and capital, and how these distributions affect fishing returns. The results support mechanisms associated with bargaining power, monitoring costs and outside options, and also reveal higher fishing return with larger crew profit shares. Effects seem to differ across fisheries. The second chapter uses a balanced panel of rural households from Mozambique to provide an empirical examination of the impact of weather shocks on crop portfolio choices as well as on the persistency of these changes. Results indicate that crop choice is sensitive to past weather shocks, and reallocation seems temporary. This is consistent with a self-insurance approach and buffer stock arguments. The third chapter employs rural household data of rice producers from Vietnam to examine the risk effect of pesticide use. Results reveal that higher uncertainty regarding rainfall relative to pest may cause pesticide use is to exhibit risk-increasing characteristics. This finding is consistent across a lottery and a production function approach. The fourth chapter studies the link between spatial market efficiency and weather shocks using market price and transport cost data from Mozambique. Results indicate that price dispersion is lower during drought period and higher after a flood. This finding is consistent with a supply shock after a drought and a food transport shock emerging after a flood. Moreover, flood effects are larger among closer markets and connected with poorer infrastructure.

Resumé (Danish)

Denne afhandling består af fire selvstændige artikler, som alle undersøger, hvordan produktionsrisici, stammende fra stød fra naturens hånd, påvirker beslutninger angående styringen af naturressourcer og landbrug i en udviklingskontekst. Denne udfordring gribes empirisk an fra forskellige tilgange ved hjælp af mikroøkonometriske metoder. Tre af kapitlerne udforsker husholdningers risikostyringsstrategier ved ressourcebaserede aktiviteter, mens et fjerde kapitel fokuserer på markedsforhold i lyset af klimastød. Det første kapitel er udviklet på grundlag af et unikt datasæt om ikke-industrielt fiskeri i Chile. Målet er at undersøge mekanismerne, hvorved indtægter fordeles mellem arbejdskraft og kapital, og hvordan denne fordeling påvirker indtjeningen ved fiskeri. Resultaterne understøtter mekanismer, som forbindes med forhandlingsstyrke, overvågningsomkostninger og alternative beskæftigelsesmuligheder og afslører desuden større indtjeningved højere profitandele til besætningen. Effekterne synes dog at variere mellem fiskerier. Det andet kapitel bruger et balanceret panel af husholdninger fra Mozambiques landdistrikter til en empirisk undersøgelse af effeckten af vejrstød på valget af afgrøder såvel som persistensen af disse ændringer. Resultaterne indikerer, at valget af afgrøder er følsomt over for tidligere vejrstød og reallokering synes midlertidig. Dette er konsistent med en selvforsikringstilgang samt brugen af lagrede afgrøder som en buffer. Det tredje kapitel benytter husholdningsdata for risproducenter fra landdistrikter i Vietnam til at undersøge effekten på risiko ved pesticider samt kilden til denne risiko. Resultaterne afslører, at pesticider øger risici pga. større usikkerhed ved nedbør relativt til skadedyr. Dette fund er konsistent i forhold til både en lotteri- og produktionsfunktionstilgang. Det fjerde kapitel undersøger forbindelsen mellem spatial markedseffektivitet og vejrstød ved brug af markedspriser og transportomkostningsdata fra Mozambique. Resultaterne indikerer, at prisspredningen er lavere under en tørkeperiode og højere efter en oversvømmelse. Dette fund er i overensstemmelse med et udbudsstød efter en tørke og et fødevaretransportstød efter en oversvømmelse. Derudover er effekterne af en oversvømmelse større mellem markeder der ligger tæt på hinanden og er desuden forbundet med dårligere infrastruktur.

Chapter 1

Introduction

In agriculture and extractive activities, the quality and quantity of output are not known with certainty due to random factors underlying the production process. Production uncertainty is generally associated with fluctuating climate conditions, economic oscillations, policy uncertainty and individual-specific shock (Bardan and Udry, 1999; Dercon, 2002). In this context, decision making under uncertainty is characterized by risk because some possible outcomes have undesired effects. In particular, the incidence of natural hazards may lead producers to harvest failure, and more volatile market prices, with important implications for production and input decisions. This is aggravated in developing countries because credit and insurance markets are incomplete, asset holdings are limited and economies relies more on natural resources-based activities. Consequently, ex post coping mechanisms cannot be totally relied upon to protect against these exogenous shocks (Paxson, 1992; Townsed, 1994). Furthermore, poor functioning of markets make little in ameliorating the impact of climate shocks. Thus, population in developing countries tends to be more vulnerable to natural shocks, and more dependent on ex-ante risk management strategies.

This thesis consists of four self-contained research papers in which I (and my co-authors) employ microeconometric methods to provide novel and empirical evidence to understand how production risk from natural shocks in resources-based activities relates to household risk-behavior and market functioning in developing countries. While all the chapters include elements of risk, the three first chapters follow closely the literature of risk-taking behavior, focusing on household-individual outcomes. The last chapter explores market functioning, instead. Chapter 2 conducts an empirical analysis using the fisheries sector as case. Chapters 3, 4 and 5 document empirical evidence focusing on agriculture. While Chapter 2 studies the importance of the remuneration regime in fisheries under risk sharing and moral hazard arguments, Chapters 3 and 4 examine the role of risk in output and input decisions as ex-ante risk management strategies in agriculture. Chapter 5 discusses the importance of agricultural market efficiency to enhance resilience to natural shocks.

Chapter 2, "*Share Contract Choices and Economic Performance. Empirical Evidence From the Artisanal Fisheries Sector in Chile*" (published in Marine Resource Economics 30(1):71-95, 2015) investigates the mechanisms by which fishing revenues are distributed to labor and capital, and how these distributions affect fishing returns in Chilean artisanal fisheries. The literature is extensive in assessing incentives involved in sharecropping land tenancy and testing it against alternative remuneration regimes. Yet, empirical evidence in fisheries is almost non-existent. This limited literature focus on one species and assume a binary status for the share contract regime. I instead exploit the variation in crew profit shares and introduce the analysis of multiple species to explore divergence across fisheries. I use the generalized propensity score (GPS) methodology and the dose-response function approach to estimate the marginal effects of changes in crew profit shares on economic performance. The results support share contract choices based on bargaining power, monitoring costs, technology, state of fishing resources, and outside option arguments. I find significant effects of increasing crew profit shares on vessel owner returns. The results are robust in fisheries with limited observability of labor efforts.

Chapter 3, "*Weather Shocks and Cropland Decisions in Rural Mozambique*", (joint with Sam Jones and Finn Tarp, accepted for publication in Food Policy) provides an empirical examination of the impact of weather shocks (drought and flood) on crop portfolio choices as well as on the persistence of these portfolio changes of small-scale farmers in Mozambique. We rely on external data on water availability to distinguish between drought and flood events, as opposed to self-reported data. We also account for the bounded nature of land shares and estimate a Pooled Fractional Probit (PFP) model. Our results show that crop choice is sensitive to past weather shocks. Farmers shift land use away from cash and permanent crops one year after a drought and from horticulture and permanent crop after a flood. However, this reallocation seems temporary as farmers devote less land to staples after two periods. This is consistent with the aim of maintaining a buffer stock of staples for home consumption.

Chapter 4, "*Pesticide Use and Agricultural Risk. The Case of Rice Producers in Vietnam"* (joint with John Rand) examines the risk effect of pesticide use by applying a lottery in combination with a production function approach using a dataset of rice producers in Vietnam. We also investigate the source of this risk by comparing pesticide productivities under pest and water shortage events. Production function results show that an increase in pesticide use can make production more risky. This result is supported by the lottery approach showing that more risk averse farmers use less pesticide, implying that pesticide is a risk-increasing input. Our results suggest that higher rainfall uncertainty (relative to pest) is likely to drive the risk increasing effect.

of pesticides. This highlights the importance of considering multiple uncertainties when determining risk properties of agricultural inputs.

Chapter 5, "*Weather Shocks and Spatial Market Efficiency: Evidence from Mozambique*" (joint with Hailemariam Ayalew and Peter Fisker) studies the association between weather shocks and agricultural market performance in Mozambique. Employing dyadic regression analysis and using data on monthly maize prices, transport costs and spatial identification of droughts and flooded areas, results show differentiated effects across weather shock types. While price differences reduce during drought periods, suggesting a supply shock effect, price dispersion increases after a flood, along with increases in food transport costs. Results also reveal some heterogeneity. Floods are found to increase price dispersion more in areas where markets are closer to each other and in locations that have poorer transport infrastructure.

Chapter 2

Share Contract Choices and Economic Performance. Empirical Evidence from the Artisanal Fisheries Sector in Chile.

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Abstract

Typically, crew members in fisheries are remunerated through a share of the total revenues. However, there is little empirical evidence on the mechanisms by which revenues are distributed to labor and capital, and how these distributions affect economic performance. Under an agency problem framework, we estimate a dose-response function to study the formation of contracts and identify the marginal effects of changes in crew profit shares on fishing returns in Chilean artisanal fisheries. The results support share contract choices based on bargaining power, monitoring costs, technology, state of fishing resources, and outside options. We find significant effects of increasing crew profit shares on vessel owner returns in the interval (0.25, 0.65). The results vary across fisheries, however. While the effects are not significant in the fish group, they are larger and robust for molluscs and crustaceans. The latter finding is expected given the differences in the observability of effort across fisheries.

Key words: Artisanal fisheries, share contracts, remuneration regime, continuous treatment effects.
JEL classification: Q22, D86, D13.

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1 Introduction

The share contract remuneration system is broadly adopted in activities that involve the exploitation of natural resources such as agriculture, mining, and fishing. In particular, share contracts are almost the universal form of remuneration in fisheries. Under this regime, a vessel owner's and crew earnings are tied to crew effort, state of the natural environment, and the proportion of the catch value given to the crew. In a context of high uncertainty, missing insurance markets, and substantial supervision cost, share contracts are superior to other remuneration regimes in coping with both production risk and opportunistic behavior (Platteau and Nugent, 1992). The literature is extensive in assessing incentives in the form of both risk sharing and agency problems involved in sharecropping land tenancy and testing its potential inferiority[1] over alternative regimes. [2] Yet, empirical evidence in fisheries is almost non-existent. Exceptions are the works by Nguyen and Leung (2009) and Thuy et al. (2013). Unlike these previous studies, in which the share system is assigned a binary status as compared to a fixed wage regime, we exploit the continuity in our data by observing crew profit shares in order to understand the mechanism by which revenues are distributed to labor and capital owners and how these distributions affect economic performance. The latter is more in line with theoretical models, which predict that the greater the proportion of crew profit, the larger the vessel owner profit will be (McConnell and Price, 2006). Furthermore, rather than focusing on one particular species, we take advantage of the richness of a unique census data from artisanal fisheries in Chile to introduce the analysis of multiple species and explore divergence across fisheries (INE, 2009). Additionally, treating the share contract variable as continuous may also uncover potential non-linear effects and shed some light on optimal levels of crew profit. We use the generalized propensity score (GPS) methodology and the dose-response function approach, as suggested in Hirano and Imbens (2004), to calculate the marginal effects. Given the fractional nature of our profit share variable, we employ the Fractional Logit model proposed by Papke and Wooldridge (1996) to compute the propensity scores. This new, novel methodology has not been applied in fisheries economics.

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[1] Earlier, Marshall (1920) suggested that agrarian share contracts are inefficient compared with owner-operated land farming, which has been named by the share contract literature as "the Marshallian inefficiency." However, lately this statement has been conditioned on the magnitude of the monitoring and enforcement costs borne by the landlord (Johnson 1959; Cheung 1969).

[2] For more information, see Allen and Lueck (1992); Allen and Lueck (1999); Ackerberg and Botticini (2000), Ackerberg and Botticini (2002); Dubois (2002); Pandey (2004); Pender and Fafchamps (2005); Arcan, et al. (2007); Jacobsy and Mansuri (2009); and Bellemare (2009).

The rest of the article is structured as follows: Section 2 describes the fisheries sector and briefly exposes general aspects of the regulation and functioning of share contracts in Chile. Section 3 presents the theoretical approach that underlies share contract decisions and the labor-enhancing mechanism. Section 4 introduces the empirical strategy to estimate a continuous treatment effect; and Section 5 the data used to carry out this study. Finally, Section 6 discusses the main results; and Section 7 concludes.

2 Description of the fisheries sector in Chile

Chile is rich in marine resources. Fisheries are the third most important exporting sector, contributing to 1.2% of gross domestic product and generating around 2% of total employment. It is officially divided in two sectors: the industrial and the artisanal, or small-scale. While the industrial sector represents 69% of total national landings and almost all fishes, the artisanal sector contributes with a greater variety of resources, including fishes and benthic resources, accounting for 13% of total volume.[3] The pelagic fisheries are multispecies, with the jack mackerel (*Trachurus symmetricus*) as the predominant species. Other relevant species are the common sardine (*Strangomera bentincki*), anchovy (*Engraulis ringens*), and South Pacific hoki (*Macruronus magellanicus*). The Chilean hake *(Meluccis gayi gayi)* is the main species exploited in the demersal fisheries. Pelagic and demersal fisheries are exploited by both industrial and artisanal fishers. In contrast, exploitation of benthic resources is almost exclusively undertaken by artisanal fishermen. The main benthic species are the Chilean abalone (*Concholepas concholepa)*, blue mussels (*Aulacomya ater*), and the Chilean wedge clam (*Tagelus nombeii*).

The extraction of marine resources in Chile is regulated by the General Law of Fishing and Aquaculture (GLFA).[4] In addition to traditional regulatory instruments, such as the annual total allowable catch (TAC), temporal closure, minimum size, etc., this law contains important innovations in the management of the fisheries sector. These are the benthic resource management and exploitation area (BRMA), maximum harvest limits (MHL), and the AER (artisanal extractive regime). The BRMA basically allocates exclusive rights for fishermen' organizations to use and exploit benthic resources within five miles of the coast, or in inland and interior waters

[3] In spite of this lower participation, the artisanal sector generates a number of jobs similar to the industrial sector and constitutes the main source of direct income for approximately 75,000 households (INE, 2009).
[4] General Law of Fishing and Aquaculture. Law No.18.892 of 1989 and its modifications: Laws No.19.079 and 19.080, both of 1991, and Law No 20657 of 2013. In Spanish ''Ley General de Pesca y Acuicultura (LGPA).

(SUBPESCA, 1995). The MHL is basically an individual quota system with limited transferability aimed at creating and allocating individual use rights among vessel owners of the industrial fleet operating over main pelagic and demersal species. Finally, the AER system assigns collective quotas per area or fishermen organization, allowing great autonomy on distribution, use, and control of their collective quotas. These regulations have been ratified in recent modifications introduced in the GLFA by the Law No. 20,657 enacted on January 31, 2013. Furthermore, for the first time, this new law explicitly regulates the contractual relationship between a vessel owner and crew members. The incorporation of this section in the GLFA recognizes the need and importance of regulating share contracts, giving support for studies addressing the formation of contracts and their economic implications.

The share contract system diverges between industrial and artisanal fisheries. While the crew in the industrial sector is remunerated with a combination of a fixed wage per hour and percentage participation in the total catch, artisanal vessel owners mainly use share contracts to reward labor efforts. According to the latest figures of the fishing census, a fraction of less than 2% of vessel owners pay fixed wages, and quite few of them adopt fixed rent contracts (INE, 2009). Thus, share contracts are almost the universal remuneration mechanism in artisanal fisheries. Under this scheme, vessel owners and crew member prior to the start of the trip, determine how to distribute the results of the fishing operation, which will depend on the contribution of each party. This way the revenues (after fuel and food expenses are deducted),[5] are divided among the vessel owner and crew members.[6] If, for instance, the capital owner directly participates in extractive activities onboard, he will take a proportion of the share that goes to the crew. Commonly, vessel owners contribute not only with capital, but also with their expertise as manager-skippers of the boat.

3 Theoretical approach to the choice of contractual forms

3.1 Literature review

Many settings that involve production decisions are characterized by asymmetric information and production risk. Contract theory rises as a result of needs for formalizing these two features, as often observed in agrarian contracts (Cheung, 1969; Stiglitz, 1974). In the sharecropping case, the

[5] The deduction of operating costs before distributing gains further strengthens the incentive mechanism via cost sharing, promoting the efficient use of inputs. Sharing operation costs is discussed in detail by Matthiasson (1999).

[6] In cases where fishing equipment is provided by a third party, the equipment owner may also receive a portion of the benefits. However, the evidence indicates that the latter can be neglected since in less than 2% of the cases, the equipment owner participates directly in the distribution (INE, 2009).

landowner lets a tenant work a piece of a field and requires part of the tenant's harvest in return. As a tenant's labor effort is not perfectly unobservable, this gives rise to an agency problem where the landowner expects tenants to behave opportunistically. In this setting, sharecropping will dominate owned cultivation because of the attenuation of labor shirking problems, and it will be superior to fixed rents because of its risk polling advantage (Stiglitz, 1974). The prevailing understanding of the literature is that in a riskless environment with perfect information, agents are indifferent among fixed wages, and share and fixed rental contracts (Stiglitz, 1974; Reid, 1976)[7]. Further, share contracts emerge, as the transaction costs of monitoring and enforcing are costless (Cheung, 1969). As soon as risk is taken into consideration, a flat wage is only established in the case of a risk-neutral landlord (Stiglitz, 1974).

Although a sharecropping model is a good starting point for obtaining some insights into the functioning of lay systems in fisheries, there are some characteristics that differ from those in agriculture. First, share contracts are far more dominant in fisheries than in other sectors. Second, unlike the fisheries sector, agricultural activities are not usually task oriented; rather they operate in a feudalistic environment and within a hierarchical structure that lacks competitiveness. Finally, agricultural production is sequential and discontinuous, and the risk of both asset misuse and loss of human life are lower in comparison to fisheries (Plourde and Smith, 1989; Platteau and Nugent, 1992).

As in agriculture, two are the main arguments driving decisions regarding the choice of remuneration system in fisheries: risk pooling and opportunistic behavior. In relation to the risk pooling argument, Sutinen (1979) and Plourde and Smith (1989) show that when boat owners and crew members are risk averse, share contracts are the optimal remuneration system in a stochastic environment.[8] On the other hand, and under the assumption that vessel owners do not directly supervise their crews, opportunistic behavior may arise in the form of labor shirking, asset mismanagement, output underreporting, and input overreporting. In this context, McConnell and Price (2006) point out that share contracts emerge as a mechanism to prevent shirking among crew. Empirical evidence investigating the formation of contracts and the impact of the

[7] Reid (1976) argues that this result remains even in a stochastic environment.
[8] Alternatively, other contractual relationships have been adopted in fisheries, such as piece rate wages and fixed rent contracts. The former consists of paying salaries in accordance with catch volume. Although this system may help deal with labor shirking and output underreporting, it has disadvantages when catch quality is relevant. The latter makes price risk entirely borne by vessel owners. Fixed rent contracts consist of a fixed payment for renting boats. Thus, workers have to bear the entire burden of risk, and asset misuse is more likely to occur.

remuneration regime on economic performance in fisheries is scarce. Exceptions are the works by Nguyen and Leung (2009) and Thuy et al. (2013). Nguyen and Leung (2009) find that share contracts are more likely to be preferred over fixed wages when it is easier for vessel owners to find a local crew. Furthermore, they assert that vessels owners with larger crews prefer flat wages over share contracts. This result was also supported by Thuy et al. (2013). The latter additionally finds that share contracts are more likely to emerge in a rural area, probably since the bargaining power of crew members is weaker than that of vessel owners. Both studies find support of share-contracted vessels yielding higher profits than flat-wage contracted vessels. They particularly rely on the insurance incentive mechanism in the choice of a remuneration contract.

Risk sharing requires risk aversion in order to explain the origin of share contracts. However, recent empirical evidence in both commercial and artisanal fisheries finds that a substantial percentage of fishers behaves in either a risk-neutral or a risk-seeking manner (Holland and Sutinen, 2000; Eggert and Martinsson, 2004; Eggert and Tveteras, 2004; Strand 2004; Eggert and Lokina, 2007).[9] This has led to the claim that the emergence of share contracts is more in line with the problems of moral hazard (McConnell and Price, 2006; Eggert and Lokina, 2007). Therefore, empirically speaking the study of incentives given to the crew in the form of profit sharing is relevant. Consequently, we follow the model of McConnell and Price (2006), who provide an explanation of share contract choices based on the existence of an incentive mechanism to alleviate a potential team agency problem.

3.2 The model

McConnell and Price (2006)'s model assumes two contracting parties: the vessel owner and crew. The owner selects a contract, s, that specifies a proportion of the ex-post profit to be paid to the crew that maximizes his share of total vessel profit. In this choice, capital owners take as given the effect of the share contract on the determination of the quantity and quality of crew labor effort. Vessel owner profits under a share contract regime are given by:

$$\pi^O = (1 - s)(p\alpha x \sum_{i=1}^{N} e_i - VC), \tag{1}$$

[9] The authors explain this finding based on evidence showing that fishers make decisions concerning fishing ground locations, target species, and gear on a shorter-term basis than farmers do, involving a relatively smaller stake in each trip. Thus, repeated risk- aversion behavior would not be optimal because of substantially reducing fishing incomes in the long run (Eggert and Lokina, 2007).

and for a representative crew member:

$$\pi^C = \frac{s}{N}(p\alpha x \sum_{i=1}^{N} e_i - VC), \quad (2)$$

where i=1,…, N denotes the individual crew member; p denotes price; α the catchability coefficient; x the resource stock that is assumed to be random with $E(x) = \bar{x}$; and VC non-labor input costs, mainly fuel and food expenses. Production technology is represented by $y = \alpha x E$, where $E = \sum_{i=1}^{N} e_i$, and e_i is the effort level exerted by the *ith* crewmember. In the model, it is assumed that the crew will exert low effort (e_L) or high effort (e_H) at a non-monetary cost represented by a strictly convex function $v(e_i)$. The expected utility of the vessel owner and crew members is defined as follows:

$$U_O = E[\pi^O] = (1-s)(p\alpha\bar{x}\sum_{i=1}^{N} e_i - VC) \quad (3)$$

$$U_i^C = \frac{1}{N}E[\pi^C] = \frac{s}{N}(p\alpha\bar{x}\sum_{i=1}^{N} e_i - VC) - v(e_i). \quad (4)$$

The capital owner and crew are assumed to be risk-neutral. The vessel owner chooses a contract parameter, s, to induce the crew to select a level of effort, $\hat{e}_i$, that maximizes the vessel owner's welfare, subject to an individual rationality constraint *(i)* and an incentive compatibility constraint *(ii)*.[10] The problem is formalized as follows:

$$\begin{aligned} \max_{s,\gamma,\hat{e}} \quad & U_O = E[\pi^O] = (1-s)(p\alpha\bar{x}\sum_{i=1}^{N} e_i - VC) \quad (5) \\ \text{s.t} \quad & (i)\ U_i^C/\hat{e} \geq \overline{U}_i, \\ & (ii)\ U_i^C/\hat{e} \geq U_i^C/e \neq \hat{e}. \end{aligned}$$

By substituting equation (4) into (ii) and assuming two levels of effort such that $e_i \in (e_{L,} e_H)$, a solution for s gives us (McConnell and Price, 2006):

[10] In this particular case, *(i)* means that the crew receives a higher utility with the contract offered by the vessel owner compared to an outside option that generates utility $\overline{U}$, and *(ii)* means that the crew is better off by accepting this specific contract than taking any another contract.

$$s^* = \frac{[v(e_H)-v(e_L)]N}{p\alpha\bar{x}[e_H-e_L]}. \tag{6}$$

Equations (5) and (6) define the optimal profit share and guide the inclusion of a series of factors that underlie share contract decisions. Hence, we should observe that vessel owners who operate in fisheries with lower prices, experience scarce resources, and use labor-intensive fishing technology would be more likely to share a larger proportion of the total profit. Furthermore, vessel owners that hire larger crews who have better outside opportunities and a higher disutility of labor, would grant a larger profit share to their crews.

Finally, from equation (6) we can see that there is a positive relationship between s^* and e^* such that $s^* = h'(e^*) > 0$. Thus, $e^* = g(s^*)$ >0, where *g(.)* is the inverse function of *h'(.)*. The latter expression describes the labor effort-enhancing mechanism. However, the effect on vessel owner profit is less clear. Plugging $e^* = g(s^*)$ in equation (1), we obtain: $\pi^O = (1-s*)(p\alpha x \sum_{i=1}^{N} g(s^*) - VC)$. Thus, there exists a tradeoff when analyzing whether or not to increase the profit share. On the one hand, there is a marginal cost of increasing *s* when the capital owner gives up a proportion of the total gains. On the other hand, there is a marginal gain of increasing the profit share through better incentives that enhance labor effort.

3.3 Other predictions from related literature

There are other factors affecting the choice of share contracts that are not derived from the model; however, they have been supported by an extensive literature on agrarian contracts. A landlord's monitoring ability and bargaining power are often mentioned as relevant principal's characteristics in explaining the formation of contracts in agriculture. For instance, landlords practicing non-agricultural occupations, with plots located further from home, and contracting with tenants whose abilities are not known, are more likely to have higher costs of monitoring (Ackerberg and Botticini, 2000; Jacobsy and Mansuri, 2009), and would thus be more inclined to agree to a contract with better incentives for the tenants. Furthermore, landowners with higher ex-post bargaining power are more likely to sign a contract with lower power incentives. If the agent's ex-post bargaining position is weak, the principal cannot commit to high-powered incentives, thus agents end up accepting contracts with less favorable conditions (Kvaløy, 2006).

Finally, we expect that the incentive mechanism may be species-specific, since observability of efforts can differ across fisheries (see Allen and Lueck, 1995) for arguments in the sharecropping case). For instance, molluscs and crustaceans are extracted from the bottom of the sea by diving, employing traps, or simply by gathering. In these cases, crew members have to get enter the sea, making monitoring more difficult for an onboard vessel owner. Moreover, crew members (divers, mainly) have the chance to be more selective in choosing where to search and which individuals to harvest, considering characteristics such as size and weight. This would have a direct influence on their benefits. On the contrary, if the target species is fish, crew members remain onboard irrespective of the fishing technology, making effort easier to observe. Even though there are always some imperfections in the observation of efforts associated with less tangible aspects, such as motivation, proactivity, and teamwork,[11] supervision costs are expected to be much higher in the former case.

4 Estimation procedure

We use a continuous treatment effect approach, as proposed by Hirano and Imbens (2004), to study the formation of share contracts in artisanal fisheries and identify the marginal effects of increasing crew profit share on vessel owner profit. This methodology is an extension of the well-established and broadly used propensity score methodology for binary treatments (Rosenbaum and Rubin, 1983) and multivalue treatments (Imbens, 2000; Lechner, 2001). Hirano and Imbens (2004) generalize the *unconfoundedness* assumption for the binary treatment, renaming it as the *weak unconfoundedness* assumption, since it is not necessary to assume the joint independence of all potential outcomes, but only conditional independence for each value of the treatment. This methodology, which is highly relevant when assessing training programs with different durations (Kluve et al., 2012; Flores et al., 2012), has also been shown to be useful beyond program evaluation contexts (see Fryges and Wagner, 2008; Fryges, 2009; and Du and Girma, 2009 for some evidence).

We assume a random sample of vessel owners, indexed by $i=1,\ldots, N$, where each observation, i, has a set of potential outcomes, $Y_i(s)$ – the vessel owner return – for $s \in \Psi$, which corresponds to

[11] For instance, in order to diminish potential conflicts between the skipper and crew onboard, the skipper, under a share contract mechanism, usually motivates his workers and fosters teamwork by making use of a consultation mechanism by which the skipper encourages the crew to participate in decisions regarding the scheduling of fishing trips, and the choice of fishing zones, nets, gear, and procedures to be followed onboard or in port.

the level of treatment dose – crew profit share. In the continuous case, Ψ is an interval $[s_1, s_2]$. For each vessel owner, we observe a covariate vector, X_i (boat characteristics, vessel owner characteristics, etc.); the crew profit share, s; and vessel owner returns given the crew profit share, denoted as $Y_i = Y_i(s)$. The aim is to estimate the average dose-response function $\mu_i(s) = E[Y_i(s)]$. The implementation consists of two parts. First, the methodology requires estimating share contract choices to calculate the GPS. Second, the GPS are used to estimate the average dose-response function.

4.1 Estimations of share contract choices

The principal–agent framework assumes that decisions on choosing contracts are modeled as a proportion of the profit paid to the crew. Consequently, standard linear models may fail to model proportions, as predicted values are not guaranteed to fall into the interval (0,1). Therefore, it is crucial to look into models that impose a bounded relationship on the dependent variable. We use the Fractional Logit model, as suggested by Papke and Wooldridge (1996), to estimate the formation of share contracts. The maximization procedure maximizes the Bernoulli log-likelihood function as follows:

$$l_i(\beta) = s_i log[\Lambda(X_i\beta)] + (1-s_i) log[1 - \Lambda(X_i\beta)], \tag{7}$$

where $l_i(\beta)$ denotes the log-likelihood function; s_i corresponds to the crew profit share; $\Lambda(\cdot)$ is the cumulative distribution function of the logistic satisfying $0 < \Lambda(\cdot) < 1$, which ensures that the predicted values of s lie in the interval (0,1); β is a vector of the parameters to estimate; and X_i is the vector of relevant covariates explaining share contract choices.

Then, the estimated GPS calculated based on a Bernoulli distribution are as follows:

$$\widehat{R}_i = \left[\Lambda\left(X_i \hat{\beta}\right)\right]^{s_i}\left[1 - \Lambda\left(X_i \hat{\beta}\right)\right]^{(1-s_i)}, \tag{8}$$

where $\widehat{R}_i$ are the calculated GPS, and $\hat{\beta}$ denote the estimated coefficients from equation (7).

4.2 Estimation of the dose-response function

In the second stage, we estimate the conditional expectation of the outcome variable of interest, Y_i, as a function of the observed value of treatment s_i and the estimated GPS, $\hat{R}_i$. As suggested by Hirano and Imbens (2004), we employ a quadratic functional form and ordinary least squares (OLS) as follows:

$$E\left(Y_i/s_i, \hat{R}_i\right) = \hat{\alpha}_0 + \hat{\alpha}_1 s_i + \hat{\alpha}_2 s_i^2 + \hat{\alpha}_3 \hat{R}_i + \hat{\alpha}_4 \hat{R}^2{}_i + \hat{\alpha}_5 s_i \hat{R}_i, \tag{9}$$

where $\hat{\alpha}s$ are the estimated parameters. In the final step, we estimate the average potential outcome at the treatment level, making use of the estimated coefficients from equation (9):

$$E\left(\widehat{Y(s)}\right) = \frac{1}{N}\sum_{i=1}^{N}[\hat{\alpha}_0 + \hat{\alpha}_1 s + \hat{\alpha}_2 s^2 + \hat{\alpha}_3 \hat{r}(s, X_i) + \hat{\alpha}_4 \hat{r}(s, X_i)^2 + \hat{\alpha}_5 s \hat{r}(s, X_i)], \tag{10}$$

where $\hat{r}(s, X_i)$ are the GPS evaluated at the treatment level of interest, s. These average potential outcomes are calculated at each level of treatment, increasing by 5% within the interval $(0,1)$. The dose-response function comes from depicting the average expected outcome at each level of the crew profit share. We bootstrap the standard errors and compute the confidence intervals of the expected outcomes at the 5% significance level (1,000 replications). The GPS has the property that $X \perp S$; that is, within the same range of $r(S, X)$, the probability that S=s does not depend on the value of X. Hirano and Imbens (2004) demonstrate that if assignment to the treatment is weakly unconfounded given the covariate X, then it is also unconfounded given the GPS. Thus, the identification of marginal effects comes from the comparison of the value of the dose-response function for a treatment value s with another treatment value s', conditioned on the GPS.

5 Data

The data we use are from the first Fishing and Aquaculture Census carried out in Chile between the years 2008-2009, with questions designed covering the period 2006-2007 as a reference. The Census was aimed at quantifying information on social, economic, and cultural characteristics of people involved in the fisheries and aquaculture sectors. Furthermore, questions were designed to gather information regarding physical infrastructure, equipment, and technology used in fisheries and aquaculture, so as to supplement the lack of statistics on production and costs (INE, 2009). The census was conducted on the basis of 14 questionnaires covering the artisanal sector;

including fishers, vessel owners, and fishing organizations; the industrial sector, comprising vessel owners and factory ships; aquaculture, divided in industrial and small-scale, salaried employees working in the processing industry and aquaculture; and fishing services supplied to extractive activities and aquaculture. In particular, we use the data on vessel owners operating in the artisanal sector. We dropped vessel owners who either reported their boat was undergoing maintenance, or used them for transporting passengers or cargo, and had no crewmembers.[12] Furthermore, we considered only fishing settlements formally recognized by the Chilean government.[13] Thus, we obtained 6,840 observations, distributed across the entire national territory.

Vessel owners report the profit shares given to the parties involved in extraction activities such as skipper, fishers, diver, diver's assistant, and others. We constructed our share contract variable as the sum of percentages distributed among these fisher categories. Our outcome variable is the logarithm of self-reported monthly average profit during the last fishing season.[14]

[INSERT TABLE 1 ABOUT HERE]

The distribution of the profit share variable for each category of species is shown in Table 1. Most of the crew profit shares take values smaller than 0.5 and are greater for molluscs and crustaceans. To estimate share contract decisions, we consider a set of covariates characterizing boats, vessel owners, state of resources, labor market conditions, and fishing communities. Regarding boat characteristics, we control for vessel size by including dummies for the categories of small oar boats, small motorboats, launches with a length less than 12 feet, between 12 and 15 feet, and between 15 and 18 feet;[15]. To control for vessel material, we introduce dummy variables containing categories for wood, fiberglass, and steel[16]. For advanced technology usage, we use a dummy for the onboard presence of echo sounders. We consider the number of crew members, and control for fishing technology via dummy variables characterizing the type of fishing gear

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[12] Mostly, observations with no crewmembers simply correspond to vessel owners who fish. In this case, principal–agent problems would not be present.

[13] According to executive order N°337 on November 11, 2004, which modifies N°240 on August 3, 1998, the official list of artisanal fishing settlements amounts to 447, of which we observe 409 in our data.

[14] We use logarithms since vessel owners do not report negative values for profits, and only 60 observations have a value of zero in our sample. Furthermore, as profit shares are also in percentages, we can directly calculate marginal effects by the difference between the log of profits at two distinct levels of shares.

[15] The category launches with a length between 12 and 14 feet serve as the benchmark. There are no observations in the last category for the algae group. Furthermore, there are no boats of medium and large size for the species *Chilean abalone*. Thus, the baseline changes in these cases.

[16] Vessels made from wood are the baseline. There is no observation for the category "steel" for algae and *Chilean abalone*.

including diving, purse-seine net, driftnet, long line, handline, traps, gathering, and others.[17] All these boat characteristics are intended to proxy for catchability and the use of less/more capital-intensive technology. It is expected that smaller vessels, made of wood, with more crew members and equipped with labor-intensive technologies, have a lower catchability coefficient, and consequently are more inclined to agree to a contract with higher power incentives in the form of a higher crew profit share. In addition, we introduce a dummy variable indicating if the vessel owner experienced any adverse weather or resource scarcity during the last twelve months to proxy for resource abundance. We anticipate a positive association with crew profit share, since vessel owners probably offer an increase in crew participation so as to enhance labor effort, especially in time of resource scarcity. In relation to vessel owner characteristics, we include age, education, and experience measured in number of years, to control for vessel owner bargaining power. The intuition is that older, more educated, and experienced vessel owners hold higher bargaining power and will be more likely to agree to contracts with smaller crew profit share. Similarly, we also control for crew bargaining power by introducing the average of both experience and years of education at the fishing community level.[18] Moreover, we included dummy variables indicating if the vessel owner had alternative employment in the past year and denoting if the vessel owner lives in a different community from where he works, both to proxy for monitoring costs. We expect a positive association with crew profit share when supervision becomes harder and more costly to the extent that the principal resides further from the unloading area and diverts his efforts among several activities. Also, we control for whether or not the vessel owner recently moved in the community where he currently lives, taking as reference the national census conducted in 2002. We presume that vessel owners who just moved to their current location are less familiar with their crew's abilities, and as such would have increased need to incentivize them with higher-incentive contracts. Moreover, we introduce additional variables at the fishing community level to control for labor market conditions and outside options. These are the ratios between the number of vessel owners and other fisher categories in each fishing community, the unemployment rate in the commune where the fishing community is located, a dummy variable if the fishing community is in a rural area, and the size of fishing communities measured in number of fishers. We expect that more populous fishing communities with a lower

[17] Driftnet fishing technology serves as the benchmark. As not all these technologies qualify for each group of species, we only included the relevant technologies in each case. For the fish group, these are purse-seine net, long line, and handline; for molluscs, diving and gathering; for crustaceans, diving and traps; and for algae, diving and gathering. The species *Chilean abalone* is exploited by using diving technology only.

[18] Although suboptimal, we expect that crew characteristics control for some of the unobserved agent characteristics that potentially affect contractual relationships.

vessel owners/crew member ratio have a higher crew member supply, and therefore, a lower crew share. Furthermore, it is likely that crew members residing in fishing communities located in rural areas and near communes with higher unemployment rate,[19] have fewer outside options, and are more willing to accept a smaller profit share. In addition, we include a dummy variable to denote the presence of fishing infrastructure in the community. We expect lower crew shares in fishing communities that do not have a unique, well known unloading point. Since the danger of output underreporting is likely to increase with the number of alternative landing sites, the vessel owner would pay lower crew shares to compensate for larger losses due to the potential higher underreporting. Finally, we included a set of covariates to control for regional differences.[20]

[INSERT TABLE 2 ABOUT HERE]

Table 2 summarizes the descriptive statistics regarding the vessel, fishing technology, vessel owner, and community characteristics. We divided the sample into four intervals. An artisanal vessel owner reports a monthly profit of 257,000 Chilean pesos, on average, from fishing activities.[21] At first sight, there exists a non-linear association between outcomes and shares, and higher crew profit proportions are not clearly associated with higher vessel owner profits. There are differences in both vessel and technology characteristics across the level of crew profit shares. For instance, vessels with share contracts ranging from 1 to 25% are mainly launches, they hire more workers, and use driftnet fishing technology. By contrast, vessel owners allocating profit shares greater than 25% have smaller boats, hire fewer crew members, and use diving technology. Finally, vessel owners that distribute larger profit shares to their crews are more experienced and have an alternative occupation.[22]

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[19] The unemployment rate was calculated by making use of information from the Survey of Socioeconomic Characterization 2009, conducted between November and December of that year. In spite of differences in timing, we expect that the unemployment rate does not differ too much from that observed in the period of the collection of fishing census data. Information on rural zone status and the presence of a fishing infrastructure was taken from geo-referenced information collected by the National Bureau of Fishing and Aquiculture.

[20] In Chile, the administrative division occurs by region. Currently, there are 15 regions. All estimations were performed by controlling for regional fixed effects. Descriptive statistics and results are not shown for space reasons. They are available upon request.

[21] Approximately, this amounts to US$541 at the exchange rate on December 17, 2012. This is slightly higher than the minimum wage set as 193,000 Chilean pesos (US$406) for 2012.

[22] There are reasons to believe that a potential correlation may arise among several variables. For instance, the rural zone is presumably correlated with unemployment rate; crew size with vessel size, materiality and eco-sunder; and age with experience of vessel owner. We explore this concern by computing the coefficients of correlations. We obtained a coefficient of correlation of 0.15 for rural area and unemployment rate, 0.52 for crew size and large-size launches, 0.24 for large-size launches and steel vessels, 0.40 for large-size launches and usage of eco-sounder, and 0.78 for age and experience. Except for the correlation between age and experience, this matter does not seem to be a big problem. We checked it by reestimating the share contract equation without either age or experience, finding similar results. These are not shown here, but are available upon request.

6 Results

Before starting the discussion, we checked for the sensitivity of the results by addressing several concerns. First, as previously argued, the observability of effort can differ across fisheries; thus the labor-incentive mechanism may be more important in some fisheries than in others. We examine this by estimating the model for the total sample and several groups of species, namely fish, molluscs, crustaceans, and algae. Second, it is expected that price variations determine profit crew shares. We lack the necessary data to test this directly. However, we expect that by focusing on one particular species whose producers are price takers, the chances that share contracts are driven by price differences should diminish. Thereby, we replicate the results by using data exclusively for one fishery, Chilean abalone (C*oncholepas concholepas*). This marine resource is one of the main molluscs exploited in artisanal fisheries throughout the Chilean coast, and its production is almost entirely commercialized in international markets, mainly Asia. Moreover, Chilean participation in the abalone market does not exceed 10%. All these characteristics lead us to expect that local producers of that Chilean abalone should be price takers and that domestic prices paid to fishers from processing plants should follow external market trends (Chávez et al., 2010). Results for the Chilean abalone fisheries are not that different from those reported for the group of molluscs. Thus, the impossibility of controlling for price differences does not appear to be a matter of concern. Third, as a regular practice in artisanal fisheries, some vessel owners who are also skippers choose to completely link their gains to their effort and not be rewarded for providing capital. However, the central question remains, as it is not obvious that a higher proportion rewarding labor relative to capital would lead to an increase in vessel owner profit. We investigate this by pooling the skipper and capital shares when observed vessel owner shares are zero. Results do not seem to change dramatically (see Table A3). Fourth, there are several variables that were insignificant in all or most of the models. They are: the age and experience of vessel owner, the average education and experience of crewmembers in a fishing community, rural area, and population. New estimations made after dropping these covariates provide similar results, and do not seem to change the results substantially (see Table 3 and Table A4).

We now present the results concerning share contract choices, and then discuss the effect of the crew profit share on vessel owner returns.

6.1 Determinants of share contract choices

Results of the Fractional Logit estimations are shown in Table 3.[23] We focus on the covariates that were significant to explaining the formation of contracts. Regarding vessel characteristics, a crew receives a higher portion of gains when operating either small oar boats or small motorboats. Furthermore, the probability of negotiating a lower crew profit share is higher for vessels with better materiality and equipped with an echo sounder. However, it is only significant for the total sample. Larger, better equipped vessels are able to undertake longer fishing trips, reach more remote fishing grounds, and tolerate extreme weather conditions. Thus, these results are consistent with a lower power of the crew incentive mechanism in more capital-intensive vessels. The characteristics of fishing technologies also play a role in determining share contract decisions. Having as baseline the use of driftnet, whose performance is less labor dependent, vessel owners that employ diving, purse-seine net, handline, traps, gathering, and other technologies[24] are more willing to offer a larger profit share. The latter is expected since the share contract mechanism would be much more effective as vessels owners employ more labor-dependent fishing techniques.[25] For instance, handline fishing is an old, simple way of catching fish, whose success relies on human skills. Furthermore, divers have the opportunity to be more selective in choosing where to fish and which individuals to catch, which may have more influence on vessel owner returns.

[INSERT TABLE 3 ABOUT HERE]

Crew size also affects share contract decisions. Vessel owners cede a higher proportion of fishing returns when they hire fewer workers. Similar evidence was found by Nguyen and Leung (2009). They argue that moral hazard problems are likely to be more serious in contexts where fishing returns depend more on labor quality. Thus, vessel owners with fewer crew members may be more concerned about quality than quantity and may attempt to induce an increase in the labor productivity of each crew member by offering a higher profit share.[26]

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[23] Note that the sum of observations per column does not add up to the total sample since we were not capable of identifying the first reported species in 15 cases. Furthermore, observations for the species Chilean abalone are also contained in the main category, molluscs.

[24] Among them, we included fishing with spear guns and a diving technique called the "spider technique."

[25] In the design of agrarian contracts, Pandey (2004) demonstrates that as capital is relatively more important than labor effort, incentives offered directly through capital sharing are more effective. We can reinterpret this result in the context of fisheries by saying that to the extent that labor is more important than capital in achieving better results in fishing, vessel owners should reward labor with higher profit shares.

[26] According to alternative arguments, in fisheries with stronger social ties one should encounter a positive association between the share and crew size when it is the moral responsibility of vessel owners to take care of crew needs. However, recent technological changes, which have reduced the

Moreover, the results show evidence that vessel owners who face environmental problems that make it difficult to operate with regularity are more willing to negotiate higher profit shares. The latter supports the effort-enhancing mechanism of share contracts in encouraging crew to double efforts, especially in times of resource shortages or bad weather conditions. This finding is significant for the total sample and the category that groups different species of fish.

There is also evidence on individual characteristics that underlie share contract decisions. Level of education is negatively correlated with the level of the crew profit share in the fish group and total sample. The latter may respond to differences in bargaining power, as more educated vessel owners with better negotiation skills would arrange better conditions for themselves at the expense of a lower profit share for crewmembers.

Moreover, vessel owners that have a second occupation or do not reside in the same community where they work are more willing to cede a higher percentage of gains. These results are significant for the total sample. However, having a second occupation is only significant in the categories of fish and molluscs, and not residing in the same community is significant in the algae group only. Moral hazard problems are more likely to arise in settings where the principal has less chance to exert control over agents or faces higher monitoring cost. Therefore, vessel owners may lose control over crew effort when they divert their attention to an alternative activity or they do not reside in the fishing settlement in which work is carried out, and probably where most crew members live or spend most of their time.[27] This finding is consistent with similar arguments in the sharecropping literature (Ackerberg and Botticini, 2000; Jacobsy and Mansuri, 2009).

In addition, we find that whether or not vessel owners have recently moved to their current location matters in explaining levels of crew profit shares. Although the positive and significant estimate in one of the groups is consistent with vessel owners giving a higher profit portion to unfamiliar crew members, a negative relationship was more recurrently observed. Likely, vessel owners, in terms of the choice of contractual partners, seek to hire people in which they can be

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substitution elasticity between labor and capital in fishing operations, may have shifted this relationship due to the higher productivity-reducing effect of working spread under this new setting (Platteau and Nugent, 1992).

[27] Although we cannot truly ensure that vessel owners are indeed manager-skippers, it is highly probable that it is the case. Thus, distance should matter lower for monitoring costs. However, another aspect that also affects supervision costs is associated with vessel owners' opportunity to know crew abilities (Ackerberg and Botticini, 2000; Jacobsy and Mansuri, 2009). Therefore, if vessel owners do not reside in the fishing settlement where probably most crewmembers live or spend most of their time, it is more likely that they contract with a crew whose abilities are less known.

confident of hard work and cooperation to attenuate the problems of adverse selection and/or moral hazard. Thus, since trust relationships need time to be strengthened, vessel owners will be more willing to set contracts that involve a higher crew participation insofar as they have belonged to the fishing community for a longer time. These problems are even more serious as there is no legal proof that confirms the veracity of deals, which makes it more difficult to enforce contracts.

Labor market characteristics seem to be important in the negotiation process of share contracts. We find dissimilar evidence for the variable vessel owner/crew, however. On the one hand, we find a positive sign of the estimate for the total sample, implying that the more the vessel owners per crew members in a community, the higher the profit share paid to the crew. In other words, to the extent that the supply of potential crew members in a fishing community is not sufficiently high to cover the vessel owner's demand, the profit share offered to the crew should be higher.[28] On the other hand, we obtain opposite signs in the mollusc group and for Chilean abalone, which questions the validity of the prior statement. We believe that the negative sign observed in the extractive activities of molluscs may capture the greater bargaining power of divers, which is enhanced in fishing communities where diving is the principal activity. Furthermore, we find that we are more likely to observe lower profit shares in fishing communities near communes that have a higher unemployment rate. The estimations using the total sample and mollusc group confirmed these results. The latter is expected when outside opportunities and reservation wage decline as a result of difficulty finding a job. Finally, the presence of fishing infrastructure positively affects the proportion of the total gains paid to the crew. Having a unique, defined unloading point should considerably reduce the crew's chances for output underreporting, as the costs of measuring and dividing the output decrease significantly. Thus, the positive link between labor effort and profit share enhanced by higher crew participation is strengthened as the crew has less room to underreport. The latter seems to be more important in the extraction of molluscs.

6.2 The effect of share contracts on vessel owner returns

Before conducting estimation of the continuous treatment effects, we investigate the common support and balancing properties of the GPS. We test common support graphically as in Flores et al. (2012), following this procedure. First, we divided the sample into three groups according to

[28] Local labor supply and demand may be less relevant to explain profit share sizes when vessel owners and crew members do not live in the fishing community. Although there are some cases, this fraction is still small (3% for vessel owners, see Table 1), suggesting that the availability of local crew members is still important.

the values of profit shares, cutting off at the 30^{th} and 70^{th} percentiles of distribution. Second, we computed the GPS for the total sample at the median of the treatment value in each group. Finally, we plotted the distribution of the GPS of each group against the distribution of the remaining groups. We then evaluated common support by looking at the overlap between these two distributions. Graphically, there seems to be some overlap among the groups, which would validate the use of propensity score methods (see Figure A1). However, this does not guarantee that the balancing property of GPS is satisfied. We assess this by regressing each observable characteristic on either the predicted values of the treatment or the GPS distribution, as in Imai and van Dyk (2004) and Kluve et al. (2012), respectively. Results are reported in Table A1. We observe many significant correlations for the covariates in the unconditional regressions. However, once controlling for either the predicted values of the treatment or the GPS, the coefficients become insignificant and clearly decrease, which provides evidence that the GPS properly balances the observable characteristics.[29]

The results of the OLS estimates for the conditional expectation of the outcome are shown in the Table A2. The estimated parameters do not have any causal interpretation. However, as emphasized by Hirano and Imbens (2004), the coefficients associated with the GPS terms can indicate whether the bias introduced by the covariates is significant.

Given these estimated parameters, we calculate a dose-response function to analyze the effect of increasing crew profit shares on the economic outcomes. The 95% upper and lower confidence intervals are also computed. The dose-response functions plot the conditional expected monthly profit estimated at each level of the crew profit share, ranging from zero to one. This is depicted in Figure 1 for the total sample and Figure 2 for the categories of species. In addition, the marginal effects and significant ranges are shown in Table 4.

[INSERT TABLE 4 ABOUT HERE]

[29] Some additional issues concerning endogeneity can emerge as this method lies in the assumption of weak unconfoundedness. This assumption can be violated in case of reverse causality. For instance, vessel owners reporting larger gains may adjust profit shares downward such that they satisfy reservation wages; and thus paying a smaller profit share. However, contractual forms are set before profits are realized and are kept invariant in the short term. Moreover, share contracts arise as a strategy to deal with uncertainty through risk sharing, which makes changes in profit shares less likely to depend on the contingency. A second possibility is as arising potential unobserved characteristics. For instance, it is likely that particular types of principals end up contracting with particular types of agents. For example, vessel owner practicing diving may decide to contract with less risk-averse crew members, which would require a lower compensation to take a higher risk. Even though we do not observe crew data, we try to address this issue by including crew-community level characteristics, and reducing the heterogeneity as focusing on a particular group of species or only one species. Furthermore, if we rely on the recent literature, which finds that a substantial fraction of fishers are risk neutral, concerns on matching based on risk preferences should be less relevant.

Figure 1 shows a non-linear relationship between the level of crew profit share and outcomes. At the beginning, vessel owner profit goes down to the extent that they increase crew profit shares until the level of 0.20. After that point, each additional increase in profit share affects vessel owner returns positively until the level of 0.75. From that point, the vessel owner profit starts decreasing. In particular, the share contract mechanism has two conflicting effects on vessel owner profit. On the one hand, it works as a labor-enhancing system that brings extra gains via reduced labor shirking. On the other hand, by increasing the profit share, vessel owners give up profit. The results show that the second effect seems to dominate in the range from 0.01 to 0.20. After that level, the labor-enhancing mechanism starts playing a role. That is telling us two things. First, vessel owners can choose to remunerate crew poorly and increase their own profit at the expense of crew participation in total gains. However, the latter would be a welfare-reducing allocation, since vessel owners would be better off and crew members would be worse off. Second, there is a level of share (0.20) from which an increase in crew profit shares would be welfare improving, benefiting both vessel owner and crew members. However, raising the profit share above 0.55 is not statistically significant. Furthermore, a change in profit share from 0.01 to 0.2 does not significantly affect vessel owner profit. Thus, the relevant range is 0.25–0.55. The right hand side of Figure 1 depicts on the vessel owner's marginal gains of increasing profit share at 5%. The positive slope and concavity of the treatment effect function tells us that elasticity converges from negative to positive levels at a decreasing rate until it reaches a maximum value of 0.012. After that point, marginal effects start decreasing and become negative after a share of 0.75.

[INSERT FIGURE 1 ABOUT HERE]

Figure 2 shows that potential outcomes and relevant intervals differ across the categories of species. Potential outcomes start increasing above 0.35 for fish and 0.55 for algae. However, these results are not statistically significant. Results for molluscs, crustaceans, and Chilean abalone are much more consistent under the labor-enhancing mechanism argument. Regarding molluscs, we find an inverted U-shaped association between crew profit shares and outcomes, significant at the 5% level until a value of 0.65. The estimations using only Chilean abalone confirm the inverted U-shape of the dose-response function, although the significant range of profit shares narrows. Fewer significant estimates are likely the result of less variability in crew profit share as focusing on one species only. We also find higher outcomes for larger crew participation in crustaceous activity, with significant values ranging from 0.4 to 0.65. This association seems to be linear, though. The results in Table 4 indicate that an increase of 5% in crew profit share would have a positive effect on the vessel owner profit of 0.008%, on average, on the relevant interval for the total sample. This value is much lower compared with the marginal effects obtained for molluscs and crustaceans. Whereas the average marginal effect on the relevant range is 0.022 for molluscs (0.025 for Chilean abalone), it reaches a value of 0.035 for crustaceans. The higher sensitivity of output to the crew's profit share found in these cases is in line with the higher efficacy expected when using share contracts in settings where crew efforts are harder to monitor. Differences among fisheries support the notion that vessel owners may still experience trouble observing crew efforts in spite of closer monitoring in artisanal fisheries. For instance, the extraction of molluscs and crustaceans is carried out by diving; alternatively, molluscs are gathered and crustaceans are caught using traps. In any case, it is highly probable that crew members are out of sight of the onboard vessel owner-skipper. This gives the labor-enhancing mechanism of share contracts special relevance in those fisheries in which the observability of effort is more reduced.

[INSERT FIGURE 2 ABOUT HERE]

7 Discussion and conclusion

In this article, we study the determinants of share contract choices in artisanal fisheries in Chile and their effect on economic performance. Owing to the differences in vessel and operation characteristics along levels of crew profit shares, we estimate a continuous treatment effect using the GPS approach. Because of the fractional nature of share contract decisions, we estimate the Fractional Logit model to compute the propensity scores.

The results indicated that less educated vessel owners and those with another occupation are more likely to pay a higher profit ratio. The latter supports arguments based on bargaining power and monitoring costs, respectively, in explaining the different levels of contract incentives. Furthermore, vessel owners with smaller boats that are equipped with technologies, that require are more labor-intensive methods, and experience more volatile environmental conditions were more likely to pay higher profit shares. This evidence backs up the arguments based on differences in dependence on human effort and the state of fishing resources. Moreover, vessel owners that resided in fishing communities with lower unemployment rates and those endowed with a fishing infrastructure are more willing to negotiate a higher profit share. The latter findings support explanations based on differences in outside options and fishing community infrastructure.

We found significant effects of increasing crew profit shares on vessel owner returns; however, significant ranges vary from a lower limit of 0.25 to values around 0.65, depending on the group of species under study. This effect is larger and robust in the mollusc and crustacean groups, which is in line with expected differences in the observability of efforts in the vessel owner–crew relationship across fisheries. The latter supports allocations with high crew participation in attaining maximal fishing returns in artisanal fishing communities in Chile.

The results have relevant policy implications. First of all, our findings suggest that a fair distribution of the gains without favoring any of the parties performs well in economic terms. Incentive-based instruments have been criticized for their distributional implications; in particular, the level, nature, and remuneration of the crew aboard harvesting vessels (Grafton et al., 1996; Brandt and Ding, 2008; Abbott et al., 2010). Under a right-based regime, vessel owners are given more autonomy on distribution, use, and control of their resources. This implies that increased capital owner's bargaining power may lead to a reduction in profit crew share. Therefore, a right-based system may moderate the necessity of higher power incentive contracts, which can affect fishing returns. Unfortunately, data limitations do not allow us to conduct an evaluation of right based instruments on share contract choices and total fishing returns in Chile. Furthermore, these instruments have been gradually extending to the entire artisanal fishery, which makes identification harder as relying on cross sectional variation only. Ex-ante and ex-post data to the introduction of these incentive-based instruments are necessary to perform a more exhaustive evaluation of their distributional impacts and economic consequences.

We found that share contracts are sensitive to the unemployment rate. This may cause difficulty for vessel owners meeting their labor needs as economic conditions are better in other sectors-Moreover, this may make crew members more vulnerable in times of higher unemployment in other sectors since they have to accept lower profit shares because of their fewer outside opportunities. The arrangement of a minimum income may help crew members insure against low catch rates and, at the same time, augment their reservation wages. This would also attenuate vessel owners' trouble meeting their labor requirements, especially in times of labor scarcity.

There is no explicit mention of a minimum income in the modifications introduced in the (GLFA) that regulate share contracts in Chile. However, during the debate of this law, it was discussed to stipulate that shares corresponding to each crew member must not be below the minimum wage. Undoubtedly, this change may generate conflicting effects as the incentive mechanism weakens, especially in mollusc and crustacean fisheries. Our results do not permit us to suggest an optimal minimum income that balances these potential impacts since share contracts are broadly dominant in Chilean artisanal fisheries. Future research should aim to assess the functioning of share contracts in contexts where the crew is also remunerated by a combination of a fixed income and a percentage of total profit.

We note some limitations. Firstly, our results rely on the assumption of the weak unconfoundedness of GPS, which is also known as selection on the observables. Unobserved heterogeneity across agents may potentially result in endogeneity issues when particular types of principals end up contracting with particular types of agents. For example, vessel owners extracting mollusks may decide to contract with highly skilled divers, which would imply a larger remuneration share. Our results rely mainly on vessel owner characteristics. Future research should include crew member covariates and potentially matched data between principals and agents to more closely study the formation of contracts. Secondly, we argue that it is likely that the vessel owner can play the role of skipper, which would substantially attenuate labor shirking problems, as the crew would be more closely monitored. Unfortunately, we cannot observe this feature in our data. We attempt to deal with this issue by extending the analysis to several fisheries that potentially vary in terms of observability of crew effort. However, more accurate data on the vessel owner's multiple roles is required to explore this further.

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Tables

Table 1. Distribution of the crew profit share variable.

Interval	Fish		Mollusc		Crustacean		Algae		Chilean Abalone		Total	
	N°	%	N°	%	N°	%	N°	%	N°	%	N°	%
(0,0.25]	946	0.24	216	0.10	59	0.16	38	0.09	28	0.07	1,261	0.18
(0.25,0.50]	2,240	0.57	1,108	0.53	180	0.49	265	0.63	188	0.50	3,803	0.56
(0.50,0.75]	641	0.16	653	0.31	121	0.33	91	0.22	145	0.39	1,509	0.22
(0.75,1]	120	0.03	114	0.05	7	0.02	26	0.06	15	0.04	267	0.04
Total	3,947	1.00	2,091	1.00	367	1.00	420	1.00	376	1.00	6,840	1.00

Note: Own elaboration.

Table 2. Summary statistics for vessel and fishing technology characteristics.

Variable	Crew Profit Share								Total	
	(0,0.25]		(0.25,0.50]		(0.50,0.75]		(0.75,1]			
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Monthly Profit	300,209	627,279	233,566	402,142	281,355	483,912	257,322	429,117	257,322	471,142
Vessel										
Small oar boat	0.055		0.119		0.102		0.161		0.105	
Small motor boat	0.537		0.664		0.772		0.797		0.670	
Launch (length<12)	0.317		0.210		0.130		0.097		0.208	
Launch (12≤length≤15)	0.065		0.015		0.014		0.011		0.024	
Launch (15≤length≤18)	0.055		0.119		0.102		0.161		0.105	
Wood vessel	0.786		0.861		0.902		0.862			
Fiberglass vessel	0.196		0.136		0.141		0.138		0.148	
Steel vessel	0.018		0.003		0.004		0.000		0.006	
Echo sounder	0.206		0.090		0.094		0.082		0.112	
Crew's size	2.808	1.870	1.936	1.434	2.050	1.481	2.041	1.239	2.126	1.561
Technology										
Diving	0.176		0.311		0.480		0.531		0.332	
Purse-seine net	0.061		0.031		0.029		0.056		0.037	
Long line	0.383		0.316		0.113		0.074		0.274	
Handline	0.038		0.056		0.079		0.074		0.059	
Drift-net	0.274		0.186		0.176		0.188		0.201	
Traps	0.038		0.036		0.053		0.018		0.039	
Picking	0.024		0.043		0.033		0.022		0.036	
Others	0.006		0.021		0.037		0.037		0.022	
Activity										
Ecological problem	0.343		0.296		0.192		0.217		0.278	
Vessel owner										
Age	45.065	10.483	45.868	11.409	46.697	11.256	47.677	11.352	45.974	11.222
Education	7.672	2.800	7.341	2.834	7.517	2.954	7.449	2.929	7.445	2.860
Experience	26.641	11.30	26.798	12.013	28.296	11.987	28.863	12.287	27.180	11.911
Another occupation	0.183		0.220		0.167		0.258		0.203	
Not residing in workplace	0.032		0.027		0.037		0.033		0.030	
Move	0.090		0.062		0.044		0.063		0.063	
Community										
Crew experience	22.406	3.656	22.942	4.035	24.218	4.258	24.926	4.131	23.202	4.084
Crew education	7.818	0.714	7.717	0.753	7.883	0.723	7.941	0.921	7.781	0.751
Vessel owner/crew	0.341	0.234	0.386	0.356	0.407	0.435	0.400	0.428	0.383	0.361
Unemployment rate	0.105	0.032	0.110	0.033	0.104	0.036	0.103	0.034	0.107	0.034
Fishing infrastructure	0.559		0.539		0.747		0.715		0.596	
Rural	0.518		0.586		0.502		0.471		0.550	
Population size	472.416	513.84	424.91	514.329	406.919	512.925	359.996	427.99	427.16	511.36
Observations	1,261		3,803		1,509		267		6,840	

Note: Own elaboration based on Census data

Table 3. Estimated parameters for the Fractional Logit model.

Variable	Fish		Mollusc		Crustacean		Algae		Chilean Abalone		Total Sample	
	Coef	Se+	Coef	Se+	Coef	Se+	Coef	Se+	Coef	Se+	Coef	Se+
Vessel												
Small oar boat	0.13**	0.06	0.21**	0.09	-0.18	0.19	0.77	0.23	-0.18	0.19	0.14***	0.05
Small motor boat	0.12**	0.05	0.25***	0.08	-0.17	0.17	0.12	0.20	0.24**	0.12	0.14***	0.04
Launch(length<12)	0.03	0.05	0.12	0.08	-0.26	0.16	0.12	0.18			0.05	0.041
Launch(15≤length≤18)	0.03	0.09	-0.03	0.23	0.35	0.27					0.002	0.09
Fiberglass vessel	-0.04	0.04	0.01	0.05	-0.01	0.13	0.03	0.14	-0.15	0.09	-0.05*	0.03
Steel vessel	-0.15	0.17	0.06	0.23	1.49***	0.17					-0.12	0.16
Echo sounder	-0.03	0.041	-0.11	0.07	-0.12	0.10	0.05	0.21	0.24	0.15	-0.07**	0.03
Crew size	-0.10***	0.01	-0.05***	0.02	-0.19***	0.05	-0.13***	0.04	-0.04	0.05	-0.09***	0.01
Technology												
Diving			0.15***	0.05	0.35***	0.11	0.29***	0.08			0.34***	0.03
Purse-seine net	0.04	0.07									0.14**	0.07
Long line	-0.001	0.04									-0.01	0.03
Handline	0.14***	0.05									0.15***	0.04
Traps											0.05	0.05
Picking											0.16***	0.05
Others											0.28***	0.05
Activity												
Ecological problem	0.08***	0.02	-0.02	0.04	-0.06	0.11	0.04	0.08	-0.15**	0.08	0.06***	0.02
Vessel owner												
Education	-0.01*	0.003	-0.00	0.01	0.001	0.01	-0.01	0.01	-0.01	0.01	-0.01*	0.003
Another occupation	0.09***	0.03	0.11***	0.04	0.04	0.12	0.05	0.07	0.05	0.07	0.09***	0.02
Not residing in work	0.04	0.07	0.13	0.08	0.10	0.16	0.41**	0.19	0.09	0.14	0.08*	0.05
Move	-0.10**	0.05	-0.10*	0.06)	0.37*	0.22	0.08	0.13	0.06	0.20	-0.09**	0.04
Community												
Vessel owner/crew	0.10***	0.03	-0.13*	0.07	0.01	0.04	0.05	0.24	-0.17	0.13	0.06***	0.02
Unemployment rate	-0.16	0.44	-1.81***	0.57	-0.10	1.76	-1.51	1.27)	0.85	1.55	-1.13***	0.32
Fishing infrastructure	0.03	0.026	0.08**	0.03	-0.11	0.09	0.01	0.07	0.00	0.09)	0.06***	0.02
Constant	0.17*	0.10	0.01	0.16	0.44	0.34	0.33	0.34	-0.20	0.34	0.07	0.08
Log pseudo-likelihood	-1797.1		-977.2		-167.5		-194.7		-174.3		-3154.2	
Observations	3,947		2,091		367		420		376		6,840	

Note: Own elaboration based on estimations, *** p<0.01, ** p<0.05, * p<0.1, and + robust standard errors.

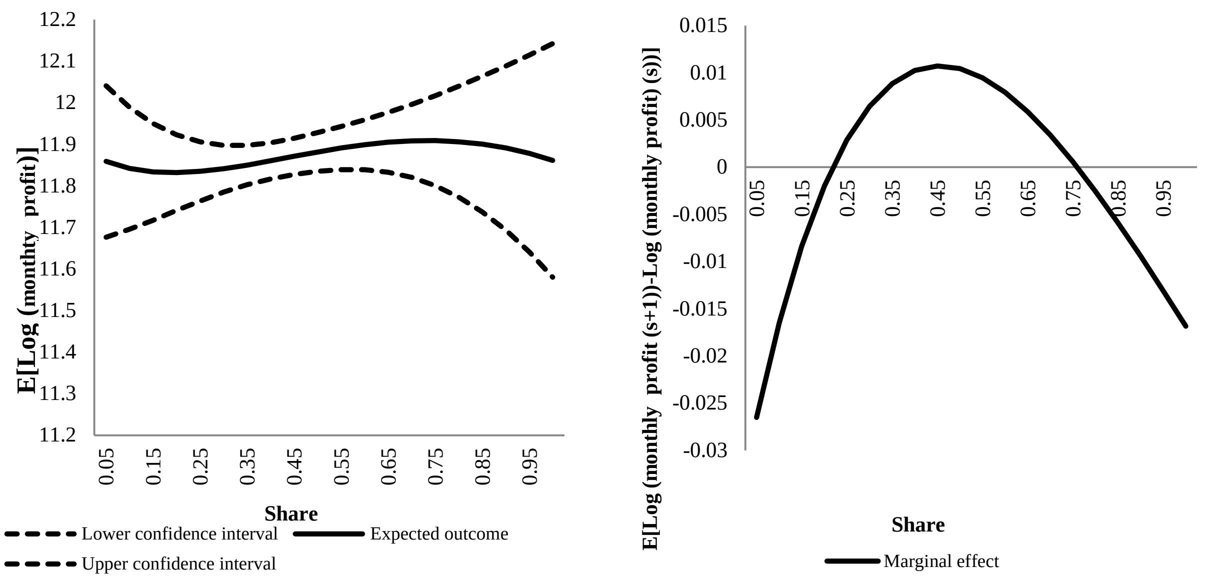
Table 4. Marginal effects of increasing crew profit shares by 5%.

Level of Treatment	Marginal Effects					
	Fish	**Mollusc**	**Crustacean**	**Algae**	**Chilean Abalone**	**Total**
0.05	-0.069	0.051	-0.046	-0.085	0.169	-0.026
0.10	-0.052	0.04	-0.028	-0.077	0.152	-0.016
0.15	-0.038	0.047	-0.013	-0.06	0.136	-0.008
0.20	-0.026	0.044	0.000	-0.061	0.120	-0.001
0.25	-0.01	0.040	0.009	-0.053	0.105	0.002**
0.30	-0.009	0.037**	0.018	-0.046	0.089	0.006**
0.35	-0.003	0.033**	0.024	-0.038	0.075	0.008**
0.40	0.000	0.029**	0.029**	-0.03	0.060	0.010**
0.45	0.003	0.024**	0.032**	-0.021**	0.046**	0.010**
0.50	0.005	0.020**	0.035**	-0.013**	0.032**	0.010**
0.55	0.005	0.015**	0.036**	-0.005**	0.018**	0.009**
0.60	0.005	0.010**	0.037**	0.004	0.005**	0.007
0.65	0.003	0.005**	0.038**	0.012	-0.007	0.005
0.70	0.001	0.000	0.03606	0.022	-0.020	0.003
0.75	0.000	-0.004	0.035	0.032	-0.032	0.000
0.80	-0.004	-0.009	0.03372	0.042	-0.044	-0.002
0.85	-0.008	-0.015	0.03233	0.053	-0.055	-0.005
0.90	-0.012	-0.020	0.03099	0.064	-0.066	-0.009
0.95	-0.017	-0.025	0.0298	0.075	-0.076	-0.013
1.00	-0.022	-0.030	0.02891	0.088	-0.086	-0.016

Note: Own elaboration based on estimations, ** p<0.05.

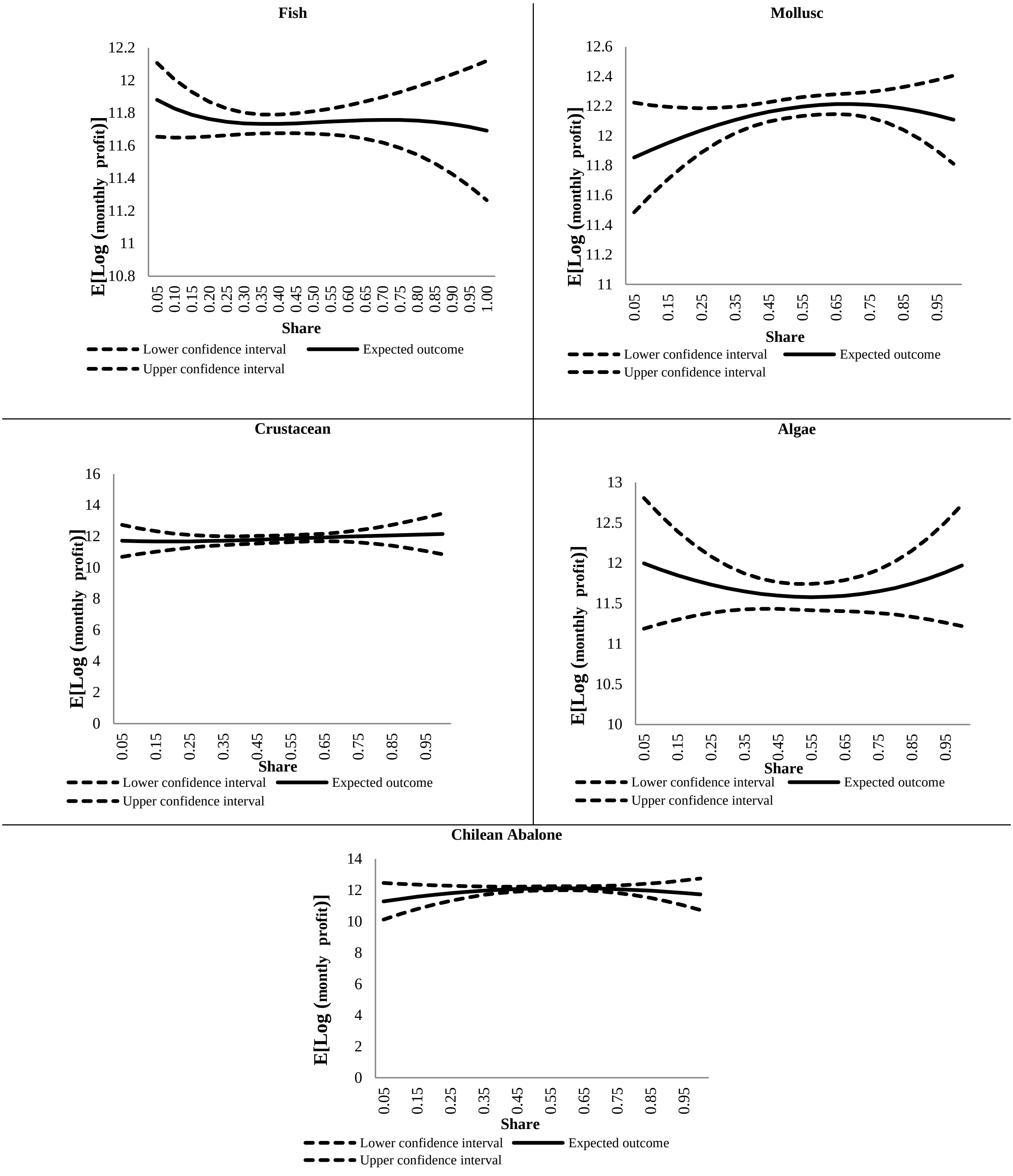
Figures

Figure 1. Estimated dose-response function and treatment effect function given a change of 5% in profit share (Total sample).



Note: Own elaboration based on estimations.

Figure 2. Estimated dose-response function and treatment effect function given a change of 5% in profit share. Categories of species.



Note: Own elaboration based on estimations.

Appendix A: Additional Tables and Figures.

Table A1. Covariate balance with and without adjustment. Total sample.

Covariate	Total sample					
	Unconditional effect of shares		Effect of shares conditional on $E[S/X_i)$		Effect of shares conditional on R_i	
	Coef.	**Se**	**Coef.**	**Se**	**Coef.**	**Se**
Vessel						
Small oar boat	0.15***	0.023	0.0003	0.023	-0.0009	0.023
Small Motor boat	0.42***	0.03	0.0008	0.34	0.004	0.034
Launch(length<12)	-0.36***	0.026	-0.0007	0.029	-0.009	0.029
Launch(12≤length≤15)	-0.11***	0.012	-0.041**	0.014	-0.041*	0.013
Launch(15≤length≤18)	-0.10***	0.01	-0.0002	0.012	0.004	0.011
Wood vessel	0.15***	0.023	-0.004	0.025	-0.014	0.026
Fiberglass vessel	-0.11***	0.023	-0.0002	0.027	0.007	0.026
Steel vessel	-0.03***	0.005	-0.00005	0.006	0.001	0.006
Echo sounder	-0.22***	0.021	-0.0004	0.023	0.004	0.023
Crew's size	-1.48***	0.10	-0.003	0.114	0.031	0.113
Technology						
Diving	0.50***	0.03	0.0009	0.34	0.006	0.034
Purse-seine net	-0.05***	0.012	-0.00009	-0.01	0.001	0.015
Long line technology	-0.53***	0.028	-0.001	0.032	-0.011	0.03
Handline technology	0.09***	0.015	0.0002	0.018	-0.0008	0.018
Drift-net fishing	-0.13***	0.026	0.0007	0.031	0.007	0.029
Traps	0.03***	0.013	0.00006	0.015	-0.001	0.015
Picking	0.02*	0.012	0.00004	0.01	-0.002	0.014
Others	0.059***	0.009	0.0001	0.011	0.001	0.011
Activity						
Ecological problem	-0.23***	0.029	-0.0004	0.034	-0.007	0.034
Vessel owner						
Age	4.2***	0.73	0.008	0.86	0.034	0.863
Education	-0.40**	0.18	-0.0007	0.222	0.026	0.221
Experience	4.5***	0.77	0.009	0.916	0.053	0.91
Another occupation	0.001	0.02	0.000002	0.03	-0.004	0.03
Not residing in work	0.01***	0.01	0.00002	0.01	0.001	0.013
Move	-0.08**	0.02	-0.0002	0.018	0.002	0.019
Community						
Crew experience	4.04***	0.26	0.008	0.29	0.03	0.296
Crew education	0.186***	0.049	0.0003	0.06	0.014	0.056
Vessel owner/crew	0.13***	0.024	0.0002	0.027	0.007	0.027
Unemployment rate	-0.005**	0.002	-0.00008	0.003	-0.0001	0.003
Fishing infrastructure	0.34***	0.03	0.0007	0.037	0.016	0.036
Rural	-0.10***	0.032	-0.0002	0.038	-0.005	0.038
Population size	-185***	33.3	-0.36	39.3	-7.12	39.2
Observations	6,840		6,840		6,840	

Source: Own elaboration based on the OLS regression of each covariate against profit shares either unconditioned or conditioned on the predicted valued of profit shares and the distribution of propensity scores, respectively, *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Estimated parameters for the estimation of the expected outcomes.

Variable	**Fish**		**Mollusk**		**Crustacean**		**Alga**		**Chilean abalone**		**Total**	
	Coef.	**Se**	**Coef.**	**Se**	**Coef.**	**Se**	**Coef.**	**Se**	**Coef.**	**Se**	**Coef.**	**Se**
Share	3.01*	1.59	5.85***	1.95	7.66	5.49	-2.39	5.75	-4.10	7.06	0.57	1.12
Share^2	-1.92***	0.63	-2.18**	0.78	-2.92	2.88	0.67	1.99	-3.24	2.26	-1.72***	0.46
GPS	-25.09***	8.22	-37.52**	12.79	-56.44	37.25	-37.71	26.41	-13.86	67.84	-38.75**	6.84
GPS^2	28.36***	6.93	41.59***	12.95	62.69*	34.69	33.69	28.60	6.14	67.34	39.25***	5.97
Share*GPS	-1.96	2.66	-6.71	3.15	-8.61	8.63	3.18	8.92	15.92	11.34	2.58	1.93
Constant	16.68***	2.43	19.84**	3.15	23.41**	9.96	22.21**	6.16	16.38	17.09	20.94***	1.95
Observations	3,947		2,091		367		420		376		6,840	

Note: Own elaboration based on estimations, *** p<0.01, ** p<0.05

Table A3. Marginal effects of increasing crew profit shares by 5%, vessel owner and skipper shares pooled together.

Level of the treatment	Marginal effects					
	Fish	**Mollusk**	**Crustacean**	**Alga**	**Chilean abalone**	**Total**
0.05	-0.108**	0.035	-0.231	-0.156	0.168	-0.073**
0.10	-0.084**	0.035	-0.191	-0.143	0.152	-0.057**
0.15	-0.064**	0.033	-0.155	-0.129	0.136	-0.044**
0.20	-0.048**	0.032	-0.124	-0.115	0.120	-0.032**
0.25	-0.034**	0.030	-0.097	-0.100	0.105	-0.023**
0.30	-0.023**	0.027	-0.073	-0.086	0.090	-0.015
0.35	-0.014**	0.025	-0.051**	-0.071**	0.076	-0.008
0.40	-0.007**	0.022**	-0.031**	-0.057**	0.062	-0.002
0.45	-0.001	0.018**	-0.013**	-0.041**	0.048**	0.002**
0.50	0.003	0.015**	0.004	-0.026**	0.035**	0.006**
0.55	0.005	0.011**	0.020**	-0.010**	0.022**	0.009**
0.60	0.007	0.008**	0.035**	0.006	0.009**	0.012**
0.65	0.008	0.004	0.050**	0.023**	-0.004	0.014
0.70	0.008	0.000	0.066**	0.040**	-0.016	0.015
0.75	0.007	-0.004	0.081	0.057**	-0.028	0.017
0.80	0.006	-0.008	0.098	0.076	-0.039	0.018
0.85	0.005	-0.011	0.115	0.094	-0.050	0.019
0.90	0.002	-0.015	0.133	0.114	-0.061	0.020
0.95	0.000	-0.018	0.153	0.134	-0.072	0.020
1.00	-0.002	-0.021	0.175	0.155	-0.082	0.021

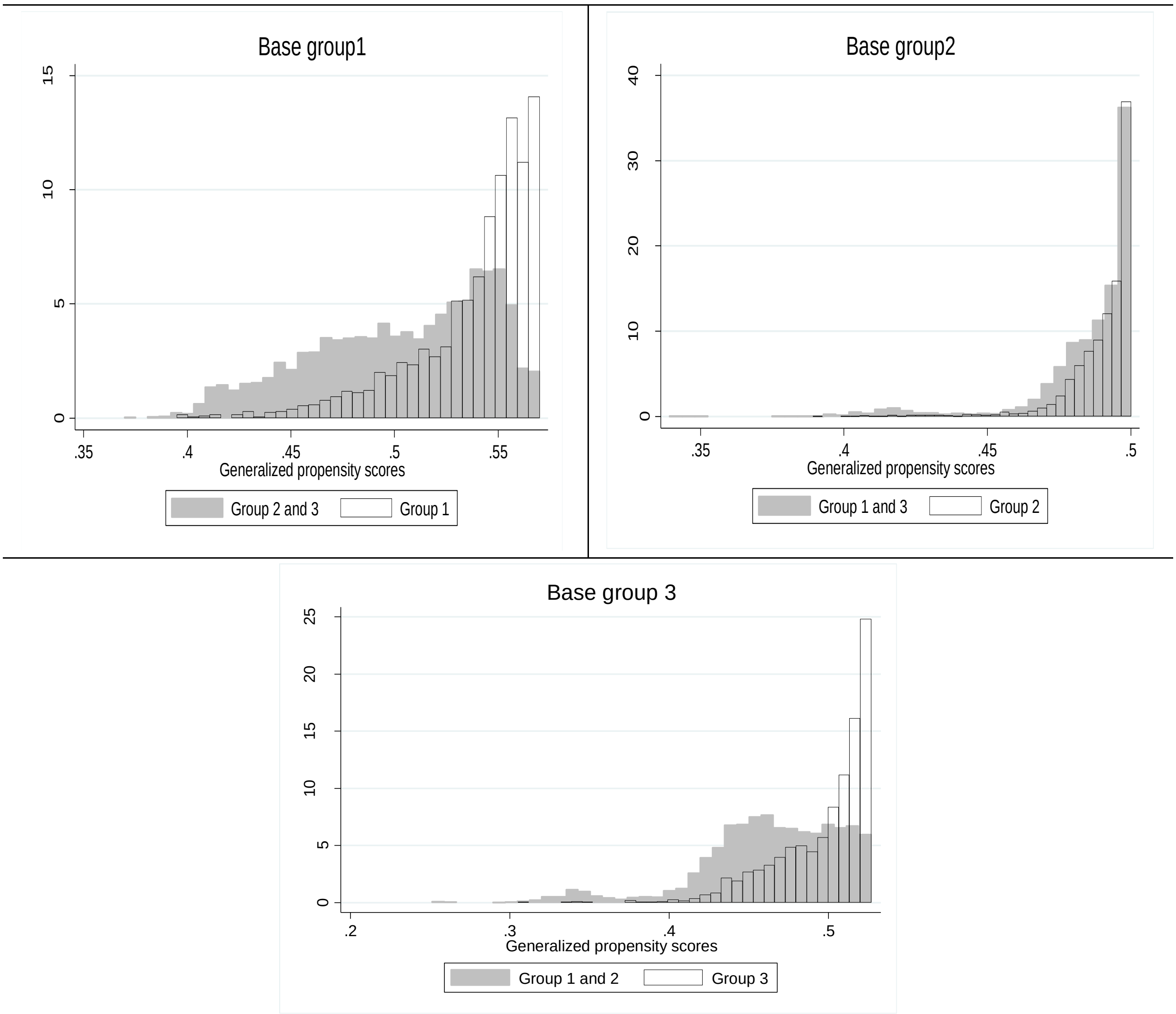
Source: Own elaboration based on estimations, ** $p<0.05$

Table A4. Estimated parameters for the Fractional Logit model (including the whole set of covariates).

Variable	Fish		Mollusk		Crustacean		Alga		Chilean abalone		Total sample	
	Coef	Se+	Coef	Se+	Coef	Se+	Coef	Se+	Coef	Se+	Coef	Se+
Vessel												
Small oar boat	0.13**	0.06	0.20**	0.10	-0.20	0.19	0.08	0.22	0.02	0.18	0.15***	0.05
Small Motor boat	0.13**	0.05	0.24***	0.08	-0.17	0.17	0.13	0.19	0.38***	0.12	0.14***	0.04
Launch(length<12)	0.03	0.05	0.11	0.08	-0.25	0.16	-0.11	0.17			0.05	0.04
Launch(15≤length≤18)	0.03	0.10	-0.03	0.24	0.31	0.26					0.00	0.09
Fiberglass vessel	-0.05	0.04	0.01	0.05	-0.02	0.13	-0.04	0.14	-0.19*	0.10	-0.05*	0.03
Steel vessel	-0.13	0.17	0.06	0.24	1.55***	0.18					-0.12	0.16
Echo sounder	-0.03	0.04	-0.10	0.07	-0.11	0.10	-0.06	0.21	0.19	0.15	-0.07**	0.03
Crew's size	-0.10**	0.01	-0.05**	0.02	-0.19**	0.05	-0.12**	0.04	-0.01	0.05	-0.09**	0.01
Technology												
Diving			0.15***	0.05	0.37***	0.11	0.27***	0.09			0.37***	0.05
Purse-seine net	0.05	0.07									0.14**	0.07
Long line technology	-0.01	0.04									-0.01	0.03
Handline technology	0.14***	0.05									0.15***	0.04
Traps											0.10	0.09
Picking											0.22***	0.07
Others											0.31***	0.06
Activity												
Ecological problem	0.08***	0.02	-0.03	0.04	-0.07	0.11	0.04	0.08	-0.11	0.09	0.06***	0.02
Vessel owner												
Age	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.004	0.01	0.01	-0.00	0.00
Education	-0.01*	0.00	-0.00	0.01	0.00	0.01	-0.01	0.01	-0.01	0.01	-0.01*	0.00
Experience	-0.001	0.00	-0.00	0.00	0.00	0.00	-0.01	0.004	-0.01	0.01	-0.00	0.00
Another occupation	0.10***	0.03	0.10**	0.04	0.03	0.12	0.06	0.08	0.05	0.07	0.09***	0.0
Not residing in work	0.04	0.07	0.13	0.08	0.14	0.15	0.40**	0.19	0.06	0.14	0.08*	0.05
Move	-0.11**	0.05	-0.10*	0.06	0.39*	0.22	0.08	0.13	0.11	0.17	-0.09**	0.03
Community												
Crew experience	0.00	0.00	-0.00	0.01	0.02	0.02	-0.00	0.008	-0.03*	0.01	0.00	0.00
Crew education	-0.05**	0.02	-0.02	0.03	0.07	0.06	0.05	0.05	0.07	0.06	-0.01	0.02
Vessel owner/crew	0.1***	0.04	-0.17**	0.08	-0.01	0.04	0.11	0.28	-0.22*	0.14	0.07***	0.02
Unemployment rate	-0.43	0.46	-1.67**	0.06	1.24	1.88	-1.35	1.39	0.13	1.76	-1.29**	0.34
Fishing infrastructure	0.02	0.03	0.10***	0.04	-0.10	0.10	-0.05	0.09	0.02	0.10	0.00**	0.00
Rural	-0.02	0.03	0.02	0.04	0.01	0.10	-0.10	0.11	0.24**	0.11	0.01	0.02
Population size	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Constant	0.63**	0.28	0.21	0.41	-0.88**	0.91	0.07	0.585	-0.65	0.82	0.19	0.20
Log pseudo-likelihood	-1,796.4		-15,466.4		-167.2		-194.5		-173.6		3,154	
Observations	3,947		2,091		367		420		376		6,840	

Note: Own elaboration based on estimations, *** p<0.01, ** p<0.05, * p<0.1, + robust standard errors.

Figure A1. Common support area. Total sample.



Note: Own elaboration based on estimations. Group 1 is constituted of observations below the 30th percentile of the profit share distribution; group 2 contains observation between the 30th and 70th percentiles; and finally group 3 includes observations above 70th percentile.

Chapter 3

Weather Shocks and Cropland Decisions in Rural Mozambique.

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Abstract

Economic development in low income settings is often associated with an expansion of higher-value agricultural activities. Since these activities often bring new risks, an understanding of cropland decisions and how these interact with shocks is valuable. This paper uses data from Mozambique to examine the effect of weather shocks on cropland decisions. We account for the bounded nature of land shares and estimate the Pooled Fractional Probit model for panel data. Our results show that crop choice is sensitive to past weather shocks. Farmers shift land use away from cash and permanent crops one year after a drought and from horticulture and permanent crop after a flood. However, this reallocation seems temporary as farmers devote less land to staples after two periods. This is consistent with the aim of maintaining a buffer stock of staples for home consumption.

Key words: land allocation, risk, household farms, Pooled Fractional Probit.

JEL classification: C23, C25, D81, Q12, O13, Q15.

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1 Introduction

Development of the agricultural sector in Mozambique remains a pressing policy issue. Despite rapid rates of aggregate economic growth for almost two decades, headcount poverty rates and rural incomes appear to have remained broadly stagnant, particularly amongst the majority of households that rely on smallholder agriculture (Arndt et al., 2012; Jones and Tarp, 2013). Micro-survey evidence shows few signs of increased agricultural productivity via adoption of improved inputs and/or shifting into higher-return crops (World Bank, 2008; Mather et al., 2008; World Bank, 2012). At the same time, Mozambique faces increased risks from climate shocks. For example, estimates by UNISDR (2009) ranks Mozambique third among the African countries most exposed to risks from multiple weather-related hazards.

This study provides an empirical examination of the impact of weather shocks on crop portfolio choices of small-scale farmers in Mozambique. We address the following questions: are crop choices sensitive to weather shocks? If so, is there any pattern of reallocation in response to shocks? And, are there systematic patterns in response to shocks? For instance, farmers may be more sensitive to more severe shocks or farmers living in higher risk areas may be less responsive to weather shocks.

The motivation for studying these questions relates to the impact of risks (and their realization in actual shocks) on the economic behavior of households. In the absence of functioning markets for credit, insurance and savings, rural households must largely rely on crop choice decisions to manage risk (Deron, 2002; Kurukulasuriya et al., 2006). Furthermore, the incidence of shocks may shape farmers' perceptions of the general riskiness of their environment and influence crop portfolio choices. Following Gollier and Pratt (1996), farmers may be 'risk vulnerable' in the sense that the presence of an exogenous background risk (climate) raises their aversion to other risks (e.g., through crop choices).

Existing empirical evidence suggests that farmers react to weather risks by diversifying their cropping system, which acts as a form of self-insurance (Benin et al., 2004; Di Falco et al., 2010; Bezabih and Sarr, 2012; Bezabih and Di Falco, 2012). Rather than focusing on diversification *per se*, we explore changes in cropland allocation across different crop categories. In the case of Mozambique, some staples show risk-reducing properties in terms of drought tolerance and ease of storage. As such, it is an attractive choice for risk-averse farmers (Arndt and Tarp, 2000; Tarp et al., 2002). Equally, it is reasonable to assume that buffer stocks of staple foods, particularly grains, may be reduced in response to weather shocks to smooth consumption (Kazianga and Udry, 2006). Following a shock, households may prefer to devote a larger share of their land to staple foods in order to replace this buffer, implying income from higher value crops may be reduced. Accordingly, while diversification is of interest it is important to understand exactly how cultivation choices respond to shocks (if at all) as well as the persistence of these portfolio changes.

The remainder of this study is organized as follows: Section 2 reviews literature linking risk and crop choice. Section 3 describes key characteristics of the agriculture sector and climate patterns in Mozambique. Section 4 presents the data, including geospatial data on water availability, which we use to distinguish between drought and flood events. Reliance on external as opposed to self-reported data on shocks is helpful. It addresses concerns of systematic reporting bias since weather shocks are a function of geographical location (Cameron and Shah, 2013). Section 5 describes our econometric model. We model cropland decisions as proportions; and, in order to address the fact that proportions are bounded between zero and one, we estimate the Pooled Fractional Probit (PFP) estimator due to Papke and Wooldridge (2008). We are unaware of existing studies that apply the PFP while controlling for unobserved characteristics. Section 6 discusses the main results; Section 7 considers a number of robustness tests; and Section 8 concludes.

2 Existing literature

Large fluctuations in weather conditions are generally associated with sizeable yield and price risk in agriculture. Moreover, since such shocks often affect an entire network, local mutual insurance schemes can break-down (Dercon, 2002). Consequently, in contexts of incomplete markets and limited asset holdings, *ex post* coping mechanisms cannot be relied upon to protect against exogenous shocks (Paxson, 1992; Townsed, 1994).[1] Exposure to risk is therefore likely to affect *ex ante* crop choices (Fafchamps, 1992a; Chavas and Holt, 1996; Kurosaki and Fafchamps, 2002).

The concepts of 'risk' and 'shock' are often used to refer to situations characterized by uncertainty. Following Cohen et al. (2008), perceptions of context can be understood as being derived from a sequence of past events. The evaluation of risks by individuals can be expected to be dependent on

[1] Credit constraints, commitment failure and imperfect flows of information among members of the community have been identified in the literature as potential causes of inefficiency of these institutions (Deaton, 1991a, 1991b; Fafchamps, 1992b)

past experiences. Under this process of adaptive expectation formation, weather risk can be proxied by past realizations of weather-related shocks. This means that droughts and floods occurring in the (recent) past are likely to shape farmers' perceptions of the current riskiness of their environment.

The incidence of a natural hazard is one element of background risk. If farmers are risk vulnerable, in the sense of Gollier and Pratt (1996), they may display more risk-averse behavior. The latter would be consistent with farmers preferring a crop-portfolio with a larger share of staples.[2] Farmers may switch to staples after weather shocks for several reasons. First, some staples are relatively more drought resistant and less prone to crop failure during water shortage periods. Consequently, if the household consumes one of its crops, this provides self-insurance against production and consumption price risk (Fafchamps, 1992a). Second, some staples are less perishable and can be stored for future consumption. Food is likely to be expensive after weather shocks when the harvest is poor. In this case, households will use their stock of staples to smooth consumption in the current period and will expand staples production in the next period so as to replace the depleted stock. Even though general empirical evidence suggests that consumption smoothing is limited in low income contexts, evidence does point to smoothing through the accumulation and depletion of staples stocks (Fafchamps et al., 1998; Kazianga and Udry, 2006). Indeed, Carter and Lybbert (2012) find that staples stocks play a more important role amongst very limited consumption smoothers.

A large literature studies the cropland decisions of small landholders in developing countries (see for example, Fafchamps, 1992a; Dercon, 1996; Kurosaki and Fafchamps, 2002; Masanjala, 2006; Damon, 2010; Chibwana and Fisher, 2012). One strand of the literature has investigated the potential advantages of multi-cropping as a risk management device (Adger et al., 2003; Benin et al., 2004; Di Falco and Chavas, 2009; Di Falco et al., 2010; Bezabih and Sarr, 2012; Bezabih and Di Falco, 2012). In addition, crop choice is identified as an adaptation strategy to climate change. For instance, Seo and Mendelsohn (2008) and Kurukulasuriya and Medelson (2008), using data of South-American and African farmers respectively, found that crop choices are highly sensitive to changes in precipitation and temperature under different climate change scenarios. Di Falco and Veronesi (2013) find that crop adaptation is more effective when it is implemented within a portfolio of actions rather than in isolation. For example, crop adaptation yields high net revenues when coupled with water

[2] Some psychological studies suggest that individuals who are continually exposed to high risk environments may not care about the addition of a small independent risk (Kahneman and Tversky, 1979). This suggests that controlling for background risk may be important.

conservation strategies or soil conservation strategies. We build on this literature, focusing on the Mozambican context, to which we now turn.

3 Agriculture and climate in Mozambique

Primary sector activities, which include agriculture and extractive industries, contribute around 30% of Mozambique's GDP; and agriculture alone employs 80 percent of the work force (Jones and Tarp, 2013). The agricultural sector remains relatively unproductive and consists mainly of smallholder farmers, who represent 85 percent of all rural households (World Bank, 2012). While rural agricultural markets are widespread, more than half of total household incomes correspond to the value of retained food. Major cash crops are sugar cane, coconuts, cotton, sesame, tobacco and cashews, and the main staple crops are maize, sorghum, millet, rice, beans, groundnuts, vegetables and cassava. More than 75 percent of small farms cultivate maize or cassava or both, which are also the main staples. Agriculture is predominantly rain-fed with less than 0.5 percent of total cropland under irrigation, almost all in sugar cane production (World Bank, 2010).

Mozambique has a rainy season lasting from October to April, with an annual average precipitation around 1,000 mm. The rural population is frequently affected by extreme weather variations, where droughts and floods are the most common weather-related disasters (EM-DAT, 2013). Droughts are the most frequent natural phenomenon, occurring mainly in the southern and central districts, with a frequency of 7 in 10 and 4 in 10 years, respectively. Although less frequent, floods are more destructive and their effects can prevail for a longer time. They primarily occur in southern and central regions, along river basins, in low-lying areas, and in zones with poor drainage. They are caused by either heavy rainfall or increases in water levels in upstream neighboring countries. Climate change will likely make weather fluctuations more frequent and extreme in the future. In particular, projections for Mozambique indicate that climate change is expected to increase the frequency and magnitude of droughts and floods, imposing important costs on Mozambique's economy and further complications for existing development challenges. Estimations for the worst case scenario suggest that GDP may fall between 4 percent and 14 percent relative to baseline growth in the 2040–50 decade in Mozambique if adaptation strategies are not implemented (World Bank, 2010). However, strongly negative outcomes are unlikely (Arndt and Thurlow, 2013). Changes in cropland are one of the key adaptation strategies to understand in order to assist planning by policymakers and quantify the impact of climate change (Seo and Mendelsohn, 2008).

4 Data

4.1 Household data

We use a balanced panel of households from the 2002 and 2005 waves of the *Trabalho de Inquérito Agrícola* (TIA) survey collected by the Ministry of Agriculture of Mozambique in collaboration with Michigan State University (Ministério da Agricultura e Desenvolvimento Rural, 2002; 2005).[3] The TIAs are representative of small and medium-size farm households across rural areas of the 11 provinces in Mozambique (one province, Maputo City, is exclusively urban and not included here).[4] The survey consists of a series of questions concerning household demographic characteristics, assets, farming techniques, access to services and community characteristics. Data also contains farmers' reports of amounts of hectares allocated to different crops. We use 3,752 observations for which data on land shares are available.

Panel (a) of Table 1 reports descriptive statistics on changes in crop decisions from the dataset. It shows an increase of 2% in non-staple cropland share between 2002 and 2005. While cash crop and horticulture area increased during the period, permanent crop area decreased. The upward trend in non-staple crops was due to an overall increase in the cultivation of cash crops and horticulture. On average, farmers allocate around 50% of their land to cassava and maize. This percentage has remained unchanged during the study period. The uncultivated land share decreased around 2% between 2002 and 2005. The decrease in uncultivated land is more likely to reflect an expansion of cultivated area rather than changes in fallow land. This in line with the view that agricultural growth observed during that period was mainly driven by expansion in land use rather than productivity improvements (Mather et al., 2008).

[INSERT TABLE 1 ABOUT HERE]

[3] There are 8 TIA surveys conducted with interruptions during the period 1996-2012 (1996, 2002, 2003, 2005, 2006, 2007, 2008 and 2012). However, only the TIA 2002 wave contains a sample that was re-interviewed latter on in 2005, which makes it possible to make a panel solely using these two years. We exploit the panel structure of the TIAs since controlling for household heterogeneity is a critical issue when studying land allocation.

[4] The sampling frame of the TIA survey was derived from the Census of Agriculture and Livestock 2000, and used a stratified, clustered sample design that is representative of small- and medium-scale farm households at the provincial and national levels, leaving out large commercial farms from the design. In particular, households cultivating more than 50 hectares of land or owning more than 20,000 fruit trees, more than 100 heads of cattle or more than 500 goats and pigs are classified as large-scale farmers and are not covered by the TIA surveys. Potentially, large-scale farmers may face very different trade-offs regarding crop choices than farmers in our sample. Heterogeneity between large and small landholders may be interesting to explore in future research.

4.2 Geospatial data

To identify which villages (locations) experienced weather shocks, we rely on information on villages' GPS coordinates recorded in the TIAs. To identify areas that have been flooded, we employ geospatial data recorded in the Global Active Archive of Large Flood Events from the Dartmouth Flood Observatory (Brakenridge, 2013). To identify drought areas, we use calculations of the Standardized Precipitation Index (SPI) by the National Centre for Environmental Predictions (NOAA) (McKee, et. al. 1993; 1995).[5] Specifically, we use a SPI index constructed on 0.5° lat/lon grid monthly precipitations of 1949-2014 in Mozambique.[6] We consider two time-scales. First, we compute the SPI over the main rainy season (November-April). When taking into account the rainy season, we assume that farmers respond to prospects of a good/bad season which is a function of how good/bad the general growing condition was in previous periods. Second, we compute a 3 months SPI index over the main planting/sowing period (October-December). That is relevant for most cash and staple crops. In a country dependent on rain-fed agriculture, erratic rains in the planting/sowing season will increase the probability of crop failure.

The SPI index includes both positive and negative values. Positive SPI values indicate that rainfall was above the median precipitation and negative values show that precipitation was below the median for that period. We define shock occurrence at the village level. Natural hazards are covariate shocks that are highly likely to have a common effect on the whole area of occurrence, and then over the entire village's population. We have a sufficient number of villages (525) to generate enough variation in our shock variables. We define two drought variables. First, we compute a drought indicator if the SPI value falls at or below minus 0.5. In addition, we exploit the continuity in the negative range of the index to explore drought intensity. We use the absolute values. Thus, a larger value would indicate a more severe dry cycle. Finally, we construct measures of the historical occurrence of natural shocks by counting the number of events in each village, going back 20 years

[5] The SPI is based on a long-term precipitation record of at least 50 years of monthly values. This long-term record is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero.

[6] Some other rainfall data sources may eventually be used. For example, remote sensing estimations developed by the Famine Early Warning Systems Network (FEWS NET) provide a higher resolution rainfall data at 0.1 degree, corresponding to around 10x10km cells at the equator. However, this data is only available from 1995. Thus, the shorter temporal coverage makes it problematic to compute a reliable SPI index since it is highly recommended to have at least 50 years of historical rainfall data (McKee et al., 1993, 1995). Alternatively, data with longer temporal coverage is also provided by the Climate Research Unit from the University of East Anglia at 0.5 degree. The data used here also has a resolution of 0.5 degree and goes back more than 50 years, fulfilling the criterion outlined above.

to 1984. We use these measures to split the sample and study how weather shocks affect crop land decisions conditioned on background risk.[7]

We focus on whether a village was affected by a weather shock in *t-1* and/or *t-2*. That is, shocks in 2000-2001 and 2003-2004 are used to explain the cropland allocations observed in 2002 and 2005, respectively. This lag is used because we are interested in how past events shape future behavior. Table 1, panel (b) summarizes the weather shock data; and Figure 1 maps flooded areas for the years of interest overlaid with the locations of surveyed villages. It shows that flooding predominantly affected villages in southern and central regions, although northern villages were also hit by the 2003 flood.

All floods identified here were classified at least as class 1 or large flood events. This implies significant damage to structures or agriculture, fatalities, and/or a 1-2 decades-long reported interval since the last similar event (Brakenridge, 2013). However, floods vary in duration and extension. For example, floods in 2004 affected few cities or districts, covering around 4,400 sq. km and lasting for almost two weeks. In contrast, floods in 2000, 2001 and 2003 were national-scale disasters as effects extended to multiple provinces. To illustrate, these large scale floods covered areas between 200,000 and 440,000 sq. km, and in some cases lasted for months (2000 and 2001). These large scale natural hazards affected around 20 percent of households included in our sample (see Table 1). In particular, the 2000 flood is classified as a very large event (class 2) and is remembered as one of the worst natural disasters in 50 years in Mozambique (World Bank, 2010).[8]

[INSERT FIGURE 1 ABOUT HERE]

Figure 2 maps findings from the SPI for different years. For 2000 we see a dry cycle in central districts and wet cycles in the south. This extremely wet period is consistent with the flood identified in Figure 1 in the same year. In addition, drought events are detected in the south region in 2001 and

[7] In order to guarantee sufficient observations, we use convenient thresholds to distinguish between low and high risk areas. We define a low flood risk village as that one has experienced between zero and one flood event in the last 20 years, and a high flood risk village as that one has been hit by a flood between 2 and 5 times. Similarly, we use the information on the number of droughts to distinguish low (between zero and 7 droughts] from high drought risk villages (between 8 and 11 events). We aim to identify the effect of recent weather shocks on cropland decisions, conditional on villages' background risk.

[8] The available data only allows us to distinguish intensity levels across different flood events but not within floods, which makes it difficult to formally test the effect of the duration/severity/magnitude of floods on cropland decisions.

in all regions in 2003.[9] According to the SPI calculated over the rainy season, no droughts occurred in 2004. However, the SPI over the plating season does detect erratic rains at the beginning of the growing season in the south in 2004. Furthermore, it also shows a delay in precipitation in 2000, as illustrated in Figure A1. Table 1 panel (b) shows that the percentage of households included in our sample affected by droughts ranges from 5 percent in 2001 to 33 percent in 2003.

[INSERT FIGURE 2 ABOUT HERE]

5 Empirical strategy

Cropland decisions are commonly measured as proportions bounded between zero and one (Papke and Wooldridge, 2008). One challenge in modelling crop allocations in Mozambique is that there is a significant fraction of farmers that do not actually allocate land to non-staple crops (more than 50%, see Table 1), meaning many observations are corner solutions at zero. We address this statistical challenge by using the Pooled Fractional Probit (PFP) estimator. This relies on Bernoulli quasi-likelihood methods to ensure that estimates of predicted land shares vary between zero and one (Papke and Wooldridge, 1996). Furthermore, this model is appropriate for panel data that contains a large cross-sectional dimension and relatively few time periods (Papke and Wooldridge, 2008).

We consider a random sample of farmers $i = 1,\dots, N$, repeated across time period $t=1,\dots,T$. The dependent variable y_{it} corresponds to the land share allocated to a particular crop category (see below). Our empirical model is specified as:

$$E(y_{it}|x_{it}, z_{it}, c_i) = \Phi(\beta x_{it} + \gamma z_{it-1} + c_i) \tag{1}$$

where x_{it} is a vector of household and farm physical characteristics. z_{it-1} represents a vector of past weather shocks, i.e. flood and drought events. Coefficients β and γ denote parameters to be estimated; c_i refers to individual-specific unobserved characteristics; and Φ is the normal cumulative density function. In order to account for the unobserved effects c_i, Papke and Wooldridge (2008)

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[9] We could have used flooded area data and the positive scale of SPI identifying wet scenarios to classify flood events according to the extent of seriousness, as in the drought case. However, a flood is a much more complex phenomenon that responds to other parameters than rainfall, which would invalidate any classification exclusively based on precipitation levels. For instance, the flood recorded in 2001 affecting mainly the central region originated from a very wet season in neighboring Zambia and Zimbabwe that led to the opening of floodgates at the Kariba dam, and waters released from the Cahora Bassa Dam in Mozambique, flooding low-lying areas located further downstream.

propose a conditional normality assumption to restrict the distribution of c_i, given time averages of covariates:[10]

$$c_i = \psi + \xi \bar{x}_i + \varphi \bar{z}_i + a_i \tag{2}$$

where $\bar{x}_i = T^{-1} \sum_{t=1}^{T} x_{it}$ and $\bar{z}_i = T^{-1} \sum_{t=1}^{T} z_{it-1}$ are vectors of time averages; and $a_i \sim N(0, \sigma_a)$ is a residual orthogonal term. With these assumptions, vectors β and γ and associated average partial effects (APEs) can be identified up to a positive scaling factor. To see this, plugging (2) in (1) yields:

$$E(y_{it} | x_{it}, z_{it}, a_i) = \Phi(\psi + \beta x_{it} + \gamma z_{it-1} + \xi \bar{x}_i + \varphi \bar{z}_i + a_i) \tag{3}$$

Or equivalently:

$$E(y_{it} | x_{it}, z_{it}) = E(\Phi[\psi + \beta x_{it} + \gamma z_{it-1} + \xi \bar{x}_i + \varphi \bar{z}_i + a_i] \mid x_{it}, z_{it}) \tag{4}$$

Next, we employ a standard mixing property of the normal distribution (Wooldridge, 2010), yielding:

$$E(y_{it} | x_{it}, z_{it}) = \Phi[(\psi + \beta x_{it} + \gamma z_{it-1} + \xi \bar{x}_i + \varphi \bar{z}_i)/(1 + {\sigma_a}^2)^{\frac{1}{2}}] \tag{5}$$

which can be estimated via maximum likelihood methods treating σ_a as a parameter to be estimated.

To verify estimates from the PFP approach, we also estimate the Correlated Random Effects (CRE) Tobit model for panel data, which assumes crop land decisions are simply censored at zero. However, if household decisions regarding crop participation and land amounts are determined by different underlying decision processes, this approach may be restrictive. Thus, we also estimate the Double-Hurdle (D-B) model due to Cragg (1971).[11] Finally, for comparison, we show results of a simple linear fixed effect (FE) model. Note that in all estimations we control for a large number of covariates. Descriptive statistics for these covariates are shown in Table 1, panel (c). Further details can be obtained on request.

[10] This strategy was first suggested by Chamberlin (1980).
[11] We follow the same strategy as in the PFP model to account for household heterogeneity.

With respect to the dependent variable(s), we begin by classifying the household production portfolio into staple and non-staple crops; we then study changes in the land share allocated to non-staples. Subsequently, we consider a more disaggregated classification covering nine non-overlapping categories: cash crops, permanent crops, horticulture, cassava-maize, sorghum-millet, groundnut-beans, rice, sweet potatoes, and uncultivated land.[12] This disaggregation is important. First, while annual crops are produced from plants which last one season, permanent crops are perennial and not replanted after each harvest. Thus, it is not as easy to adjust permanent crop land in the short-run. Second, the distinction between cash and food crops is important. Whilst all crops have potential to be sold, cash crops are those that are non-edible and which cannot serve as (food) self-insurance. Third, similar to staple crops, horticulture has a short farming cycle, needs minimal capital investment, and part of its production can be used to satisfy food needs.[13] However, horticulture is generally irrigated and is found more extensively near main urban areas.

Fourth, we distinguish maize and cassava from other staples. These two crops are the main staples in rural diets and are also important cash generating source. Fifth, we aggregate sorghum and millet. They can be considered general substitutes for maize, but are more drought resistant, and have roughly the same growing season. Sixth, groundnuts and beans are studied together. They are often used in rotation with the main cereal. Seventh, we distinguish rice from other staples since rice is not sensitive to flooding and is mostly sold as a cash crop to urban areas. Finally, we study land allocations to sweet potatoes, a classic crop for food security. This crop has a shorter and flexible farming cycle and has the capacity to grow in poor growing conditions.

6 Results

6.1 Weather shocks and non-staple cropland share

Columns 1-3 of Table 2 report our main results. They are derived from the PFP estimator, from which average partial effects are calculated. Column 1 includes only the flood shock variables; column 2 replaces the flood shocks with drought shocks; and column 3 includes both flood and drought shocks simultaneously, which is our preferred specification.[14] All specifications include a full set of control covariates (shown) as well as the average of covariates to control for unobserved

[12] Uncultivated land is defined as land that has been ploughed and harrowed previously but has been left without being sown, typically because of lack of means to work it, to restore its fertility or to avoid surplus production.
[13] In 2002, there were some missing observations for the horticulture category. For this year, we computed estimates of horticulture land shares by subtracting all the rest of crop categories from total land. We then replaced the missing information with these estimates.
[14] Standard errors for the APEs were obtained using 500 bootstrap replications clustered at the household level.

household fixed effects (not shown). The remaining columns of Table 2 report results for the same specification using alternative estimators. Column 4 is a simple fixed effects panel estimator; column 5 reports APEs of the CRE model; and columns 6-7 report the participation and quantity equations from the D-H model.

Across all specifications and estimators, we note that cropland decisions are sensitive to recent weather shocks. Whilst, there are some differences in the magnitude of estimated coefficients, they are similar. Results from the D-H model are not directly comparable to the other columns. However, they continue to indicate a significant effect of weather shocks on both participation and quantity allocated to non-staple crop farming.

Taken together, the estimates show that farmers switch away from higher-value non-staple crops in response to prior flooding. On average, farmers reduce the land share allocated to non-staple crops by 4.2 percent and 2.5 percent following a flood in *t-1* and *t-2*, respectively (Table 2, column 1). The marginal effect due to a flood in *t-2* is reduced while the marginal effects associated with a flood in *t-1* slightly increase to 4.7 percent after controlling for recent drought shocks (see column 3). In comparison, the average farmer reduces the land share allocated to non-staple crops by 8 percent after a recent drought event (*t-1*). In sum, the evidence indicates that farmers are more responsive to droughts and that responses to shocks are strongest in the short run.[15]

6.2 Weather shocks and crop portfolio changes

Table 3 reports results for the effect of past weather shocks on disaggregated crop categories. In keeping with the results discussed above, floods drive a switch away from permanent crops and horticulture toward both maize-cassava crop farming and uncultivated land. Changes in uncultivated land are also driven by the effect of a flood in *t-2*. While we investigate this latter result further in Section 7; we note here that this may be due to the extreme devastation of flooding in 2000 (World Bank, 2010). Substantial losses in terms of arable land, equipment and livestock, as well as actual displacement of households, may account for the increase in uncultivated land share since many farmers were left with limited means to work their land.[16] We also note that farmers respond to flood

[15] This difference is significant at 1% (t =124).

[16] On the other hand, more land left without being sown may simply reflect a farmer's decision to avoid surplus production or more time required to restore land fertility after this devastating flood.

events in *t-1* by reducing the sorghum-millet land share at time *t*, which is consistent with farmers substituting sorghum-millet for other staples.

[INSERT TABLE 3 ABOUT HERE]

Recent droughts produce a similar pattern of reallocation. Farmers move away from cash and permanent crop farming to staple crops. While groundnuts-beans increase after a drought in *t-1*, farmers respond by increasing sorghum-millet and sweet potatoes land shares after a drought in *t-2*. However, we did not find statistically significant changes in maize-cassava land shares after a drought. The negative effect of droughts on the permanent crop land share must, as already noted, be interpreted with caution. However, the most plausible explanation of this result refers to how permanent crop farming is carried out and estimated. In most cases, farmers practice inter-cropping meaning that it is unusual for tree crops to be the only cultivated crop in an area. Consequently, a negative change in permanent crop land share probably indicates that farmers are simply intensifying intercropping practices.

We also note that farmers respond to drought events in *t-1* by increasing the horticulture land share at time *t*. Horticulture in Mozambique is predominantly carried out in peri-urban areas, and therefore is more likely to have access to reliable (e.g., piped) water sources. Additionally, the rice land share is reduced after a drought in *t-1* and *t-2*. This persistent effect responds to the fact that the flooded condition of rice fields is necessary for rice growth, implying that drought events are an important source of production risk for rice. Finally, we note that farmers also tend to increase the land share that is uncultivated after a drought in *t-2*. This may appear to contradict the need to restore household food stock. However, although arguably less devastating than floods, droughts can generate important material and human losses. Also, depending on their severity, they can exhaust soil quality (FAO, 2005). The implication is that farmers may consider it optimal to work intensively on a smaller cropped land area following a drought, thereby allowing land to recover.

7 Robustness

7.1 Timing of drought events

Poor and erratic rains in the planting/sowing season may lead to a reduction in potential yields and overall crop production. In turn, this may induce farmers to alter their crop portfolio. Thus, rather than defining drought events with respect to rain shortages during the rainy season, we re-estimate the model and define drought shocks with reference to the main planting/sowing period (October-December). Since this period is most relevant for cash and staple crops, we focus on these categories for clarity.

Table 4 reports our results now using the modified drought indicator. The results suggest that the timing of rain shortage is relevant. Specifically, farmers respond to a drought in *t-1* by reducing land shares to maize-cassava and groundnuts-beans and increasing land allocated to sorghum-millet and sweet potatoes. This reduction in the maize-cassava land share may seem inconsistent with food security concerns. However, sorghum and millet resist drought better than maize. Also, evidence indicates that sorghum, although mostly substituted by maize in the 1940s, is now being promoted to provide greater resilience to drought. Furthermore, sweet potatoes are well known for being a classic crop for food security. This crop provides, on average, more micro-nutrients per hectare and day than maize and cassava, has a shorter and flexible farming cycle and has the capacity to grow in poor growing conditions and during post-disaster periods. These characteristics also make sweet potatoes one of the preferred crops when maize and cassava fail. Finally, we also note that, farmers respond to drought events in *t-2* by reducing the sorghum-millet land share at time *t*. This is consistent with a re-adjustment of their buffer stocks of food staples. That is, in *t-1* farmers may have deliberately over-produced sorghum-millet to replace a diminished buffer stock. At time *t*, farmers then lower the sorghum-millet land share in line with normal consumption needs.

[INSERT TABLE 4 ABOUT HERE]

7.2 Drought intensity

A further concern with our definition of drought shocks is that it relies on a binary distinction between events. To explore whether this is material, we re-estimate the models in Table 3 replacing the binary drought variable with the underlying continuous SPI metric, where a larger number indicates a more severe dry cycle. These results are reported in Table 5. As before, we find a negative and significant effect of rain shortages on the share of land allocated to non-staple crops. The results also show a similar pattern of reallocation – farmers move to sorghum-millet cultivation from cash, rice and permanent crop farming. Moreover, impacts are larger in zones affected by more severe drought events. In line with previous results, we also find that uncultivated land increases in the face of a more severe drought.

[INSERT TABLE 5 ABOUT HERE]

7.3 Background risks

Our main results assumed that responses to shocks are homogenous. However, it may be the case that individuals who live in higher (background) risk environments react differently to those living in lower risk areas. This is important because the decreasing trend in precipitations observed in the last years in Mozambique suggest a higher incidence of natural disasters. This may have shaped adaptation – i.e. a shock in high risk areas may have a lower impact since farmers are more prepared for it.

In Table 6, we test if responses to recent weather shocks vary according to the magnitude of background risk. To do so, we interact dummies for low and high risk areas with the drought and flood event variables. We define a high flood risk village as one that has been hit by a large flood more than once in the last 20 years. High drought risk villages are those that have experienced more than 7 droughts over the same period. The table focuses on the effect of recent weather shocks on the land share allocated to cassava-maize crops. This is to ease interpretation and minimize chances results are driven by agro-ecological conditions.

[INSERT TABLE 6 ABOUT HERE]

We find that farmers living in higher drought-risk villages are more sensitive to floods, but are not more/less sensitive to droughts. The latter suggests a reinforcement effect rather than adaptation in high risk areas. Since droughts are more frequent in Mozambique than floods (on average), farmers in high drought risk areas may be more aware of the losses from these natural hazards, making them more resistant to adoption of a riskier production portfolio.

7.4 Other input choices

A further concern with our model is that we implicitly ignore how production decisions other than crop allocation may adjust to weather shocks. Put differently, interpretation of the estimated APEs for the shock variables requires that all other aspects of production remain fixed. However, it is reasonable to suppose that fertilizer use, livestock activities, off-farm employment and remittances (among others) may respond to shocks and that changes in these factors may indirectly affect crop allocations. If so, then their presence in the model as covariates effectively over-controls for the impact of shocks on crop allocation decisions, ruling out indirect effects. To address this, we first remove all 'suspect' covariates and re-run the baseline model. These results are reported in column 1 of Table A1. The results remain fundamentally unchanged, implying that the direct effect of shocks on crop allocations is significant and dominant.

As an alternative approach, which also extends our analysis, we consider models for alternative outcomes. For instance, previously we noted that the increase in uncultivated land after a weather shock may be due to displacement of households from their farm (or part of it). It would also be consistent with household members seeking alternative, off-farm income sources. Thus we run the reduced form model presented above using the following outcome variables: the share of family members in off-farm jobs (i.e, who have wage labor outside the farm); the proportion of family members who are self-employed (i.e., undertake activities other than farming); use of fertilizer; and receipt of remittances. We find that the occurrence of flood shocks increases the proportion of off-farm labor as well as the probability of receiving remittances, supporting the notion that these act as coping mechanisms for flood events, but not for drought shocks. Moreover, we find that the probability of using fertilizer increases after a weather shock. As argued above, this result may be in line with a decline in soil quality after a flood/drought, leading farmers to purchase inputs to recover productivity soil.

7.5 Crop rotation

Rotation of crops may be an important driver of land allocation changes.[17] Again, this was not captured (controlled for) in our main specification. To address this, a history of crop allocation patterns would be required for each household. However, this is not available in our data. Minimally, however, we do have basic information on whether or not the household employed rotation practices. According to this, which is only available in 2005, about 35 percent of farmers pursue some form of rotation. To examine whether our results may be confounded with crop rotation, we simply re-

[17] For example, beans are normally planted in rotation with the main cereal and cultivations without fertilizers may benefit from the input remains of the preceding year from intensive productions, mainly cash crops.

estimate our full model excluding households that rotate. Overall our main findings are unchanged (results are available on request). Finally, we include crop rotation as an outcome variable and re-estimate the reduced form model discussed in the previous sub-section. These results are shown in the final column of Table A1. They show that rotation is lower among farmers after a weather shock. Since food insecurity substantially increases after a natural disaster, agricultural practices whose productivity benefits are ambiguous (at least during/after a shock) may be of reduced concern during such periods. In sum, we conclude that crop rotation is unlikely to be a key driver of our results.

8 Conclusions

Agricultural growth and development typically involves transformation in the form and structure of rural activities. In particular (some) farmers reallocate resources away from food self-sufficiency towards higher value, higher risk agricultural activities. However, farmers may be reluctant to exit food crop cultivation as it helps insure them against food shortages. This suggests that an understanding of cropland decisions and how they interact with weather shocks is an important policy relevant challenge. It is an even more crucial issue in light of the expected higher frequency of natural disasters due to climate change.

In this study we combined panel data and geospatial information for Mozambique to analyze the impact of weather shocks on cropping activity. We took into account the bounded nature of land allocation decisions and used the Pooled Fractional Probit model due to Papke and Wooldridge (2008). We found that crop choice is sensitive to recent weather shocks and farmers are more responsive to more severe droughts. Farmers tend to reallocate land from high risk to low risk cropping activities after a natural hazard. While farmers mainly move out of horticulture and permanent crops after a flood, they reallocate resources away from cash and permanent crops when hit by a drought. We also found that crop reallocation seems to follow a short-term pattern, which is consistent with the maintenance of a buffer stock of food staples within the household.

These findings were found to be robust to alternative definitions of shocks as well as to the exclusion of variables that also may be affected by weather events. This indicated that these shocks primarily have a direct effect on cropland decisions. In addition, we noted that the share of land that is uncultivated tends to rise as a consequence of some weather shocks; and that farmers living in higher drought risk areas appear more responsive to flood shocks.

Some caveats with respect to our results merit comment. First, in our examination of the disaggregated production portfolio, we do not account for simultaneity and correlation among crop categories. Second, our framework implicitly assumes that one type of crop is a substitute for others, which does not take land suitability constraints into account. Nonetheless, switching to staples is less likely to be constrained by agro-ecological conditions – e.g., the distribution of maize-cassava production is less dependent on geographical factors. Third, given the limited temporal dimension of our panel, we are not able to fully explore longer-run dynamics in cropland decisions. These may be important, especially in explaining changes in permanent crops, use of annual rotation, and in exploring the role of prices on crop choices. Moreover, while we have uncovered clear evidence of short-term farmer responses to weather risks, future development of the sector will depend in fundamental ways on structural changes in the wider economy, including the articulation between industry and agriculture.

Despite these considerations, an important implication of our empirical findings is that climate change, which is expected to increase the frequency of extreme weather events, is likely to have a material effect on crop choices in developing countries such as Mozambique. More specifically, it may slow the adoption of new commercial crops (or technologies) by smallholder farmers, especially where these expose households to food security risks. Additionally, climate change may accelerate movement out of agriculture into off-farm activities, potentially spurring an increase in rural-urban migration.

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Tables

Table 1. Descriptive statistics for 2002 and 2005 by crop category.

Variables	2002		2005	
	Mean	Dev	Mean	Dev
Panel (a)				
Non-staple crop land share	0.12	0.16	0.14	0.19
Non-staple crop land (hect.)	0.33	1.59	0.49	1.56
Ln(Non-staple crop land)	0.19	0.33	0.27	0.41
1= Non-staple crop land >0	0.44	0.50	0.44	0.49
Cash crop land share	0.04	0.11	0.05	0.12
Permanent crop land share	0.06	0.12	0.05	0.14
Horticulture land share	0.02	0.04	0.04	0.09
Maize-cassava land share	0.49	0.22	0.49	0.23
Sorghum-millet land share	0.08	0.16	0.08	0.15
Groundnut-beans	0.18	0.16	0.19	0.17
Sweet potatoes land share	0.02	0.06	0.02	0.05
Rice land share	0.07	0.16	0.05	0.15
Uncultivated land share	0.04	0.12	0.02	0.09
Panel (b)				
1= village was hit by a flood (t-2)	0.21	0.41	0.21	0.41
1= village was hit by a flood (t-1)	0.22	0.41	0.01	0.12
# times a village has been affected by a flood (last 20 years)	1.29	1.25	1.29	1.25
1= village was hit by a drought (t-2) (rainy season)	0.12	0.32	0.33	0.47
1= village was hit by a drought (t-2) (planting season)	0.05	0.22	0.48	0.50
1= village was hit by a drought (t-1) (rainy season)	0.05	0.22	0.00	0.00
1= village was hit by a drought (t-1) (planting season)	0.00	0.00	0.23	0.42
# times a village has been affected by a drought (last 20 years)	8.10	1.6	8.10	1.6
Panel (c)				
Total landholding (ha)	2.14	2.75	2.41	2.94
Ln(total landholding)	0.97	0.53	1.06	0.52
# plots	2.43	1.32	2.02	1.15
# family members	5.78	3.51	6.14	3.83
% family members with off farm jobs	0.07	0.16	0.13	0.23
% family members self-employment	0.15	0.23	0.21	0.27
Head's education level (years)	2.04	2.33	2.43	2.55
1= HH received remittances	0.20	0.40	0.24	0.43
Wealth index	1.96	0.97	2.03	1.02
% plots with irrigation system	0.06	0.19	0.04	0.18
% plots with land title	0.01	0.11	0.03	0.15
1= HH used animal traction	0.21	0.41	0.18	0.38
1= HH used fertilizer	0.05	0.22	0.05	0.22
1= HH received extension services	0.15	0.36	0.19	0.39
1= HH belonged to farm organizations	0.05	0.22	0.09	0.29
1= HH received market price information	0.31	0.46	0.39	0.49
Average regional retail maize price (t-1)	2393.29	477.56	2378.46	481.14
1= village has electricity	0.08	0.26	0.13	0.33
% sick family members	0.01	0.06	0.02	0.09
1= HH suffered a death (t-1)	0.04	0.19	0.07	0.26
1= HH suffered a divorce (t-1)	0.01	0.09	0.03	0.16
Observations	3,752		3,752	

Source: Authors' calculations based on TIAs 2002 and 2005, using the balanced panel (N=3,752).
Note: Panel (a) describes the dependent variables. Panel (b) shows the weather shock variables. Panel (c) displays the descriptive statistics for the controls.

Table 2. Average partial effects for land allocated to non-staple crops.

Variables	(1) PFP	(2) PFP	(3) PFP	(4) FE	(5) CRET	(6) Double hurdle model Probit	(7) Tobit
Flood (t-2)	-0.025***		-0.012*	-0.013*	-0.010	0.033**	-0.046***
	(0.005)		(0.007)	(0.009)	(0.010)	(0.017)	(0.012)
Flood (t-1)	-0.042***		-0.047***	-0.048***	-0.060***	-0.077***	-0.066***
	(0.007)		(0.007)	(0.008)	(0.011)	(0.026)	(0.020)
Drought (t-2)		0.001	0.001	0.002	0.013	0.059***	-0.032*
		(0.008)	(0.01)	(0.009)	(0.013)	(0.023)	(0.017)
Drought (t-1)		-0.085***	-0.083***	-0.120***	-0.142***	-0.258***	-0.184**
		(0.01)	(0.012)	(0.022)	(0.021)	(0.068)	(0.087)
Ln(landholding)	0.054***	0.055***	0.057***	0.062***	0.267***	0.117***	0.290***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.015)	(0.021)	(0.021)
# plots	-0.010***	-0.009***	-0.011***	-0.012***	-0.016***	-0.009**	-0.009*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
# family members	-0.004**	-0.003**	-0.004**	-0.004**	-0.005*	-0.002	-0.006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)
% family members with off farm jobs	0.037**	0.037**	0.036**	0.036***	0.031*	0.028	0.063**
	(0.014)	(0.015)	(0.015)	(0.014)	(0.019)	(0.037)	(0.032)
% family members self-employment	0.034***	0.029**	0.033***	0.033***	0.039**	0.024	0.062**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)	(0.029)	(0.024)
Head's education level (years)	0.004	0.004	0.004	0.004	0.005	0.004	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)	(0.005)
1= HH received remittances	0.009	0.009	0.010	0.009	0.013	-0.002	0.021
	(0.007)	(0.008)	(0.008)	(0.008)	(0.010)	(0.018)	(0.015)
Wealth index	0.009*	0.006	0.007	0.008	0.011	0.003	0.015
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.014)	(0.009)
% plots with irrigation system	0.029*	0.027	0.028	0.031*	0.060***	0.079*	0.048
	(0.018)	(0.017)	(0.017)	(0.018)	(0.023)	(0.046)	(0.032)
% plots with land title	-0.021	-0.018	-0.019	-0.020	-0.032	-0.031	-0.064
	(0.021)	(0.020)	(0.020)	(0.021)	(0.033)	(0.059)	(0.056)
1= HH used animal traction	0.007	0.004	0.0030	0.004	-0.003	0.027	0.001
	(0.012)	(0.012)	(0.011)	(0.012)	(0.017)	(0.025)	(0.022)
1= HH used fertilizer	0.099***	0.100***	0.106***	0.113***	0.180***	0.096***	0.119***
	(0.021)	(0.021)	(0.021)	(0.019)	(0.036)	(0.029)	(0.026)
1= HH received extension services	0.004	0.005	0.005	0.006	0.005	0.001	-0.004
	(0.007)	(0.008)	(0.008)	(0.008)	(0.011)	(0.019)	(0.015)
1= HH belonged to farm organizations	0.013	0.013	0.014	0.016	0.031	0.042	0.010
	(0.012)	(0.012)	(0.012)	(0.013)	(0.019)	(0.028)	(0.021)
1= HH received price information	-0.007	-0.003	-0.004	-0.004	0.001	0.012	-0.017
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.015)	(0.011)
Average regional retail maize price(t-1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% sick family members	0.006	0.002	0.004	0.004	-0.011	0.024	-0.071
	(0.042)	(0.041)	(0.042)	(0.044)	(0.039)	(0.084)	(0.078)
1= HH suffered a death (t-1)	0.003	0.004	0.004	0.006	0.026	0.037	0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.018)	(0.028)	(0.023)
1= HH suffered a divorce (t-1)	0.010	0.009	0.010	0.009	0.015	0.089***	-0.040
	(0.022)	(0.021)	(0.022)	(0.018)	(0.025)	(0.035)	(0.034)
1= village has electricity	0.075***	0.069***	0.074***	0.055***	0.075***	0.085***	0.081*
	(0.021)	(0.021)	(0.022)	(0.016)	(0.029)	(0.031)	(0.042)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,504	7,504	7,504	7,504	7,504	7,504	7,504

Note: Columns (1) – (3) display APEs of the PFP estimator Column (4) presents marginal effects of the FE model. The dependent variable in these estimations is the land share allocated to non-staples crops. Column (5) shows APEs of the CRE Tobit model. The dependent variable in this model is the logarithm of the amount of land allocated to non-staples. Column (6) shows APEs of the Probit model corresponding to the first equation of the D-H model. The dependent variable in this model is the probability of farming non-staple crops. Column (6) shows APEs of the Tobit model corresponding to the second equation of the D-H model. The dependent variable in this model is the logarithm of the amount of land allocated to non-staples crops. All specifications include a full set of control covariates (shown) as well as the average of covariates to control for unobserved household fixed effects (not shown). Bootstrapped standard errors for PFP, CRE Tobit and D-H models (Replications=500), and clustered standard errors for the FE model are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Average partial effect estimates of the Pooled Fractional Probit (PFP) model for the land share allocated to different crop categories.

Variables	**(1) Cash crop**	**(2) Permanent crop**	**(3) Horticulture**	**(4) Maize-Cassava**	**(5) Sorghum-millet**	**(6) Groundnut-beans**	**(7) Sweet-Potatoes**	**(8) Rice**	**(9) Uncultivated land**
Flood (t-2)	-0.006	0.002	-0.003	0.006	0.011**	-0.012**	0.002	-0.021**	0.019***
	(0.004)	(0.005)	(0.003)	(0.009)	(0.005)	(0.006)	(0.002)	(0.004)	(0.006)
Flood (t-1)	-0.007	-0.016**	-0.008**	0.030**	-0.020**	0.002	-0.002	0.003	0.0160*
	(0.005)	(0.006)	(0.003)	(0.012)	(0.004)	(0.009)	(0.0024)	(0.005)	(0.009)
Drought (t-2)	-0.008	0.012	0.002	0.002	0.015**	-0.039***	0.011***	-0.014**	0.0243**
	(0.005)	(0.008)	(0.004)	(0.013)	(0.006)	(0.008)	(0.004)	(0.006)	(0.010)
Drought (t-1)	-0.029**	-0.048***	0.033*	0.039	0.010	0.039*	-0.004	-0.058**	0.043
	(0.011)	(0.005)	(0.019)	(0.025)	(0.267)	(0.020)	(0.005)	(0.003)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,504	7,504	7,504	7,504	7,504	7,504	7,504	7,504	7,504

Note: Dependent variables are the land share allocated to crops as indicated in the column headers and which vary between zero and one. Column (1) displays APEs for the cash crop category. Column (2) shows APEs for the permanent crop group. Column (3) presents APEs for horticulture farming. Column (4) shows APEs for cassava-maize farming. Column (5) displays APEs for sorghum-millet. Column (6) shows APEs for groundnut-beans. Column 7 presents APEs for sweet potatoes. Column 8 displays APEs for rice farming. Column (9) shows APEs for the uncultivated land category. APEs were calculated after the estimation of the PFP model. All specifications include a full set of control covariates as well as the average of covariates to control for unobserved household fixed effects (not shown). Bootstrapped standard errors are shown in parentheses (Replications=500). *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Average partial effect estimates of the Pooled Fractional Probit (PFP) model for the land share allocated to different crop categories.

Variables	**(1) Cash crop**	**(2) Maize-Cassava**	**(3) Sorghum-millet**	**(4) Groundnut-beans**	**(5) Sweet-Potatoes**
Drought (t-2)	0.010*	-0.023*	-0.026***	0.025***	0.002
	(0.006)	(0.013)	(0.006)	(0.009)	(0.003)
Drought (t-1)	-0.011	-0.053***	0.031***	-0.022**	0.015***
	(0.007)	(0.014)	(0.008)	(0.009)	(0.005)
Flood controls	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes
Observations	7,504	7,504	7,504	7,504	7,504

Note: The table replicates selected columns of Table 3. The unique difference is that the drought covariate has been modified to reflect rain shortages during the planting/sowing season. All specifications include a full set of control covariates as well as the average of covariates to control for unobserved household fixed effects (not shown). Bootstrapped standard errors are shown in parentheses (Replications=500). *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Average partial effect estimates of the Pooled Fractional Probit (PFP) using drought intensity.

Variables	(1) Non-staples	(2) Cash crop	(3) Permanent crop	(4) Horticulture	(5) Cassava-maize	(6) Sorghum-millet	(7) Groundnut-beans	(8) Sweet-Potatoes	(9) Rice	(10) Uncultivated land
Drought Int (t-2)	0.009	-0.013**	-0.001	0.020***	-0.023**	0.037***	-0.039***	0.001	-0.007	0.025***
	(0.008)	(0.004)	(0.008)	(0.003)	(0.010)	(0.006)	(0.007)	(0.002)	(0.008)	(0.006)
Drought Int (t-1)	-0.192***	-0.052*	-0.146***	0.054***	-0.0002	0.140***	-0.016	-0.012	-0.056*	0.106***
	(0.036)	(0.029)	(0.027)	(0.017)	(0.032)	(0.051)	(0.025)	(0.008)	(0.031)	(0.022)
Flood controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,504	7,504	7,504	7,504	7,504	7,504	7,504	7,504	7,504	7,504

Note: The table replicates Table 3 replacing the binary drought indicator with a continuous version. All specifications include a full set of control covariates as well as the average of covariates to control for unobserved household fixed effects (not shown). Bootstrapped standard errors are shown in parentheses (Replications=500). *** p<0.01, ** p<0.05, * p<0.1.

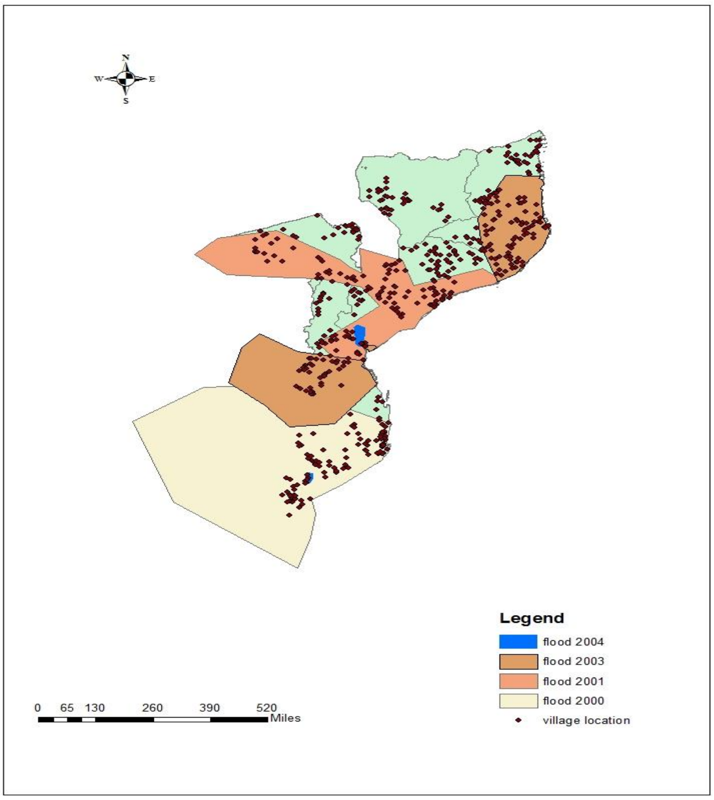
Table 6. Average partial effect estimates by background risk level.

Variables	**(1)**	**(2)**
Flood (t-1)	0.010	0.019
	(0.016)	(0.015)
Drought (t-1)	-0.068	0.059
	(0.127)	(0.108)
Flood (t-1)*high risk flood area		0.022
		(0.019)
Flood (t-1)*high risk drought area	0.035*	
	(0.021)	
Drought (t-1)*high risk flood area		-0.022
		(0.111)
Drought (t-1) *high risk drought area	0.108	
	(0.128)	
Flood (t-2)	Yes	Yes
Drought (t-2)	Yes	Yes
Control variables	Yes	Yes
Year dummy	Yes	Yes
Number of observations	7,504	7,504

Note: Dependent variable is the land share allocated to cassava-maize crops. Column (1) displays APEs for the model interacting recent weather shocks with high drought risk indicators (see text). Column (2) shows APEs for the model interacting recent weather shocks with high flood risk indicators (see text). APEs were calculated after the estimation of the PFP model. All specifications include a full set of control covariates as well as the average of covariates to control for unobserved household fixed effects (not shown). Bootstrapped standard errors are shown in parentheses (Replications=500). *** p<0.01, ** p<0.05, * p<0.1.

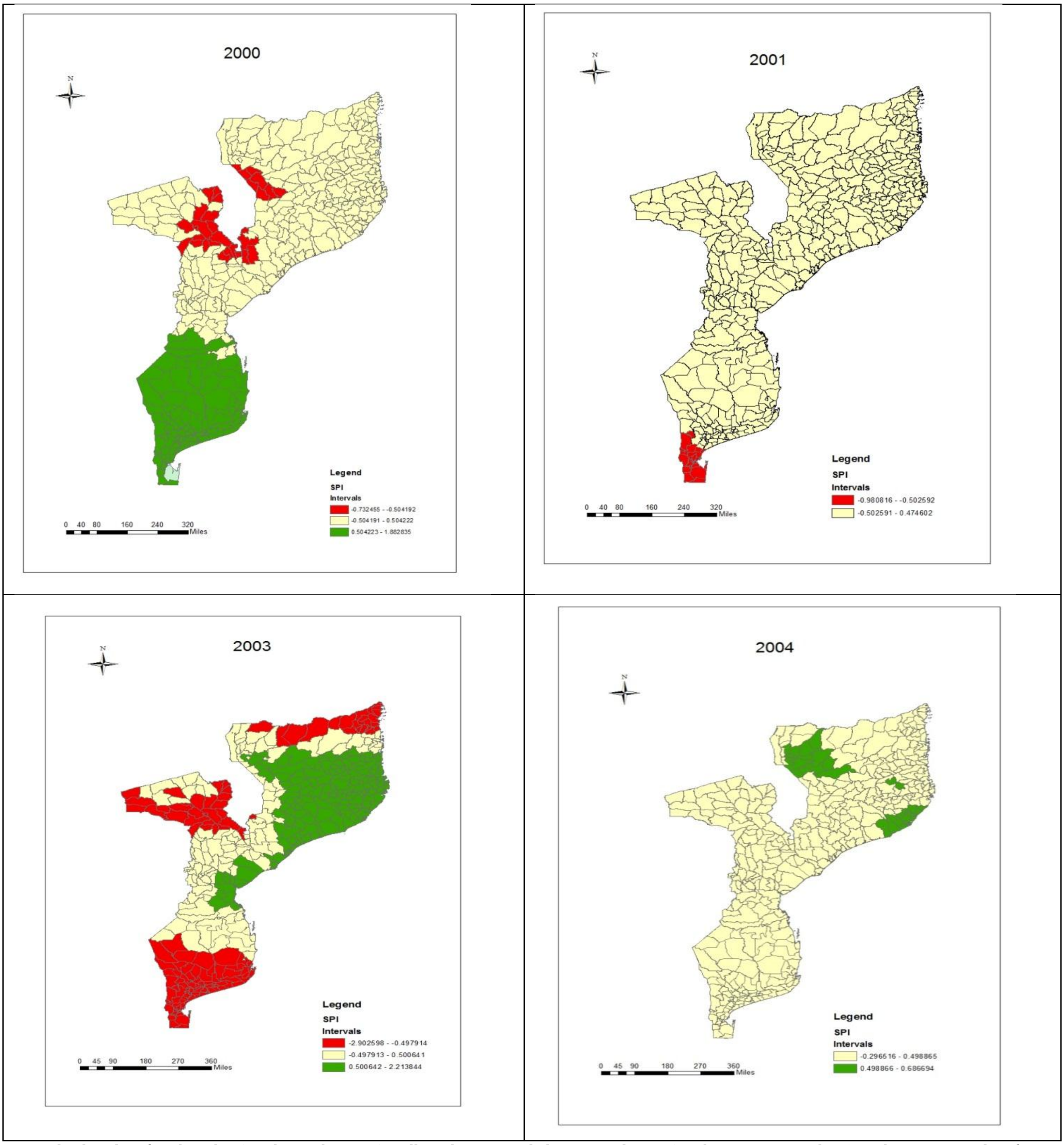
Figures

Figure 1. Polygons of flooded areas and villages' locations.



Source: Authors' elaboration using TIA data and information from Dartmouth Flood Observatory.

Figure 2. Drought identification based on a 6-month SPI (November-Abril).



Note: Red color identifies droughts (SPI lower than -0.5); yellow show normal climate conditions (SPI between -0.5 and 0.5); and green areas identify wet periods (SPI greater than 0.5).

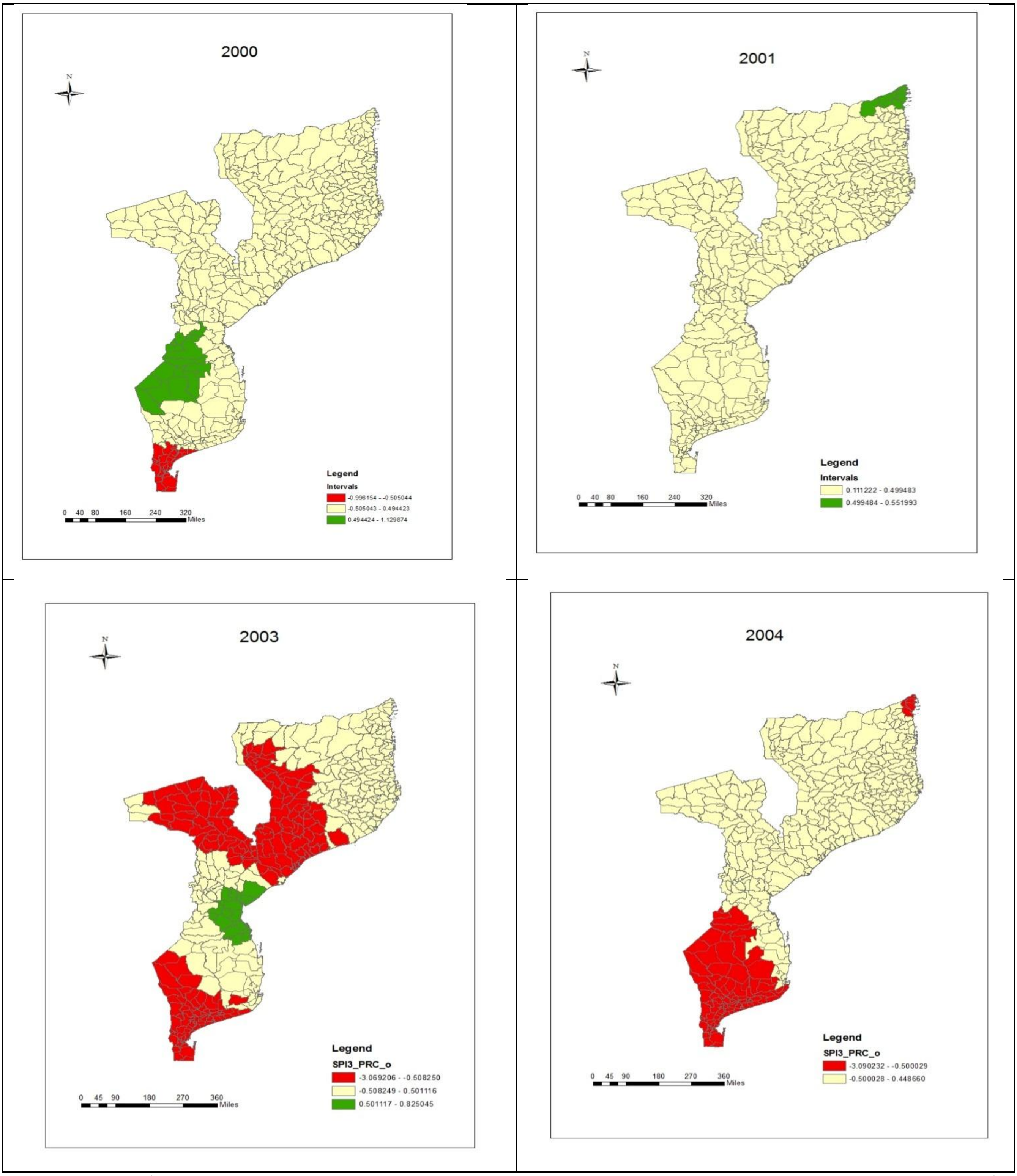
Appendix A: Additional Tables and Figures.

Table A1. Average partial effect estimates for reduced form model, with alternative dependent variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Flood (t-2)	0.002	0.023**	0.029**	-0.018***	0.015	0.135***
	(0.008)	(0.011)	(0.013)	(0.006)	(0.019)	(0.026)
Flood (t-1)	-0.054***	-0.004	0.026*	0.035***	0.037*	-0.142**
	(0.007)	(0.011)	(0.014)	(0.009)	(0.019)	(0.065)
Drought intensity (t-2)	0.007	-0.001	0.004	-0.012*	0.019	-0.042*
	(0.008)	(0.010)	(0.013)	(0.007)	(0.019)	(0.022)
Drought intensity (t-1)	-0.191***	0.005	0.003	0.040*	0.031	-0.668**
	(0.036)	(0.031)	(0.041)	(0.0237)	(0.064)	(0.283)
Ln(landholding)	0.058***	-0.003	0.008	-0.011	0.014	0.050***
	(0.008)	(0.008)	(0.011)	(0.009)	(0.018)	(0.018)
# plots	-0.008***	0.007**	0.018***	0.014***	-0.002	0.021**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.007)	(0.008)
# family members	-0.003*	-0.001	-0.007***	0.004*	-0.002	-0.008***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
Head’s education level (years)	0.00418	0.007**	-0.004	0.003	-0.0005	0.005
	(0.00258)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)
Wealth index	0.00851*	-0.003	0.005	0.010*	0.003	0.015
	(0.00484)	(0.006)	(0.007)	(0.005)	(0.012)	(0.009)
% plots with land title	-0.0224	-0.032	-0.006	-0.006	-0.062	0.108*
	(0.0199)	(0.022)	(0.029)	(0.034)	(0.052)	(0.056)
1= HH received extension services	0.008	0.018*	0.029**	0.017*	0.016	0.075***
	(0.008)	(0.009)	(0.011)	(0.009)	(0.017)	(0.021)
1= HH belonged to farm organizations	0.0172	-0.009	0.025	0.032**	0.008	0.057**
	(0.012)	(0.011)	(0.017)	(0.016)	(0.028)	(0.029)
1= HH received price information	-0.0004	0.029***	0.036***	-0.008	0.018	0.057***
	(0.006)	(0.007)	(0.008)	(0.006)	(0.013)	(0.017)
Average regional retail maize price(t-1)	0.000	0.000	0.000	0.000	0.000	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% sick family members	0.005	0.013	0.031	-0.013	0.138*	0.030
	(0.042)	(0.051)	(0.058)	(0.028)	(0.077)	(0.077)
1= HH suffered a death (t-1)	0.006	-0.005	0.032**	0.001	-0.005	-0.009
	(0.012)	(0.012)	(0.016)	(0.009)	(0.027)	(0.030)
1= HH suffered a divorce (t-1)	0.012	0.021	0.035	0.003	-0.009	0.044
	(0.021)	(0.020)	(0.033)	(0.022)	(0.045)	(0.046)
1= village has electricity	0.061***	-0.029**	-0.027	-0.002	0.005	0.024
	(0.020)	(0.012)	(0.018)	(0.015)	(0.038)	(0.027)
Year dummy	Yes	Yes	Yes	Yes	Yes	No
R square	-	-	-	0.026	0.010	0.070
Observations	7,504	7,504	7,504	7,504	7,504	3,752

Note: Column 1 shows the APEs for the land share allocated to non-staple crops without potential endogenous variables (irrigation, fertilizer) and controls that may potentially respond to shocks (off-farm activities, remittances and animal traction). Column 2 shows the APEs for the proportion of family members with off-farm jobs. Column 3 reports the APEs for the proportion of family members self-employed. These models are estimated by the PFP and include a full set of control covariates and the average of covariates to control for unobserved household fixed effects (not shown). Column 3 shows the marginal effects for fertilizer use (1 if farmer uses fertilizer). Column 4 reports the marginal effects for the receipt of remittance (1 if farmer receives remittances).These models are estimated by the FE and include a full set of control covariates. Column 5 presents the marginal effects for crop rotation (1 if farmer practices rotation).This model is estimated by the OLS for 2005 and include a full set of control covariates, regional and agro-ecological dummies. Bootstrapped standard errors are shown in parentheses (Replications=500). *** p<0.01, ** p<0.05, * p<0.1.

Figure A1. Drought identification based on a 3-month SPI (October-December).



Note: Red color identifies droughts (SPI lower than -0.5); yellow show normal climate conditions (SPI between -0.5 and 0.5); and green areas identify wet periods (SPI greater than 0.5).

Chapter 4

Pesticide Use and Agricultural Risk. The Case of Rice Producers in Vietnam.

César Salazar-Espinoza and John Rand*

Abstract

The excessive and unsustainable use of pesticides has generated concern due to their potential detrimental effects on farmers' health, environment and agricultural sustainability. Thus, the overuse of chemical pesticides remains an important development issue, and understanding pesticide input decisions is a key requisite to sound policy-making. This paper examines risk effects of pesticide use by applying a lottery game in combination with a more traditional production function approach employing a dataset on rice producers in Vietnam. Using pest and water shortage shock events for identification, production function results show that an increase in pesticide use can make production more risky. This result is supported by the lottery approach showing that more risk averse farmers use less pesticide, implying that pesticide is a risk-increasing input. Our results suggest that higher rainfall uncertainty (relative to pest) is likely to drive the risk increasing effect of pesticides. This highlights the importance of considering multiple uncertainties when determining risk properties of agricultural inputs.

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Key words: pesticide, risk effect, shocks, lottery, Just-Pope production function.

JEL classification: O13, Q11, Q12, Q15.

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1 Introduction

The adoption of yield-enhancing chemical inputs such as pesticides has broadly been promoted in developing countries as a manner to boost agricultural productivity (Fernandez-Cornejo et al., 1998). However, the excessive and unsustainable use of toxic pesticides has created concerns due to its detrimental effects on health, the environment and agricultural sustainability (Pimentel et al., 1992; FAO, 2001). These negative effects include damage to agricultural land, fisheries, fauna and flora, and destruction of natural predators of pests. Furthermore, increased mortality and morbidity of humans due to exposure to pesticides are also recorded to be important (Antle and Pingali, 1994; Crissman et al., 1994; Pingali et al., 1994). These concerns are even more serious in developing countries due to lower skill/knowledge levels, limited provision of extension services to disseminate less intensive pesticide practices, financing constraints with regards to acquisition of suitable safety equipment, and a weak legislation (Wilson and Tisdell, 2001).

Use of pesticides is remarkably high in Asian economies (Pingali et al., 1994). In particular, it has more than tripled in Vietnam since 1990, and pesticide regulation has not evolved accordingly as it remains far less rigorous than pesticide regulations in more advanced economies (Phung et al., 2012).[1] Consequences on farmer's health have been reported to be serious (Dasgupta et al., 2007), and it has also been found that farmers overuse pesticide inputs beyond the economic optimum (Dung and Dung, 1999; Huang et al., 2002; Pemsl et al., 2005). Thus, understanding the overuse of pesticides remain an important issue, and is for Vietnam in line with the challenge of entering into a new development phase, in which sustainability of agriculture production and the environment are fundamental pillars (World Bank, 2011).

This paper analyzes the relationship between pesticide use and farmer specific risk characteristics, which is key for understanding pesticide input choices. A risk-reducing input is normally identified through two distinct characteristics observed in data (Quiggin, 1991): First, an input is labelled risk reducing when its use reduces the variance of production. Second, all else equal, a risk averse producer would use more risk-reducing inputs than a risk neutral one.[2] Empirical evidence using

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[1] Since the early 1990s, the Plant Protection Department of Vietnam's Ministry of Agriculture and Rural Development is in charge of the pesticide management, including the approval, restriction, and prohibition of chemicals.

[2] Quiggin (1991) also argues that a producer with output insurance using less pesticide may also be consistent with the risk-reducing view. However, the evidence for this mechanism is mixed (Horowitz and Lichtenberg, 1993; Babcock and Hennesey, 1996; and Smith and Goodwin, 1996). Moreover, agriculture insurance is rather new in Vietnam; the government started a pilot program in 2011. Recent surveys (CIEM et al., 2011; 2013) have not found substantial adoption of such insurance, and in the following we therefore do not test this potential mechanism.

either approach is mixed. However, while most of the production variance studies obtain results consistent with the notion of pesticide being risk-increasing (see for example Regev et al., 1997; Shankar et al., 2008; Krishna et al., 2009), recent studies using lotteries to elicit risk aversion support the risk-decreasing view (Gong et al., 2012; Liu and Huang, 2013). In this paper, we test the risk effects of pesticide use by using both the lottery (experimental) and the production function (econometric) approach on a sample of farmers in Vietnam. To our knowledge, no empirical studies exploring the consistency regarding the risk property of pesticides using identical samples have been done previously in the literature. Furthermore, Horowitz and Lichtenberg (1994) argue that risk effects of pesticide use may be determined by an interaction of multiple sources of uncertainty. The importance of these sources can vary across different farming activities, locations and periods. With the exception of Shankar et al. (2008), empirical evidence regarding this aspect remains quite scarce. In this paper, we therefore also investigate the source of this risk effect by using information on the occurrence of pest and drought shocks to proxy for bad and good states of nature with regards to pest density and rainfall in rice farming, respectively.

The rest of the article is organized as follows: Section 2 describes characteristics of the agriculture sector, pesticide use and shocks in Vietnam. Section 3 reviews a conceptual framework that links pesticide use, risk-taking behavior and shocks. Section 4 presents the data used; and section 5 the econometric model. Section 6 discusses the main results. Section 7 considers a number of robustness tests; and Section 8 concludes.

2 Agriculture, shocks and pesticide use in Vietnam

Agriculture is the most important economic activity in terms of job creation in Vietnam, and constitutes the main source of livelihood for around 70% of the population. Paddy rice production is one of the main agricultural activities, covering 65% of the area under cultivation. Rice has long been the major source of food and income for rural households. Many farmers both consume and sell their rice, which is typically grown two to three times per year on small landholdings formed by multiple plots (Phung, 2012). Rice production remains a labor intensive practice, with most workers being family members, but some farms hire extra labor and rent mechanized equipment. Rice farming requires significant amount of water to flood the fields. For instance, producing one kilogram of unprocessed rice in Vietnam is estimated to use on average 2.500-3.000 liters of water (Chu Thai, 2013). Since the flooded condition of rice fields is necessary for rice growth, drought events become one of the most important sources of risk in rice production.

Pest infestation is also a substantial source of risk. If left unmonitored, it can cause enormous productivity losses or even in some cases it can lead to total crop failure. Vietnamese farmers have tackled this problem by increasing the use of pesticides. In fact, more than 95% of farmers report to apply some variety of pesticides on their crops (CIEM et al., 2011; 2013). To illustrate, the use of chemical inputs rose from 14,000 tons under 837 trade names in 1990 to 50,000 tons under more than 3,000 trade names in 2008 (Phung et al., 2012). Even though agricultural pesticide use has played a crucial role in expanding rice cultivation and enhancing rice productivity in Vietnam, incorrect pesticide application, including too frequent, more toxic[3] and excessive quantities of pesticide is common among Vietnamese farmers (Dung and Dung, 1999; Klemick and Lichtenberg, 2008).[4] The lack of knowledge about the manipulation and the correct use of safety clothing is also an issue of public concern (Meisner, 2005).[5] An improper manipulation, storage and disposal of pesticide jointly with weak pesticide law enforcement and an inadequate use of protective equipment put farmers at high risk of being harmed by pesticide exposure. Accordingly, hospital records,[6] self-reported farmer data and medical tests suggest a high prevalence of pesticide poisoning in Vietnam. For example, Murphy et al., (2002) found that around 30% of a sample of farmers surveyed in a village in Nam Dinh province in northern Vietnam reported to suffer from at least one symptom of pesticide poisoning. Similar evidence of acute pesticide poisoning was shown by Dasgupta et al. (2007) in a sample of farmers tested for blood cholinesterase in several districts in the Mekong Delta region in southern Vietnam. The most common short-term health effects were associated with dermal (skin irritation), ocular (eye irritation), neurological (headaches, dizziness and insomnia) and respiratory symptoms (exhaustion, shortness of breath and sore throat).[7] Training and farmer field school programs in Integrated Pest Control Management (IPM) have been implemented to make farmers

[3] Pesticides classified as highly toxic according to the World Health Organization (WHO) such as carbofuran, endosulfan, methamidophos, monocrotophos, and methyl parathion are banned in Vietnam. However, farmers have been found to still apply these chemical classes on their fields (Meisner, 2005).

[4] When not considering toxicity information on pesticides, on average, it is found that non-poor farmers use significantly larger quantities of chemical pesticide than the poor.

[5] The use of protective clothing such as gloves, glasses and shoes is not common among Vietnamese farmers. Apart from usual budget constraint arguments that make protective clothing unfordable for the poorer, other reasons include farmers' reluctance to wear safety clothing since they consider it uncomfortable or inappropriate when having to work under high temperatures.

[6] Health problems may be underestimated by official figures because many cases are never registered in hospitals and health centers. The most common reasons for that are erroneous diagnostics since pesticide poisoning can mimic other common health problems, reluctance to see a doctor because of fear that drawing attention to themselves can result in the loss of their job or simply budget constraints to afford adequate medical attention.

[7] There are also potential and less understood long-term health effects of using pesticides that may emerge only year to decades later. For example, a variety of pesticides are considered carcinogens, while others are associated with poor reproductive outcomes, neurologic and respiratory disorders, and impairment of the immune system (WHO, 1990).

aware about the risks of pesticide use for human health and the environment. These programs are aimed at promoting the use of alternative pest control actions through more closely monitoring and use of natural enemies. Furthermore, the government has also tried to convince farmers to refrain from insecticide sprays after rice seeding through massive campaigns. The main goal of these programs has been to decrease pesticide use, particularly the use of the most toxic chemicals. However, pesticides continue to be used broadly in rice farming beyond sustainable levels (Klemick and Lichtenberg, 2008). In this paper we focus on the production risk effect of pesticide use to understand this overuse.

3 Conceptual framework

Reducing uncertainty as regards to agricultural output over time has been one of major factors for promoting pesticide use. Pest uncertainty mainly comes from limited information on pest density, severity, chemical dosage needed to deal with it, and effectiveness of pesticide application. The latter has led to increased risk regarding both production yield and profits. Thus, the intuitive reason for applying pesticides is to reduce production risk, which would lead to adoption among capital constrained and relative more risk averse farmers (Federer, 1979). However, an alternative view states that pesticide use may in fact increase risk, arising from uncertainties related to other crop growing conditions (Lazarus and Swanson, 1983; Pannel, 1991). Horowitz and Lichtenberg (1994) demonstrate that the risk effect of pesticides will depend on the interaction and relationship between different types of agricultural uncertainties.

To see this, assume a production function, $f\left(x_p, \boldsymbol{x}, \varepsilon\right)$, where x_p denotes pesticide input, $\boldsymbol{x}$ is a vector of all other inputs, and ε is a random production error. Suppose that ε is ordered from bad states to good states of nature, implying that the derivative with respect to the random variable is positive, i.e, $f_\varepsilon\left(x_p, \boldsymbol{x}, \varepsilon\right) > 0$. In addition, we assume that pesticides increase production regardless the state of nature, i.e., $f_{x_p}\left(x_p, \boldsymbol{x}, \varepsilon\right) > 0$. Following Horowitz and Lichtenberg (1994), pesticide input x_p is risk-decreasing if $f_{x_p\varepsilon}\left(x_p, \boldsymbol{x}, \varepsilon\right) < 0$, that is, pesticides increase output more in bad states than in good states of nature. This means that pesticide use is risk-increasing if $f_{x_p\varepsilon}\left(x_p, \boldsymbol{x}, \varepsilon\right) > 0$, indicating that pesticide increases output more in good states than in bad states of nature. Quiggin (1991) proves that this definition is equivalent to saying that more risk averse producers use more (less) of a risk-decreasing (increasing) input that less risk averse producers.

When ε mainly represents uncertainty about pest density (and its distribution), one would expect pesticides to raise output more (less) when pest density is high (low), making pesticide use risk-decreasing. However, alternative sources of agricultural production uncertainty, i.e., rainfall, can also be important risk influencing factors, especially in rice production. More importantly, one would expect that pesticide productivity is higher (lower) during high (low) rainfall periods (significantly above predicted averages) since there are more (less) crops to protect, which makes pesticides a risk-increasing input when considering its use in the context of multiple uncertainties. When these multiple sources of uncertainty are highly correlated factors that promote crop growth, also encouraging weeds or insect pest, pesticide use is more likely to be risk-increasing.

Traditionally, testing the risk effect of pesticides has relied on econometric estimations of risk using a production function approach, and the evidence seems to support the risk-increasing view (see for example Regev et al., 1997; Shankar et al., 2008; Krishna et al., 2009). However, recent empirical work using experimental approaches to elicit risk preferences find that more risk averse farmers apply larger quantities of pesticide, supporting the standard view of pesticides being risk-reducing (Gong et. al., 2012; Liu and Huang, 2013). From this empirical literature, three fundamental conclusions emerge. First, results seem to be approach-dependent. The latter have been suggested by Reynaud et al. (2010). They found differences in farmers' attitudes elicited by stated and revealed methods, suggesting an effect due to the approach. Nevertheless, they prove some consistency and coherence across experimental and econometric elicitation methods. Second, risk effects have been estimated for a small number of farmers, questioning representativeness such that inconsistencies across approaches may be associated with sample characteristics. Third, differences may be driven by the context in which agricultural decisions take place. Thus, more evidence in favor of the risk-reducing view in some studies may simply reflect that pest density is more of a concern in these locations or was more serious at the time when data was collected. Alternatively, other sources of agricultural production uncertainty may have been more important in studies finding more support for the risk-increasing argument. For example, Shankar et al. (2008) studied the risk properties of Genetically Modified (GM) technology and pesticides among a sample of cotton producers in South Africa, accounting for multiple sources of uncertainty. They found a strong correlation between the random variables capturing rainfall and pest density, which is consistent with theoretical conditions under which the risk-increasing thesis is more likely to hold.[8]

Thus, whether reported differences in results can be attributed to variations in methodologies, sample characteristics, farming activities, locations, etc., is rather difficult to determine. In this paper, we try to overcome this problem and understand these differences, focusing on a sample of rice farmers in the Vietnamese context.

4 Estimation procedure

First, we present the experimental approach to study the risk property of pesticides using a lottery game. Second, we introduce the Just-Pope production function method, broadly used to examine risk characteristics of inputs in agriculture.

4.1 Pesticide input and risk aversion

The first approach consists of setting up an estimating equation in which pesticide input decisions depend on risk aversion. Given the censured nature of our dependent variable measuring pesticide use, we estimate the Tobit model, which assumes corner solutions. The model is specified as follows:

$$x_{pi} = max(0, \delta z_i + \varphi w_i + \gamma r_i + u_i)\,, \quad u_i \backslash z_i, w_i, r_i \sim N(0, \sigma_u^2) \tag{1}$$

Where x_{pi} corresponds to a measure of pesticide input applied to a farm i, z_i contains a vector of socioeconomic and farm level characteristics, w_i defines measures of states of nature with regard to pest and other growing conditions, respectively, r_i stands for a measure of risk aversion, and u_i is the normally distributed error term.

The parameters γ and φ are the coefficients of interest. If $\gamma > 0$, more risk averse farmers use larger amount of pesticides, then pesticide is risk-reducing. Similarly, if $\gamma < 0$, farmers who are more risk farmers use less inputs, then pesticide is risk-increasing. Furthermore, if pesticide use is sensitive to the risk environment, φ will be positive (negative) when pest infestation is high (low) and negative (positive) as other growing conditions are bad (good).

[8] For more evidence supporting the risk-increasing argument see Auld and Tisdell (1987), Antle (1988), Pannel (1990), Horowitz and Lichtenberg, (1993), Hurd (1994) and Regev et al. (1997).

4.2 Pesticide input and production risk

In order to investigate the risk effect of pesticides, we alternatively apply the framework outlined by Just and Pope (1979). This approach provides a method for estimating the marginal risk effect of inputs. The Just-Pope (JP) production function is specified as:

$$y_i = f(x_i, \varepsilon_i) = q(x_i, \alpha) + h(x_i, \beta)\varepsilon_i \tag{2}$$

Where y_i is the level of output for farm i, x_i is a vector of inputs for farm i, $q(.)$ is the mean function (or determinist part) that relates inputs to levels of output, α is a vector of parameters attached to the mean function, $h(.)$ is the variance function (or risk part) that associates inputs to output variability, β is the parameter vector attached to the risk function, and ε is the exogenous production shock with mean $E(\varepsilon_i) = 0$ and $Var(\varepsilon_i) = 1$. Defining $Var(y_i) = h^2(x_i, \alpha_i, \beta)$, we can observe that inputs are allowed to influence both mean output and output risk. One key requirement for this specification is that it should not impose any a priori restriction on the effect of inputs on production risk, that is, $\frac{\partial Var(y_{it})}{\partial x_{it}} <=> 0$.

The JP production function (2) is estimated by Feasible Generalized Least Squares (FGLS).[9] First, we estimate the parameters of the mean function $y_i = q(x_i, \alpha) + e^*$. Lichtenberg and Zilberman (1986) argue that pesticide is a damage control input whose contribution lies in their ability to increase the share of potential output by reducing damage from pest infestation. Thus, pesticides input should be treated differently in the production analysis than conventional inputs.[10] Following Krishna et al. (2009), we combine the damage control framework with Just-Pope econometric methods to account for this characteristic. Let us define $G(x_c)$ as the damage abatement function. This function captures the destructive capacity of the damaging agent eliminated by the application of a level of control inputs x_c.[11] By making the distinction between regular inputs x_r and control inputs x_c, the damage-production function is defined as follows: $q(x_i, \alpha) = A \prod_{k=1}^{nr} x_{irk}^{\alpha_k} G(dx_{ci})$, where nr now indicates the total number of conventional inputs, and $G(x_{ci}) = [1 - \exp(\mu -$

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[9] Saha et al. (1997a) found that the FLGS does not perform well in the case of small samples, and the Maximum Likelihood Estimator (MLE) should be applied as it is more efficient and unbiased. Given the size of our sample, our results should be robust to the use of alternative estimators.

[10] Lichtenberg and Zilberman (1986) found that standard production function specifications overestimate the productivity of damage control inputs.

[11] The abatement function is defined on the (0, 1) interval with G = 1 denoting complete eradication of the destructive capacity and G = 0 denoting zero elimination; it is monotonically increasing; and it approaches a value of unity as damage-control agent use increases.

$\sigma x_{ci})]^{-1}$ is a logistic function.[12] Ease of convergence in the nonlinear least square (NLS) method was the main reason of the choice of a logistic function.

In the second stage, the parameters of the variance function are estimated by OLS using the predicted residuals from the mean function $\hat{e}_i^* = h(x_i, \beta)\varepsilon_i$ assuming a Cobb-Douglas functional form for $h(x_i, \beta)$.[13] By taking natural logarithms on both sides, and absolute values of $\hat{e}_i^*$ yields:

$$ln|\,\hat{e}_i^*| = \beta + \textstyle\sum_{k=1}^{n} \beta_k ln x_{ki} \tag{3}$$

Where β_k corresponds to estimates of the risk marginal effect of inputs, $\frac{\partial Var(y_i)}{\partial x k_i}$. If x_{pi} denotes the amount of pesticide input used by farm *i* and β_p the marginal risk effect of pesticides, we have that pesticide is risk-reducing if $\beta_p < 0$, or risk-increasing if $\beta_p > 0$.

In a final stage, since equation (1) is a heteroskedastic regression, we attain asymptotic efficiency in estimation of the parameters α of the mean function by applying weighted regression with incorporating weights $h^{-1}\left(x_i, \hat{\beta}\right)$.

To test the relative importance of different sources of randomness in determining the risk properties of pesticides, we augment the mean function including interactions between pesticide inputs and the different uncertainty drivers (i.e. pest and rainfall). In other words, we estimate changes in productivity of using pesticides along states of nature of both pest and rainfall, that is, $f_{x_p\varepsilon_1}\left(x_p, \boldsymbol{x}, \varepsilon_1\right)$, and $f_{x_p\varepsilon_2}\left(x_p, \boldsymbol{x}, \varepsilon_2\right)$, where ε_1 and ε_2 relates to pest and rainfall, respectively. Thus, pesticide is more likely to be risk-reducing (risk-increasing) when $f_{x_p\varepsilon_1}(.)$ is relatively more (less) important than $f_{x_p\varepsilon_2}(.)$.

5 Data

We use data from the Vietnam Access to Resources Household Survey (VARHS). The VARHSs are longitudinal surveys conducted every second year from 2006 by the Institute of Labor Science and

[12] This specification has been used in the literature before, yielding sensible results (see Lichtenberg and Zilberman, 1986; Carrasco-Tauver and Moffit, 1992; Krishna et al., 2009)
[13] Alternative specifications such as linear and quadratic forms were also considered for the variance function. Results remain the same, however. Details can be obtained under request.

Social Affairs of the Ministry of Labor, Invalids and Social Affairs with the technical support from Department of Economics at the University of Copenhagen. This survey constitutes one the main data sources on the current state of the rural population of Vietnam regarding access to productive resources. Data collection is done in rural areas of 12 provinces (covering 161 districts and 456 communes). In particular, the survey collects regularly information on households' demographic characteristics, assets, saving, credit, incomes as well as production, farm inputs and shocks. Lottery questions to elicit risk aversion measures were introduced from the fourth wave of VARHS in 2010 (CIEM et al., 2011; 2013). However, farmers' responses to lotteries in 2012 show inconsistencies that make us suspect about their reliability. Consequently, we only use the 2010 data covering 2,205 households.

5.1 Lottery and risk aversion measures

To construct a measure of risk aversion, we use two hypothetical[14] questions included in the VARHS to elicit individual's risk attitudes: "Consider an imaginary situation where you are given the chance of entering a state-run lottery where only 10 people can enter and 1 person will win the prize. How much would you be willing to pay for a 1 in 10 chance of winning a prize of 2,000,000 Vietnamese Dongs (VND)?" and "How much would you be willing to pay for a 1 in 10 chance of winning a prize of 20,000,000 VND"?[15]

[INSERT TABLE 1 ABOUT HERE]

The lottery questions were submitted to the entire sample of household heads, but only around 37% of respondents answered as being willing to purchase the lottery. Out of 1,386 others, about 14% did not answer and 48% refused to pay a positive price. High non-responses and zero-answers rates were also found in Hartog et al. (2002) and Guiso and Paiella (2008) in similar lottery questions. There are two possible explanations for this pattern. First, some people may consider gambling as morally objectionable. The perception of gambling may be shaped by legal, sociological and ethical

[14] Some concerns can emerge as it is believed that subjects should perform better if they earn some money for their actions. However, Camerer and Hogarth (1999) found that the presence and amount of financial incentives do not seem to affect average performance in many tasks. In particular, they found that increased incentives do not change average behavior in risky gambles substantively. This suggests that intrinsic motivation is still sufficient to perform well in hypothetical lottery tasks.

[15] These values are equivalent to US$100 and US$ 1,000, respectively. Whereas winning the first prize would imply on average an increase of around 5% in household wealth, the second prize would raise wealth in about 50%. Thus, it is probably that the set of incentives differs between lotteries, although a correlation is expected. The second lottery represents a relatively large risk. We consider this as robustness check because expected utility maximizers behave as risk-neutral individuals with respect to small risks even if they are averse to larger risks (Arrow, 1970). Thus, we expect that the larger lottery prize is a better strategy for eliciting risk attitudes when relying on expected utility.

considerations. In Vietnam, except for the state-run lottery and a few five-star resorts running low profile casinos for foreigners only, gambling of any kind is illegal.[16] This makes it harder to distinguish the zero-answers that truly reflect strong risk aversion from those that reflect the usual variety of reasons for not answering. Second, a higher non-response rate was likely due to the complexity of the question, which might have required long time to understand and provide a sensible answer. Furthermore, lottery questions were introduced abruptly by the interviewers as part of a broader survey, without any set of introductory questions. The latter may have also led many respondents to skip this question. However, this strategy may have its advantages. First, asking questions abruptly would avoid that the way how introductory questions are framed distort the answers and therefore the elicitation of the true preference parameter. Second, the strategy with no "warm up" questions may have effectively discarded respondents with a poor understanding of the question, avoiding bringing in noisy answers (Guiso and Paiella, 2008).

[INSERT FIGURE 1 ABOUT HERE]

Figure 1 shows the distribution of the willingness to pay for non-zero answers. The reported price ranges from 1,000 to 2,000,000 and 10,000,000 for the lottery with a small and big prize, respectively (5.5% of respondents offered more than 2,000,000 in the small prize lottery. We omit these responses because such a price leads to a sure loss). For the small price lottery, the bulk of the responses are from 1,000 up to 200,000. In the big prize lottery, the distribution is more dispersed; around 80% of values are between 1,000 and 1,000,000. In both cases, the median is substantially smaller than the mean, signaling distribution with a long right tail.

These prices can be considered as reservation prices above which households would reject the lottery. We use them to compute formal measures of absolute risk aversion by applying Expected Utility (EU) theory as in Hartog et al. (2002) and Dang (2012).[17] Alternatively, we characterize attitudes toward risk qualitatively. We denote risk averse farmers with a dummy variable taking the value of 1 if farmers report a price lower than the expected gain offered by the lottery; risk neutral if this price is

[16] Around 68% of respondents in the 2012 VARHS state that gambling is a severe problem in their communities.

[17] EU implies that the utility of wealth W, without participation in a lottery with a winning price Z and probability α , is equal to expected utility when participating at reservation price λ: $U(W) = (1-\alpha)U(W-\lambda) + \alpha U(W+Z-\lambda)$. By applying a second order Taylor expansion of the right hand side around $U(W)$, we have: $U(W) = U(W) + \alpha Z U'(W) - \lambda U'(W) + U''(W)((1-\alpha)\lambda^2 + \alpha(Z-\lambda)^2)/2$. After rearranging, we yield the Arrow-Pratt-measure of absolute risk aversion as: $A(W) = -\frac{U''(W)}{U'(W)} = \frac{\alpha Z-\lambda}{0.5\lambda^2+0.5\alpha Z^2-\alpha\lambda Z}$.

equal to the expected gain; and risk lover if the price is higher than the expected gain. Descriptive statistics are shown in Table 1. Among the individuals willing to purchase the lottery, the great majority (81% in the small and 86% in big prize lottery) is risk averse; around 6% are risk neutral; and 7-8% risk lovers. A high degree of risk aversion among Vietnamese farmers has been reported in the literature before. For instance, Nielsen et al. (2013) find substantial risk aversion under different risk preference elicitation methods among a sample of 300 rural households in northern Vietnam. The authors classify 84% of the respondents as risk averse, with 52% being very risk averse. Similar levels of risk aversion are also found in Tanaka et al. (2010). Strong risk aversion among Vietnamese farmers is not surprising; given the substantial risk they have to face, i.e. natural disasters, crop and livestock diseases, illness, etc., and the lack of adequate formal insurance mechanisms and limited government assistance to deal with shocks (Nielsen et al., 2013).

5.2 Production, household and weather shock data

We use data on the total value of pesticides per square meter applied in rice production as dependent variable in equation (1).[18] In this model, we control for the following socioeconomic and farm level characteristics: a dummy to denote the gender of household head taking the value of one if the farmer is male; household head's age in number of years; schooling measured by the number of years of formal education (actual and squared values); farm size measured in total land in square meters; number of household members; a dummy denoting if at least one family member received pest extension services the last twelve months; total household wealth constructed using fixed asset values (livestock, equipment and machinery), liquid asset values (savings, crop stores), and all consumer durables; total household incomes including wages, incomes gained from agricultural and off-farm activities, sales of assets, etc.; a dummy variable indicating whether households received transfers from government and/or family members/relatives (public/private sources); and geographical characteristics such as land terrain and soil quality that may condition the negative effects of shocks on agricultural activities.[19]

[18] By simply summing the value of all pesticides, we are ignoring the fact that different substances have different levels of toxicity and degradability. A better measure that accounts for this heterogeneity should consider a higher weight to highly toxic and persistent pesticide. For example, epidemiological studies have linked the adverse effect observed on human and animal health with the use of certain classes of pesticides: carbamates, organophosphates and pyrethroids. Unfortunately, information on type, chemical class, name and therefore toxicity of pesticides are not available in the survey.

[19] We proxy land terrain and soil quality using self-reported information by household heads in the VARSH survey. Land terrain is constructed using household heads' answers on the topography of their plot: "In general, what is the slope of this plot? Flat, slight slope, moderate slope or steep slope?" This variable ranges from 1 (flat terrain) to 4 (steep slope). We define a dummy variable to proxy for land terrain, which takes the value of 1 if the average across plots is less than 2, meaning that household's plots are on average flat. Soil quality is measured by household heads' answers on land fertility of their plot: "Compared to the average land fertility in the village, is the quality of this plot: less than the average, average, or better than the average? This variable ranges from 1 (less than the average) to 3 (better than the average). To compute a household level indicator of soil quality, we

In order to estimate equation (2), we use the quantities and values of inputs used in rice production. Total output of farms consists of kilos of rice per square meter. The inputs include labor, seeds, fertilizers, pesticides, irrigation and the use of improved seeds. Labor is expressed in total number of days per square meter; seeds include total value of seed applied per square meter; fertilizer is measured by total value of fertilizers per square meter; pesticide use intensity is proxied by total value of pesticides per square meter; irrigation consists of a dummy variable that takes the value of one if the farm uses any no-manual irrigation system, zero otherwise; improved seed is a dummy variable indicating if the farmer uses this technology, zero otherwise; and proxies for land terrain and soil quality.

Finally, information on shocks is obtained by directly asking households to report whether or not they suffered any shock from a predetermined list. Then, they are requested to rank the shocks in order of importance and to provide an estimation of the monetary loss in terms of Vietnamese Dong (VND). Thus, the data allows us to disaggregate overall shocks into two groups of interest: pest and drought shocks. We assume that the occurrence of pest shocks would reflect a bad state of nature regarding pest infestation. Furthermore, the incidence of past droughts as a proxy for water availability may be a good indicator of a bad state of nature in other crop growing conditions.

Descriptive statistics of the set of controls, production and shocks variables used in the analysis are shown in Table 2.

[INSERT TABLE 2 ABOUT HERE]

From the Table we see that total rice production was lower in 2010 than other in 2008 and 2012 (CIEM et al., 2011; 2013). A higher incidence of natural shocks may have led farmers to crop failure, and then to the poorer yields observed in 2010. In this context, our data reveals that around 31 percent of households experienced a pest shock between 2009 and 2010 with an average monetary loss of 1,107 (000 VND), representing 8% decrease in household income per capita. Although pest shocks are more prevalent, drought events are also important. Our data shows that 13% of households reported to have been affected by a drought between 2009 and 2010. Average monetary losses after

define a dummy variable which takes the value of 1 if soil quality of plots is average or better than the average. Additionally, we include dummies for North, Central and South Vietnam.

the incidence of a drought, on average, amounted to 300.000 VND, representing 2% decrease in household income per capita.

6 Results

6.1 The effect of risk aversion on pesticide use

Table 3 reports results for the pesticide input demand estimation (equation 1). Columns 1-3 show the estimated coefficients for the total sample with risk aversion measures calculated with responses to the small prize lottery.[20] While columns 1-2 include measures of absolute risk aversion, column 3 considers a dummy variable for risk averse farmers. Column 1 includes dummies for shock events; column 2 incorporates monetary losses instead of dummy indicators. The remaining columns report the results as computing risk aversion measures with answers to the big prize lottery.

[INSERT TABLE 3 ABOUT HERE]

Regarding the control variables, we find that training in pest management is negatively and significantly associated with pesticide use. The latter could be the result of the expansion of Integrated Pest Management (IPM) and training programs in Vietnam. In addition, we find that wealth, income and access to credit are key determinants of pesticide use, which would indicate that budget constraints remain important for pesticide demand. Further, households with more family labor use less pesticide. The negative association could indicate that households substitute pesticides for family labor, when the adoption of pest management practices (such as manual weeding) is labor intensive. Moreover, the coefficient on farm size is positive and significant, which indicates additional evidence of the importance of budget constraints. Furthermore, pesticides are used more intensively in better plots (flat terrain and good soil). Better agro-ecological conditions imply higher yields and therefore more crop to protect in case of a severe pest. Finally, human capital characteristics such as a producer's age and education are found to be significant determinants of pesticide use. Older farmers using more pesticide may reflect reluctance of older people to switch to potentially more unknown pesticide less-intensive practices. Education is also positively associated with pesticide use. This result contradicts previous finding (Liu and Huang, 2013). However, the

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[20] Columns 1-3 in Table 3 report a smaller number of observations because we omit those responses with willingness to pay greater than 2.000.000 VND.

positive association may be related to the fact that education may ease saving and access to credit (Knight et al., 2003).

We are interested in examining the risk property of pesticide use. We find that our measure of risk aversion is significant and negative, indicating that risk averse farmers apply on average less pesticides. This result remains robust to the use of different lottery prizes, quantitative and qualitative risk aversion measures,[21] the inclusion of farm and socioeconomic characteristics, and shocks variables as controls. This finding would suggest evidence in favor of pesticide being a risk-increasing input, and an indication that multiple risks are important when analyzing production input decisions in rural Vietnam.

To explore it further, we focus our attention on the effect of pest and drought shocks on pesticide input use. We note that the occurrence of pest shocks does not enter significantly in any of the specifications in Table 3. In contrast, drought events are clearly associated with a reduction in pesticide use. This would suggest that farmers care about general growing conditions, and farmers find it optimal to reduce the amount of pesticides in water shortage periods due to reduction in production volumes. These results are robust to the use of monetary measures of shocks.

6.2 The effect of pesticide input on production risk

Table 4 reports results from estimating the mean function (equation 2) and the variance function (equation 3). Column 1 shows estimated coefficients for the mean function[22] by NLS and column 2 presents estimations of the variance production function by OLS.

[INSERT TABLE 4 ABOUT HERE]

Traditional inputs have positive marginal effects, consistent with theory. In the damage-production function, we assume that irrigation, improved seeds and pesticides are control inputs so that they do not affect yield directly but only indirectly through impacts on the potential output. The parameters of irrigation and pesticide input in the abatement damage function are positive and significant,

[21] In addition to the Arrow-Prat and qualitative measures of risk aversion, we also used the values of willingness to pay in our regressions. Results point to the same direction; farmers with smaller willingness to pay use less pesticide.
[22] We calculated the Breusch Pagan test to evaluate the null hypothesis of homoscedasticity against alternative hypotheses of heteroskedasticity. The Breusch-Pagan LM statistic is 378.93, strongly rejecting the null hypothesis. The latter supports the multiplicative heteroskedastic model and suggests that the Just and Pope specification is an appropriate framework for the analysis of the risk effect of pesticides in Vietnam.

highlighting the role that these inputs play in controlling potential crop damage coming from water stress and pest infestation, respectively.

Results for the variance function shed some light on the risk property of inputs. Overall, estimates suggest that chemical fertilizers, improved seeds and irrigation reduce yield variability and hence production risk. The finding on irrigation is in line with the argument that farmers maintain irrigation as a way of insurance against potential yield losses from water stress. The key role that irrigation plays to reduce production fluctuations confirms the importance of supplying a stable and continuous flow of hydric resources in rice production. In contrast, the positive marginal effect on seeds and pesticides suggests that these inputs are risk-increasing. Note in particular, that the positive marginal risk of pesticides is in line with risk averse farmers using less amount of pesticides (shown in section 6.1), suggesting consistency across experimental and production function methods.

6.3 What is the main source of risk in pesticide use in Vietnam?

In the previous sections we documented that the risk-increasing characteristic of pesticide use is not dependent on chosen methodology. What then is the main source of the risk effect of pesticides? Following Horowitz and Lichtenberg (1994), the risk-increasing property of pesticides is more likely to arise in settings in which uncertainty regarding other growing conditions, i.e. rainfall, is relatively more important than pest infestation. To explore this further, we expand the mean function specification and include interactions of our proxies for the state of nature regarding pest and rainfall with pesticide use. Thus, we compare marginal productivities of using pesticide during the incidence of pest and rainfall shocks. As using the damage function specification with additive error, the NLS estimator fails to converge. We therefore assume a quadratic functional form to ease convergence. Results are showed in Table 5. We interact pesticide inputs with shocks indicators in columns 1; in column 2 we replace the drought indicator with monetary losses. We find that productivity of using pesticide is not statistically different from zero when farmers are affected by pest. This result remains when using measures of pest losses. In other words, marginal damage reduction does not seem to be higher during less favorable growing conditions, such as periods of high pest density or when pests are more damaging, suggesting an unclear risk-reducing effect of pesticides. In contrast, we find that pesticide productivity is lower during drought periods (column 1), suggesting a risk-increasing effect of pesticides. The latter indicates on aggregate that the risk-increasing effects of pesticide use may be larger than its risk-reducing effect.

Although both pest and drought risk are important sources of uncertainty in agricultural production in Vietnam, farmers seem to react more to adverse drought related events as compared to pest related shocks. This could signal that farmers either have better knowledge of pest incidence probabilities and adjust optimal behavior accordingly (pests are internalized), or that application of pesticides continuously are implemented at high probability pest levels (leading on average to inefficient overuse of pesticides) independent of realized pest shocks. Our results suggest that it is the latter mechanism that dominates in the case of Vietnamese farmers, potentially with detrimental consequences for the future.

7 Robustness

7.1 Non-responses and zero price observations

One concern with the analysis is non-response bias or "zero responses". We therefore estimate the pesticide use equation excluding these observations. However, significant differences between farmers willing to participate in the lottery and those who were not can make the exclusion of non-participants problematic. To explore these divergences, Table A1 presents mean difference tests for the balancing properties between participants and non-participants in the lottery. Results confirm differences between the two groups. We therefore apply the inverse probability weights (IPW) to account for a potential bias when excluding zero and non-response observations. Results are shown in columns 1-4 of Table A2. We conclude that the exclusion of zero-price answers and non-respondents do not change results fundamentally.

7.2 Risk aversion and other inputs

An additional concern with the lottery approach is that a negative association of the risk aversion measure with pesticide use may be reflecting general aversion to investment rather than something particular to pesticide use. Put differently, risk averse farmers may use less amount of pesticides because they are not willing to incur additional risk, and if so, results may not be attributable to the fact that pesticide is risk-increasing. To address this, we explore the association between risk aversion and fertilizer use, an input that involves even larger investments (see Table 2). If results are driven by general aversion to investment, then we should find that more risk averse farmers also use fewer quantities of fertilizer. Results are shown in Table A2, columns 7 and 8, showing that risk aversion increases the use of fertilizer input. This result is therefore consistent with fertilizer use reducing production variance, and thereby being labelled as a risk-decreasing input. Thus, we conclude that our risk aversion measure is not reflecting overall aversion to investment.

7.3 Self-reported data

A further concern with our definition of drought shocks is that it relies on self-reported data. That may raise a systematic reporting bias since weather shocks data may not be a function of geographical location. Alternatively, we use calculations of the Standardized Precipitation Index (SPI) by the National Centre for Environmental Predictions (NOAA) (McKee, et al., 1993; 1995) to identify dry cycles. Specifically, we use a 9-month time scale index constructed on 0.5° lat/lon grid monthly precipitations of 1949-2014 over the main rice growing season in Vietnam (October-June).[23] Due to the absence of information on households' locations, we extrapolate this information at the district level. The SPI index is a continuous indicator that ranges from negative to positive values. Thus, larger values indicate a better state of nature with regard to rainfall. Statistics of the SPI confirms a dry cycle in 2010. In this year, the SPI ranged from -2.38 to -0.5 with a mean of -1.43, suggesting a dry agricultural season, mainly in northern and central Vietnam (see Figure A1). Results are presented in columns 5 and 6 of Table A2, and are qualitatively the same as reported in the main specifications. Farmers apply larger quantities of pesticide in periods with higher rainfall, and the inclusion of a rainfall-based drought index does not affect conclusions regarding our risk aversion measures.[24]

7.4 Specification and unobserved characteristics

A concern with the production function estimates is that they are likely to be specification dependent. As robustness check, we re-estimate the mean function for quadratic and Cobb-Douglas specifications. Furthermore, we also estimate the JP production function using panel data for 2010 and 2012. Descriptive statistics for the panel are shown in Table A3. Here, risk marginal effects of input are identified by using the variance that farmers experience within their own farms. We assume a linear quadratic functional specification for the mean function in this case. An advantage of this specification is that the farm-specific effect is additive, which is a requirement for the JP model (Eggert and Tveteras, 2004; Gardebroek et al., 2010). Results are presented in Table A4 and A5. As

[23] A drought occurs if the SPI value falls at or below minus 1.0. Similarly, wet periods are identified with values equal or greater than 1.0. A value between -1 and 1 indicates no climatic anomaly.

[24] Findings on pesticide productivity being higher during better growing conditions measured by the SPI index remains robust to the use of panel data, suggesting a more likely risk-increasing effect of pesticides (see Table A5).

before, traditional inputs have positive marginal effects, consistent with theory. The quadratic term is negative and significant for all inputs, excepting pesticides, suggesting some evidence of decreasing marginal returns. The risk-increasing property of pesticides is also robust in the FE specification, and interestingly the FE estimates for the mean function show a U-inverted shape relation between pesticides and yield, suggesting a threshold from which pesticides start becoming effective in enhancing yields. Estimates of the variance function using a Cobb-Douglas specification gives similar conclusions. In fact, pesticide use is the only input that is consistently found to be risk-increasing throughout all specifications.

8 Conclusions

The excessive and unsustainable use of pesticides has created concerns because of its detrimental effects on farmers' health, the environment and agricultural sustainability. Thus, the overuse of chemical pesticide remains an important development issue, and understanding pesticide input decisions is a key requisite to sound policy-making. This paper examines the risk effects of pesticide use by using a lottery in combination with a production function approach on the same dataset of rice farmers in Vietnam. We also investigate the sources of the risk effects of pesticides.

Results from the lottery approach indicated that risk averse farmers are more likely to use fewer quantities of pesticide. Findings from the production function approach showed that pesticides increase production risk. Thus, both approaches consistently give evidence in the same direction, supporting the hypothesis of pesticide use being a risk-increasing input. The latter discards any incidence of the approach in determining the risk property of inputs.

We also found that the reduction in pesticide productivity in drought periods may be significant and that it may offset potential higher benefits from damage reduction when pest is high, suggesting that the risk-increasing effect of pesticides may dominate. This is consistent with pesticide use being a risk-increasing input, as pest damage may not be independent of rainfall; pesticide productivity will then be lower during drought periods since pesticide use is not dynamically optimally adjusted to the lower yields. These findings were found to be robust to alternative definitions of risk aversion and weather shocks, the use of different functional forms and panel data, and the exclusion of non-lottery participation observations. In addition, we noted that our results are not driven by general aversion to investment.

However, one additional caveat deserves attention. Our results may be crop-specific since trade-offs between pest and drought risk are supposed to vary across different cropping activities. For example, maize is relatively more resistant to water stress than rice and therefore pesticides may be more likely to be risk-decreasing in maize production. However, focusing on rice has some advantages. Rice is the major crop in Vietnam and is typically grown by most rural households (CIEM, et al., 2011; 2013). This characteristic reduces concerns that our results can be confounded by selection into rice production.

Despite these considerations, our findings have important implications for the success of government interventions to address concerns of the excessive use of pesticides. For an instrument aimed at reducing a pollutant input to work, it is necessary to understand the risk character of this input. If it is found that the input is risk-decreasing/increasing, then risk management instruments are quite likely to substitute/complement the inputs in the production process (Rossen and Hennessy, 2003; Schoengold et al., 2014). For example, crop insurance has been proposed as an instrument for reducing pesticides, arguing that it provides a substitute for the risk management benefits of pesticides (Babcock and Hennesey, 1996; and Smith and Goodwin, 1996). Based on the evidence that pesticides are positively correlated with production risk, crop insurance may instead exacerbate a pollution problem. Even with moral hazard, which reduces the use of all inputs, the high level of risk aversion among Vietnamese farmers would still lead to the observed risk effects (Ramaswami, 1993). This suggests that policies promoting more sustainable agricultural practices such as the Integrated Pest Management (IPM), and communicational programs addressed to increasing farmers' awareness of pesticide risk may display advantages over other risk management instruments.

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Tables

Table 1. Descriptive statistics for lottery answers and risk attitudes. 2010.

Variables	Small prize lottery		Big prize lottery	
	Mean	**Dev**	**Mean**	**Dev**
Categories				
Non response	14.2		14.0	
Zero price	48.7		48.5	
Positive price	37.1		37.5	
Total	100		100	
Risk categories				
Risk averse	81.0		86.1	
Risk neutral	5.6		6.3	
Risk loving	7.9		7.6	
Inconsistent	5.5		0.0	
Total	100		100	
Absolute risk aversion	0.59	0.69	0.07	0.06

Note: Risk categories are defined among observations with positive willingness to pay.

Table 2. Household, production and shock variables. 2010.

Variables	Mean	St dev	Min	Max
Household characteristics				
1= HH is male	0.86	0.35	0	1
Head's age (years)	49.24	12.92	14	91
Head's schooling (N grades)	5.66	3.84	0	12
Farm size (m2)	8,600	11,372	0	138,500
# family members	4.87	1.91	1	15
1= HH received pest extension	0.35	0.48	0	1
1= HH borrowed money	0.53	0.50	0	1
Household's incomes (000 VND)	66,555	87,189	0	2,076,720
Household's wealth (000 VND)	40,962	49,796	0	814,600
1 = HH received public-private	0.86	0.35	0	1
Output and input variables				
Output (kg)	1,747	4,095	0	116,400
Land (sqr meter)	4,503	7,513	50	118,000
Labor (days)	106	75.84	0	650
Seed value (000 VND)	844	1,918	0	48,000
Fertilizer (000 VND)	2,366	7,750	0	250,000
Pesticide (000 VND)	1,057	6,565	0	250,000
Yield (kilos/sqr meter)	0.42	0.16	0	2.0
1 = farmers irrigate	0.86	0.35	0	1.0
1 = farmer use improved seed	0.75	0.43	0	1.0
Labor per sqr meter (days/sqr meter)	0.04	0.03	0	0.3
Seed per sq meter (000 VND/sqr meter)	0.24	0.24	0	6.9
Fertilizer per sq meter (000 VND/sqr meter)	0.59	0.62	0	10.0
Pesticide per sqr meter (000 VND/sqr meter)	0.15	0.21	0	2.7
1 = Good soil quality	0.77	0.42	0	1
1= Flat land terrain	0.66	0.48	0	1
Shock variables				
1= farmers was hit by a pest shock	0.31	0.46	0	1
1= farmers was hit by a drought shock	0.13	0.33	0	1
Loss after a pest shock (000 VND)	1,107	4,384	0	126,600
Loss after a drought shock (000 VND)	300	1,747	0	41,000
Observations		2,205		

Note: Own elaboration based on dataset.

Table 3. Estimates of the Tobit model for the logarithm of pesticide value per square meter. Total sample.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion						
Absolute risk aversion (small prize)	-0.025***	-0.023**				
	(0.009)	(0.009)				
Absolute risk aversion (big prize)				-0.247**	-0.246**	
				(0.104)	(0.104)	
1= Risk averse (small prize)			-0.019			
			(0.016)			
1= Risk averse (big prize)						-0.045**
						(0.019)
Shocks						
1= farmers experienced a pest	0.002		0.003	0.003		0.002
	(0.006)		(0.006)	(0.007)		(0.007)
1= farmers experienced a drought	-0.016**		-0.016**	-0.019**		-0.019**
	(0.008)		(0.008)	(0.008)		(0.008)
Monetary loss						
Ln(Loss after a pest shock)		0.001			0.001	
		(0.001)			(0.001)	
Ln(Loss after a drought shock)		-0.003**			-0.003***	
		(0.001)			(0.001)	
Control variables						
1= HH is male	-0.002	-0.001	-0.001	0.000	0.001	0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ln(Head's age)	0.030**	0.023**	0.029**	0.034***	0.034***	0.035***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Head's schooling)	0.028**	0.024**	0.028**	0.026**	0.026**	0.025**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Head's schooling)^2	-0.006	-0.005	-0.006	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(farm size)	-0.010***	-0.005	-0.011***	-0.011***	-0.011***	-0.011***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Ln(# family members)	-0.030***	-0.027***	-0.030***	-0.033***	-0.033***	-0.032***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
1= HH received pest extension	-0.013**	-0.008	-0.014**	-0.012*	-0.011*	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
1= HH borrowed money	0.013**	0.014***	0.013**	0.015***	0.015***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(Household's wage)	0.012***	0.011***	0.013***	0.012***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Ln(Household's wealth)	0.00286***	0.003***	0.003**	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1 = HH received public- transfers	0.002	0.004	0.000	-0.004	-0.004	-0.003
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
1 = Good soil quality	0.013**	0.016***	0.012*	0.011*	0.011*	0.012*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
1= Flat land terrain	0.035***	0.028***	0.035***	0.034***	0.034***	0.0345***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.065	0.091	0.070	0.059	0.059	0.079
	(0.065)	(0.064)	(0.066)	(0.066)	(0.066)	(0.067)
Zone dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,156	2,156	2,156	2,205	2,205	2,205

Note: Columns (1)-(3) display the estimated coefficients for the total sample using responses to the small lottery prize. Columns (4)-(6) use answers to the big lottery prize. The dependent variable is the logarithm of the pesticide value per square meter used in rice production. All specifications are estimated by the Tobit model and include a full set of control covariates. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimation of mean and variance functions.

Variables	(1) Mean	(2) Variance
Inputs		
1= farmers irrigate		-0.042***
		(0.006)
1 = farmer use improved seed		-0.011**
		(0.005)
Labor per sq meter	0.069***	-0.033
	(0.013)	(0.087)
Seed value sq meter	0.043***	0.049***
	(0.013)	(0.015)
Fertilizer value per sq meter	0.101***	-0.089***
	(0.009)	(0.009)
Pesticide value sq meter		0.112***
		(0.017)
1 = Good soil quality	0.054***	0.0005
	(0.015)	(0.0046)
1= Flat land terrain	0.086***	-0.001
	(0.017)	(0.005)
Damage control inputs		
μ	-0.821***	
	(0.228)	
Pesticide value sq meter	7.132**	
	(2.896)	
1= farmers irrigate	1.125***	
	(0.247)	
1 = farmer use improved seed	-0.094	
	(0.185)	
Zones dummies	Yes	Yes
Constant	0.636***	0.164***
	(0.042)	(0.008)
R square	-	0.108
Observations	2,199	2,199

Note: Column (1) displays the estimated coefficients of the yield function. The dependent variable is kilos of rice per square meter. This specification is estimated by NLS. Column (2) shows the coefficients for the variance function. The dependent variable is the absolute value of predicted errors of the mean function. This specification is estimated by OLS. Robust standard errors in parentheses for the mean function.*** p<0.01, ** p<0.05, * p<0.1.

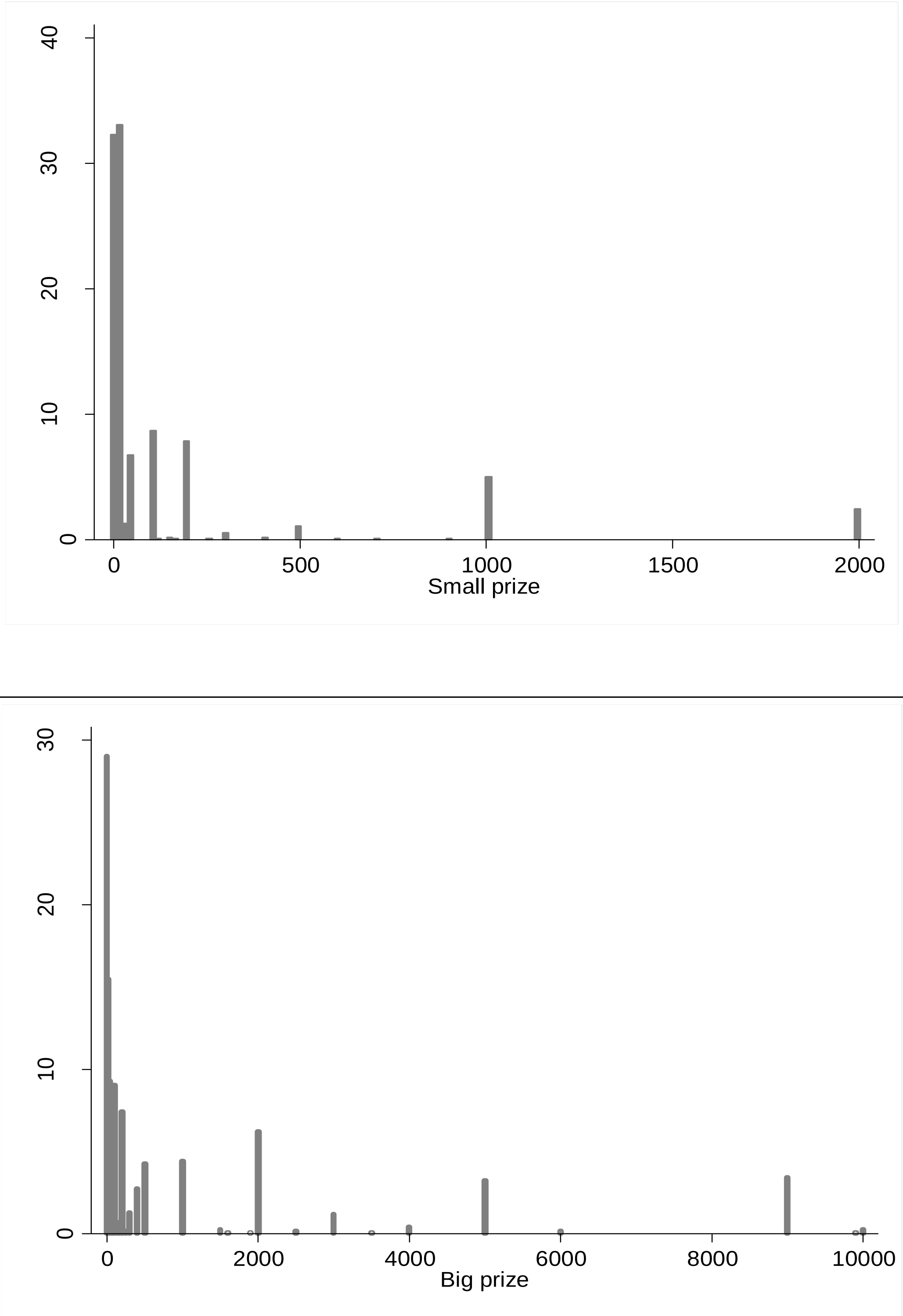
Table 5. Estimation of mean functions with interactions. Dependent variable: Yield.

Variables	(1)	(2)
Inputs		
1= farmers irrigate	0.038***	0.038***
	(0.008)	(0.008)
1 = farmer use improved seed	0.008	0.004
	(0.007)	(0.007)
Labor per sq meter	2.527***	1.947***
	(0.322)	(0.332)
Labor per sq meter^2	-9.306***	-7.325***
	(2.261)	(2.152)
Seed value sq meter	0.153***	0.177***
	(0.0251)	(0.025)
See value per sq meter^2	-0.031**	-0.037***
	(0.006)	(0.007)
Fertilizer value per sq meter	0.075***	0.070***
	(0.010)	(0.009)
Fertilizer value per sq meter^2	-0.009***	-0.009***
	(0.002)	(0.002)
Pesticide value sq meter	0.132**	0.138***
	(0.052)	(0.050)
Pesticide value per sq meter^2	0.026	0.040
	(0.042)	(0.045)
1 = Good soil quality	0.010*	0.019***
	(0.006)	(0.006)
1= Flat land terrain	0.042***	0.026***
Shocks		
1= farmers experienced a pest	-0.019**	
	(0.008)	
1= farmers experienced a drought	-0.031***	
	(0.010)	
Ln(Loss after a pest shock)		0.000
		(0.000)
Ln(Loss after a drought shock)		-0.000**
		0.000
Pesticide*pest shock	0.065	
	(0.049)	
Pesticide*drought shock	-0.109*	
	(0.064)	
Pesticide*pest loss		0.000
		(0.000)
Pesticide*drought loss		0.000
		(0.000)
Zones dummies	Yes	Yes
Constant	0.192***	0.187***
	(0.015)	(0.014)
R square	0.415	0.436
Observations	2,199	2,199

Note: Column (1) displays the estimated coefficients of the augmented yield function as assuming interaction of pesticide input with shock indicators. Column (2) replaces drought indicators with monetary losses. The dependent variable is kilos of rice per square meter. Models are estimated by OLS, and include zone dummies. We use a quadratic functional form. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Figures

Figure 1. Histogram of the willing to pay for the hypothetical lottery. Positive willingness to pay (000 VND)



Source: Own elaboration based on dataset.

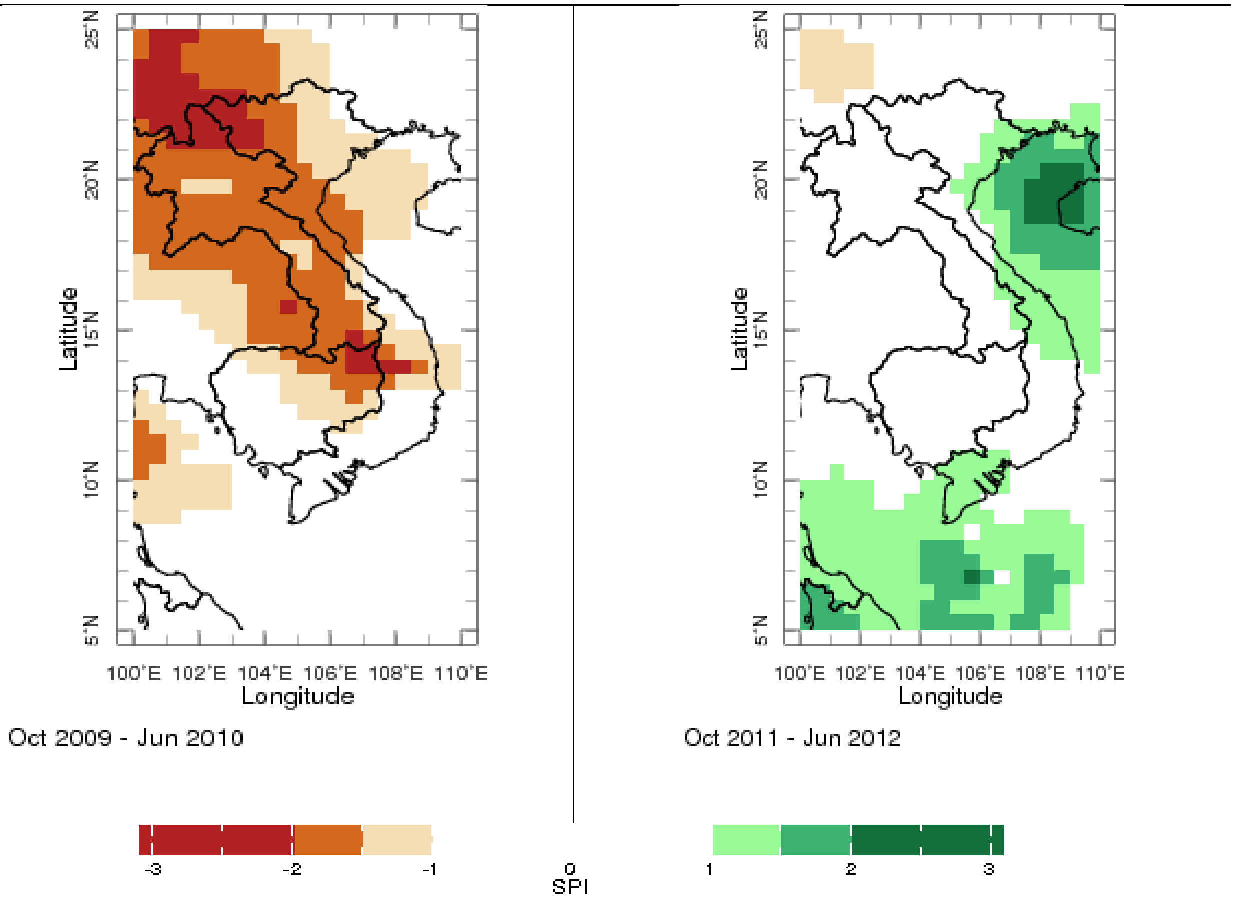
Appendix A: Additional Tables and Figures.

Table A1. Difference in means (participants vs. non-participants in the lottery)

Variables	Small prize lottery				Big prize lottery			
	Mean		Differences	p-value	Mean		Differences	p-value
	Non-part	Part			Non-part	Part		
1= HH is male	0.84	0.87	0.03	0.07*	0.84	0.88	0.03	0.03**
Head's age (years)	49.14	49.31	0.18	0.76	49.06	49.55	0.49	0.39
Head's schooling (N grades)	5.47	5.92	0.44	0.01***	5.47	5.97	0.50	0.00***
Farm size (m2)	8,973	7,973	-999.5	0.05**	9,017	7,901	-1,115	0.03**
# family members	4.92	4.78	-0.14	0.10*	4.94	4.76	-0.18	0.03**
1= HH received pest extension	0.37	0.32	-0.05	0.03**	0.37	0.32	-0.06	0.01***
1= HH borrowed money	0.52	0.53	0.01	0.69	0.52	0.54	0.01	0.53
Household's incomes (000 VND)	62,941	71,737	8,795	0.02**	63,105	72,348	9,243	0.02**
Household's wealth (000 VND)	39,279	43,083	3,804	0.09*	39,569	43,301	3,732	0.09*
1 = HH received public-private	0.80	0.75	-0.05	0.01***	0.80	0.75	-0.05	0.01***
1= farmers experienced a pest	0.33	0.27	-0.07	0.00	0.33	0.27	-0.06	0.00***
1= farmers experienced a drought	0.13	0.12	-0.02	0.23	0.13	0.12	-0.02	0.22
1 = Good soil quality	0.76	0.77	0.01	0.71	0.76	0.77	0.00	0.81
1= Flat land terrain	0.63	0.69	0.06	0.00***	0.63	0.70	0.07	0.00***
Observations	1,389	768			1,382	823		

Note: p<0.01, ** p<0.05, * p<0.1.

Figure A1. Spi index. 2010-2012.



Note: Red color identifies droughts (SPI lower than -1); while white color shows normal climate conditions (SPI between -1 and 1); and green areas identify wet periods (SPI greater than 1).

Table A2. Estimates of the Tobit model for the logarithm of pesticide/fertilizer value per square meter. Excluding non-participants (Weighted regression).

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Risk aversion								
Absolute risk aversion (small prize)	-0.026***				-0.025**			
	(0.010)				(0.010)			
Absolute risk aversion (big prize)			-0.178*			-0.185*	0.402**	
			(0.107)			(0.110)	(0.183)	
1= Risk averse (small prize)		-0.014						
		(0.016)						
1= Risk averse (big prize)				-0.034*				0.083**
				(0.020)				(0.030)
Shocks								
1= farmers experienced a pest	-0.007	-0.005	-0.008	-0.009	-0.007	-0.008	0.001	0.004
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)	(0.024)	(0.024)
1= farmers experienced a drought	-0.028*	-0.028*	-0.034**	-0.034**			0.024	0.024
	(0.015)	(0.015)	(0.015)	(0.014)			(0.029)	(0.029)
SPI index					0.066***	0.067***		
					(0.016)	(0.016)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zones dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.010	0.022	-0.017	-0.005	0.090	0.076	0.054	0.025
	(0.103)	(0.105)	(0.107)	(0.107)	(0.010)	(0.101)	(0.246)	(0.247)
Observations	768	768	819	819	768	819	819	819

Note: Columns (1)-(3) display the estimated coefficients for the sub-sample of non-zero respondents to the small lottery prize. Columns (4)-(6) use answers to the big lottery prize. The dependent variable is the logarithm of the pesticide value per square meter used in rice production. Columns (7)-(8) show the estimated coefficients for the logarithm of the fertilize value per square meter used in rice production All specifications are estimated by the Tobit model and include a full set of control covariates. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A3. Production and shock variables. 2010-2012 panel.

Variables	2010				2012			
	Mean	St dev	Min	Max	Mean	St dev	Min	Max
Output and input variables								
Output (kg)	1,839	4,272	0.0	116,400	2,111	4,671	1.0	89,700
Land (sqr meter)	4,727	7,702	144	118,000	4,727	8,313	45.0	145,000
Labor (days)	109	77	0.0	650	108	87	0.0	1,000
Seed value (000 VND)	894	2,002	0.0	48,000	910	1,960	0.0	36,081
Fertilizer (000 VND)	2,496	8,148	0.0	250,000	2,319	6,264	0.0	144,401
Pesticide (000 VND)	1,147	6,942	0.0	250,000	1,048	6,621	0.0	216,597
Yield (kilos/sqr meter)	0.42	0.15	0.0	1.9	0.48	0.63	0.0	7.2
1 = farmers irrigate	0.85	0.35	0.0	1.0	0.88	0.32	0.0	1.0
1 = farmer use improved seed	0.74	0.44	0.0	1.0	0.76	0.43	0.0	1.0
Labor per sqr meter (days/sqr meter)	0.04	0.03	0.0	0.3	0.04	0.06	0.0	0.6
Seed per sq meter (000 VND/sqr meter)	0.24	0.25	0.0	6.9	0.25	0.33	0.0	3.4
Fertilizer per sq meter (000 VND/sqr meter)	0.59	0.60	0.0	10.0	0.62	0.64	0.0	12.1
Pesticide per sq meter (000 VND/sqr meter)	0.15	0.21	0.0	2.7	0.16	0.25	0.0	2.9
Shock variables								
1= farmers experienced a pest	0.31	0.46	0.0	1.0	0.30	0.46	0.0	1.0
1= farmers experienced a drought	0.13	0.34	0.0	1.0	0.09	0.28	0.0	1.0
Loss after a pest (000 VND)	1,133	4,539	0.0	126,600	1,302	5,321	0.0	138,994
Loss after a drought (000 VND)	301	1,773	0.0	41,000	91.04	637	0.0	13,745
Spi index	-1.43	0.60	-2.38	-0.5	0.50	0.55	-0.6	1.2
Observations	1,947				1,947			

Note: Own elaboration based on dataset. Figures correspond to the balanced panel. Values are deflated (2010=100).

Table A4. Estimation of mean and variance functions for alternative functional forms and panel data.

Variables	**(1) Quadratic Mean**	**(2) Variance**	**(3) Cob Douglas Mean**	**(4) Variance**	**(5) Quadratic Mean (FE)**	**(6) Variance (FE)**
Inputs						
1= farmers irrigate	0.039***	-0.003	0.119***	-0.030***	-0.006	-0.011
	(0.008)	(0.005)	(0.029)	(0.007)	(0.012)	(0.009)
1 = farmer use improved seed	0.007	-0.002	-0.001	-0.016***	0.024***	-0.000
	(0.007)	(0.003)	(0.022)	(0.005)	(0.009)	(0.005)
Labor per sq meter	2.493***	0.153**	0.067***	-0.063	-0.222	0.727***
	(0.322)	(0.067)	(0.013)	(0.097)	(0.380)	(0.091)
Labor per sq meter^2	-9.246***				9.979***	
	(2.243)				(1.671)	
Seed value sq meter	0.138***	-0.003	0.039***	0.048***	0.306***	0.047***
	(0.025)	(0.012)	(0.013)	(0.017)	(0.077)	(0.018)
See value per sq meter^2	-0.031***				-0.0811***	
	(0.007)				(0.029)	
Fertilizer value per sq meter	0.078***	-0.021***	0.092***	-0.074***	0.025	-0.003
	(0.010)	(0.007)	(0.010)	(0.010)	(0.027)	(0.011)
Fertilizer value per sq meter^2	-0.010***				0.006	
	(0.002)				(0.006)	
Pesticide value sq meter	0.137***	0.048***	0.054***	0.044**	-0.216*	0.081***
	(0.049)	(0.013)	(0.009)	(0.019)	(0.128)	(0.021)
Pesticide value per sq meter^2	0.042				0.312**	
	(0.049)				(0.146)	
Geographical variables	Yes	Yes	Yes	Yes	No	No
Zones dummies	Yes	Yes	Yes	Yes	No	No
Year variable	No	No	No	No	Yes	Yes
Constant	0.175***	0.094***	0.588***	0.176***	0.320***	0.061***
	(0.014)	(0.006)	(0.043)	(0.009)	(0.0294)	(0.010)
R square	0.403	0.039	-	0.076	0.372	0.074
Observations	2,199	2,199	2,199	2,199	3,894	3,894

Note: Column (1) displays the estimated coefficients of the yield function as assuming a quadratic functional form. This specification is estimated by OLS. Column (3) assumes a Cob-Douglas production function. The Cob-Douglas function is estimated by NLS. Finally, column (4) shows estimations using the panel 2010-2012 and assuming a quadratic function for the mean. This latter is estimated by FE and includes a dummy variable for the year 2012 (not shown). In these columns, the dependent variable is kilos of rice per square meter. Columns 2, 4 and 6 show the estimates of variance functions, respectively. The dependent variable is the absolute value of predicted errors. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A5. Estimation of mean functions with interactions. Fixed effect estimator (FE). Dependent variable: Yield.

Variables	(1)	(2)	(3)
Inputs			
1= farmers irrigate	-0.007	-0.007	-0.004
	(0.012)	(0.012)	(0.012)
1 = farmer use improved seed	0.022***	0.024***	0.019**
	(0.009)	(0.009)	(0.009)
Labor per sq meter	-0.268	-0.233	-0.202
	(0.365)	(0.374)	(0.369)
Labor per sq meter^2	10.14***	10.04***	9.786***
	(1.718)	(1.681)	(1.676)
Seed value sq meter	0.308***	0.305***	0.303***
	(0.078)	(0.077)	(0.074)
See value per sq meter^2	-0.0816***	-0.081***	-0.078***
	(0.031)	(0.030)	(0.029)
Fertilizer value per sq meter	0.025	0.025	0.028
	(0.028)	(0.027)	(0.028)
Fertilizer value per sq meter^2	0.006	0.006	0.006
	(0.006)	(0.006)	(0.006)
Pesticide value sq meter	-0.199*	-0.219*	-0.196
	(0.111)	(0.122)	(0.120)
Pesticide value per sq meter^2	0.310**	0.316**	0.285**
	(0.139)	(0.144)	(0.138)
1 = Good soil quality			
1= Flat land terrain			
Shocks			
1= farmers experienced a pest	-0.004	-0.007	
	(0.010)	(0.009)	
1= farmers experienced a drought	-0.054		
	(0.037)		
Spi index		-0.019	
		(0.013)	
Ln(Loss after a pest shock)			0.000
			(0.000)
Ln(Loss after a drought shock)			-0.000**
			(0.000)
Pesticide*pest shock	-0.092	-0.063	
	(0.087)	(0.080)	
Pesticide*drought shock	0.172		
	(0.348)		
Pesticide* Spi index		0.084*	
		(0.043)	
Pesticide*pest loss			-0.000
			(0.000)
Pesticide*drought loss			0.000
			(0.000)
Year variables	Yes	Yes	Yes
Constant	0.332***	0.323***	0.313***
	(0.029)	(0.028)	(0.0296)
R square	0.378	0.373	0.379
Observations	3,894	3,894	3,894

Note: Column (1) displays the estimated coefficients of the augmented yield function as assuming interaction of pesticide input with shock indicators. Column (2) replaces drought indicators with the SPI index; Column (3) incorporates monetary losses, instead. All the models are estimated by FE and include a dummy variable for the year 2012. We assume a quadratic functional form. In all the columns, the dependent variable is kilos of rice per square meter. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Chapter 5

Weather Shocks and Spatial Market Efficiency. Evidence from Mozambique.

César Salazar-Espinoza, Hailemariam Ayalew and Peter Fisker*

Abstract

The aim of this paper is to study the effect of weather shocks (drought and flood) on agricultural market performance in Mozambique. To do so, we employ dyadic regression analysis and use data on monthly maize prices, transport costs and spatial identification of droughts and flooded areas. Results show differentiated effects of different weather shocks. While a drought causes price differences between markets to reduce, suggesting a supply shock effect, price dispersion increases during flood periods, along with increases in food transport costs. Results also reveal some heterogeneity: Floods are found to increase price dispersion more among markets that are closer to each other and connected by poorer transport infrastructure.

Key words: weather shocks, spatial market efficiency, prices.

JEL classification: O13, O18, Q11, Q13.

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1 Introduction

In the last two decades, the world has witnessed an increase in the frequency and severity of natural disasters. Such prevalence of natural hazards has disrupted social and economic systems in a variety of ways. According to the Centre for Research on Epidemiology of Disasters (EM-DAT, 2011), since 1970 more than five billion people have been affected by natural hazards and over one trillion US dollars have been incurred in financial losses. These problems are more severe in developing countries where economies rely more on the agricultural sector, and whose population is more exposed and vulnerable to extreme natural events. In particular, Mozambique is frequently affected by extreme climatic variations: fifty-two weather-related disasters occurred during the last thirty years, of which thirty-three corresponded to either drought or flood events (EM-DAT, 2013).

In this paper, we exploit variation in the incidence of droughts and floods across periods and markets to study the relationship between weather shocks and agricultural market efficiency in Mozambique. Empirical literature has put a lot of attention on the impact of natural hazards on household-individual outcomes (see for example Paxson, 1992; Rosenzweig and Binswanger, 1993; Jensen, 2000; Rose, 2001; Ito and Kurosaki, 2009; Maccini and Yang, 2009). However, studies examining the effect of weather-related shocks on market performance are less common (Aker, 2010a).

Spatial market efficiency is one of the crucial components for successful policy transmission and effectiveness. If markets are spatially segmented, it will lead to fragmentation of economic agents and households across space. This, in turn, undermines the transmission of price incentives necessary to exploit market advantages. The latter may lower resilience to localized shocks. For example, crop failure occurring unevenly across markets leads to price differences, signaling potential benefits through spatial and temporal arbitrage. If markets work poorly, trade from surplus to deficit areas will not be promoted, which in turn exacerbates the cost of food crisis (Ó Gráda, 2007). Thus, the attainment of spatial market efficiency is crucial to exploit the comparative advantages of specialization, reduce price fluctuations and ameliorate the impacts of weather shocks, thereby accelerating the process of economic development (Baulch, 1997).

Since the end of the war in 1992, profound market liberalization reforms and substantial investments in roads have been carried out in Mozambique (Tarp et al., 2002). Accordingly, the existing empirical evidence suggests that spatial market integration has improved during the post reform period;

however, it is still inadequate due to high transfer costs (Penzhorn and Arndt, 2002; Tostao and Brorsen, 2005). The persistence of poor road infrastructure and long distances from north to south appears to be limiting spatial trade between maize surplus and deficit regions, generating large differences between farm-gate and urban prices of agricultural products. Arndt et al. (2012a) showed that these marketing margins are one of main responsible for the persistent poverty observed in Mozambique. Cirera and Arndt (2008) highlight the role of road infrastructure improvements for enhancing agricultural market performance.

Our study expands on the existing literature in the following ways: First, rather than focusing solely on drought events, we extend the analysis to flood shocks. This distinction is important given the different potential mechanisms through which weather shocks affect market price dispersion. While droughts mainly affect market performance via a negative supply shock, floods are likely to affect both production (as a supply shock) and trade flows due to an increase in transport costs. Furthermore, this natural hazard merits special attention in Mozambique since climate change will potentially have substantial economic implications through the flooding impact channel (Chinoswsky and Arndt, 2012; Arndt and Thurlow, 2013). Second, instead of using precipitation data from a few meteorological stations, this paper identifies droughts by combining satellite measures of greenness, rainfall and temperature.

The remainder of this study is organized as follows: Section 2 describes key characteristics of the agriculture sector, maize market and climate patterns in Mozambique. Section 3 introduces the conceptual framework. Section 4 presents the data, including remote sensing and climate data, which we use to distinguish between drought and flood events. Section 5 describes our econometric model. Section 6 discusses the main results; and Section 7 concludes.

2 Agriculture, maize market and weather shocks in Mozambique

The agricultural sector contributes around 30% of the Gross Domestic Product (GDP) and employs 80% of the workforce in Mozambique (Jones and Tarp, 2013). The sector remains relatively unproductive and mainly consists of small-land holders, comprising 85% of the total rural households (The World Bank, 2012). Agriculture is mainly rain-fed with less than 0.5% of the total cropland under irrigation, almost all in sugar cane production (The World Bank, 2010). Maize, which is one of main staple and cash crop, dominates the agricultural sector of Mozambique. This crop is grown in the main rainy season (October-March), harvested in April/May and mainly commercialized in the post-harvest season (May-September). Its production varies across regions. While the northern and central regions are net producers, accounting for around 90% of national production, the southern areas are net consumers.[1]

Thus, interregional trade is very important for Mozambique economy. Surplus production in central and northern areas is not only exported to the south but also to neighboring countries such as Malawi. Furthermore, the south also meets its demand through imports from South Africa.[2] Maize markets in Mozambique operate in a free market system, where the government plays a limited role. Commercialization is largely carried out by many informal traders[3] on small-scale basis with a rapid turnover of product and storage between three days and a week (Alemu and Van Schalkwyk, 2009).[4] Since informal traders have limited access to credit and are not usually the owners of the transport equipment, they are more sensitive to transaction costs (Cirera and Arndt, 2008).

Maize production is quite volatile in Mozambique due to fluctuating climate conditions (Penzhorn and Arndt, 2002; Cirera and Arndt, 2008; Acosta, 2012). Mozambique is extremely prone to weather-related shocks, ranked third in Africa. Estimations suggest that annually the country loses around one percent of GDP due to weather-related shocks (World Bank, 2014). Droughts and floods are the most frequent natural phenomena in Mozambique (EM-DAT, 2013). The incidence of drought shocks is higher in the southern region (7 times each 10 year) compared to the central (4 times each 10 year) and the northern (2 times every ten year) regions. Although less recurrent, floods are also destructive and their effects can prevail for several months (World Bank, 2010). These also primarily occur in southern and central regions, along river basins, in low-lying areas, and in zones with poor drainage system. They are caused by not only excessive rainfall but also increases in water courses from rivers in upstream neighboring countries. Estimations suggest that every year around 100 km of roads are affected by flood events, which results a direct loss of approximately US$700,000 (GFDRR, 2012).

[1] The north region concentrates more than half of the population of the country and also accounts for about 60% of Mozambique's maize sales. However, it has the lowest proportion of households growing maize in Mozambique (Tschirley et al., 2006).

[2] Imports of white maize grain from South Africa amounted to around USD 20.000.000 between 2008 and 2009 (Acosta, 2012).

[3] Informal trades are defined as those that neither have permanent physical infrastructure nor are registered with the tax authority. In Mozambique, informal traders buy maize grain in bulk and sell it to other buyers, but they may also sell maize grain in small quantities to consumers, then acting as both wholesalers and in some occasions as retailers (Abdula, D., 2005).

[4] In a survey conducted in Maputo and Xai Xai, more than half of the informal traders reported selling between 1 to 10 bags of 70 kg of maize grain per week. Furthermore, purchases of maize by informal traders take place in assembly points usually located along the main roads. Informal traders reach those points by public transportation. Transport back to the selling points (places where they intend to sell) is done by trucks that come back from rural areas after delivering consumer goods. It can take several days a truck to appear (Abdula, D., 2005).

The existence of a poor road infrastructure exacerbates the impact of floods. For example, moving grain from northern and central provinces to the south becomes practically impossible during the rainy season when the Zambezi River[5] gets flooded, disconnecting the north from the rest of the country. The consequences are aggravated because other transport options are quite limited. For example, maritime transport in Mozambique is an expensive and inefficient alternative, with limited vessel availability and low frequency of service (Tostao and Brorsen, 2005; Cirera and Arndt, 2008). Moreover, existing rail links in Mozambique were built up to facilitate east-west trade between colonial powers, as opposed to north-south trade (Tschirley et al., 2006). Projections indicate that climate change is expected to increase the frequency and magnitude of natural hazards. As a result, droughts and floods will probably present large future threats to Mozambique's economy (World Bank, 2010; Arndt and Thurlow, 2013).[6]

3 Conceptual framework

Markets are said to be integrated if it is possible to transfer physical flows of product or price shocks from one market to another. Two main approaches have been traditionally used to conceptualize market integration. The first approach follows a flow-based view, suggesting that trade flows are sufficient, but no necessary for market integration. Thus, the observation of price shocks being transmitted even in absence of trade can also be seen as a signal of market integration. The second approach follows a price-based notion of efficiency, in which two markets are in a competitive equilibrium if there is zero marginal profit to arbitrage (Barret and Liu, 2002). Under this approach, two locations may reach spatial efficiency if they do not trade because there is no positive arbitrage to do so. This is the case when transaction costs are high.[7]

This paper follows the spatial efficiency approach to market integration.[8] The standard view on spatial market equilibrium suggests that the price difference between two markets which engage in an identical good depends on the transaction costs between them (Enke, 1951; Samuelson; 1952; Stigler; 1966; and Takayama and Judge, 1971).

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[5] The Zambezi river separates the northern region from the central and south regions, acting as a natural barrier to north-south trade.

[6] The four possible scenarios for climate change indicate that climate will become hotter and more volatile in Mozambique (Arndt et al., 2012b).

[7] The argument of trade being neither necessary nor sufficient for market integration supports the inclusion of market-pair observations for which trade may be discontinuous or very limited. On the other hand, including those observations may reveal additional insights on markets being continuously in autarky, important for implications and interpretations at the face of the occurrence of floods.

[8] Since trade is not a sufficient condition for market integration and price data is more observable than trade flows, the existing economic literature has focused more on the spatial efficiency approach. Furthermore, quantity-based measures of integration tell us nothing about welfare consequences. Thus, focusing on price-based notions of market integration allows economists to inform if trade patterns are efficient, and propose policy recommendations to improve resource allocation across markets (Barret and Liu, 2002).

Consider two markets (i and j) that undertake trade of a homogeneous commodity. Assume P_{it} and P_{jt} are the autarky prices in market i and j at time t, respectively. TC_{ij} is the transaction cost from market i to j or vis versa. Market i and j are said to be spatially efficient if the price of maize in the importing market j is equal to the price in the exporting market i plus the transaction cost between the two markets (Baulch, 1997). More specifically, i and j will be in the long-run competitive equilibrium if and only if the following "no spatial arbitrage" condition holds:

$$P_{jt} - P_{it} - TC_{ij} = 0 \tag{1}$$

$$P_{jt} - P_{it} - TC_{ij} < 0 \tag{2}$$

Equation (1) and (2) are called the Euler's equations. Equation (1) represents the situation where the marginal profit of spatial arbitrage is zero and markets are spatially efficient, whereas in equation (2) spatial arbitrage is negative or not profitable, that is, price differential is below transaction cost. This condition represents the autarky regime, and does not imply necessarily spatial inefficiency but it is commonly associated with lack of integration (Barret and Liu, 2002).

Equation (1) and (2) can be used to derive some predictions regarding the association between weather shocks and spatial market efficiency. Droughts in general affect only production, and will not have any effect on transaction cost. By assuming that transaction costs between i and j remain constant and one/both markets are affected by a drought, increasing prices more in one market compared to another, arbitrage opportunities may emerge. If markets work relatively efficient, price transmission will take place, and we should expect a reduction in price dispersion between markets.

Alike droughts, floods can be considered as a negative supply shock which can adversely affect production of a commodity. The earlier predictions also apply to this case. However, floods will also affect the price differential between markets through their effect on transaction cost. Transaction costs may increase during a flooding period, because of damage or obstruction on roads and main market accesses. Predictions from the comparative static analysis suggest a positive effect on the equilibrium price dispersion at the face of floods.

4 Data

4.1 Market information

We use data on prices and transport costs from the "Sistema De Informação De Mercados Agrícolas De Moçambique" (SIMA, 2011). SIMA was established in 1991 by the Ministry of Agriculture and Rural Development (MADER) of Mozambique in order to collect and disseminate information on agricultural markets, including prices, transport costs, opportunities and market perspectives. The information is made public by bulletins published weekly on its website for selected markets. We use the data on monthly maize prices of 25 markets and transport costs between markets over the 2005:01-2012:06 period.[9] Transport costs are used to proxy for transaction costs.[10] We choose white maize as the reference good because it is relatively homogenous and broadly demanded in Mozambique, which allows comparison across markets in the country. Additionally, we employ information on mobile network, distance, road quality and diesel prices in our estimations. Mobile phone development is expected to lead to increased market efficiency (Aker, 2010b). We proxy for the presence of mobile network in a market by using village level data from the Trabalho de Inquérito Agrícola (TIA).[11] Distances between markets are calculated using longitudes and latitudes and the Vincenty formula, which serves as a rough estimate of actual travel distances. Road network information is provided by the African Development Bank Group for 2005. This data informs on quality of primary and secondary roads in Mozambique by recording the type of road connecting two markets as paved, gravel or earth (see Figure A1). Local diesel prices are estimations for Maputo city to construct the Consumer Price Index (CPI). They are provided by the National Statistics Institute (Instituto National de Estadistica, INE) of Mozambique. Descriptive statistics of the variables used in the estimations are summarized in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Maize price fluctuations are quite high in Mozambique. Prices per kilo range from around 2.000 to 14.000 MZN, with a mean of 4.800 MZN in the study period. Transport costs are less volatile,

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[9] We aggregate the weekly price data at a monthly basis because it is less likely that arbitrage operates at a weekly basis. In other words, a larger weekly price differential may be driven by other factors than arbitrage.

[10] Transaction costs may also include handling costs, fixed costs and other less measurable costs associated with identification of business and negotiation, monitoring and enforcement of contracts, risk, etc. However, transport costs are the main component of transaction costs.

[11] We only have three point of information: 2005, 2007 and 2011. A market near a village reporting to have mobile network is assumed to have also mobile network. We notice a gradual development of this technology. While in 2007, 11 out of 25 markets did not have mobile network, only 2 markets in 2007 were not found to have mobile phone coverage. From 2011 on, the TIA data suggests that all the markets included in this analysis enjoy of mobile network.

ranging from 870 to 1.130 MZN per kilo. However, these costs account for an important proportion of the total maize value: around 20% of the total price corresponds to transport costs. Overall, transaction costs are relatively high for agricultural products since their value is considerably lower compared with manufactured products or services. Thus, logistical considerations may matter more in agriculture (Barret et al., 2001). Only 57% of the routes considered here are connected by a paved road, and primary and secondary roads in the north are in relatively poorer conditions than in the central and south regions (see Figure A1). Markets are distributed over the entire territory, with inter-market distances ranging from 4 km to over 1,660 km.

Figure 1 presents a graphical inspection of monthly maize prices, transport costs and diesel prices. We notice substantial price variation during the sample period. May 2005 to June 2006 and May 2008 to June 2009 are the main periods of higher maize prices. There was also a moderate increase in prices from June 2007 to March 2008, August 2009 to January 2010 and August 2010 to January 2011. Increments in transport costs and oil prices are factors that could potentially lead to higher market prices. For example, from September to November 2005, and August to October 2009 both price of maize and transport costs exhibit a similar upward trend. Similarly, there is also a downward trend in both price and transport costs from March to July 2006 and March to May 2009. However, the major price peak periods from November 2005 to March 2006 and June 2007 to March 2008 are not in line with diesel or transport costs series. This may suggest the existence of climate-related factors. Since maize production is highly sensitive to droughts, and food transportation costs are supposed to be affected by flooding, we expect climatic shocks to have a lion's share contribution to this observed price variation in Mozambique.

[INSERT FIGURE 1 ABOUT HERE]

4.2 Weather shock data

4.2.1 Flood events

To identify flood shocks, we use data recorded in the Global Active Archive of Large Flood Events (G.R.Brakenridge, 2013) from the Dartmouth Flood Observatory. The information documented in this archive is derived from news, governmental, instrumental, and remote sensing sources, and is updated continuously. Floods recorded here are classified at least as class 1 or large flood events, implying significant damage to structures or agriculture, fatalities, and/or 1-2 decades-long reported interval since the last similar event (G. R. Brakenridge, 2013). We match flooded areas with market locations to identify whether or not a market in a determined period was flooded.[12] We define two flood indicators: a dummy variable taking the value of 1 if only one market was affected, and a second dummy denoting that both markets were hit by a flood. To disentangle a transport cost shock from a potential supply shock as the result of a flood, we exploit the timing of flood occurrence in the following way. We implicitly assume that the full impact of a flood on transportation costs is felt while the flood lasts. This approach has some limitations since road infrastructure may suffer severe damages that compromise the normal functioning of roads in the short-term. For example, during road reparation periods transport costs may remain high. Unfortunately, we do not observe whether or not a road was damaged in our data. Thus, in the absence of this information, our approach seems to be more conservative, and estimates should be considered as lower bounds. On the other hand, floods may also lead to crop failure which is consistent with a supply shock. Thus, since floods occur mainly during the planting/sowing season (November-March), the identification of floods over the "flood period" may be more in line with a transport shock, hiding relevant information on the supply shock side effect. To identify this effect, we assume that production failure will materialize stronger on price dispersion from the harvesting period on. In this period, the trade mechanism starts taking place, which will potentially ease the exploitation of arbitrage rents. Thus, we additionally create cumulative supply flood shock indicators, starting from May (harvest-commercialization month) until the end of the agricultural season (September).

Additionally, we explore an alternative strategy. We define a third flood indicator, which takes the value of 1 if the main primary/secondary road connecting two markets was flooded, and none of the markets were directly affected. Transport costs are also supposed to increase in this case.

Descriptive statistics for these indicators are presented in Table1. Flood areas are shown in Figure 2.

[INSERT FIGURE 2 ABOUT HERE]

[12] Some concerns can arise as this definition may leave out districts whose main markets were not affected, but a flood hit a considerable area of the district. To explore this further, we calculate the percentage of the total area of districts that were affected by a flood. We then calculate a correlation coefficient to study the statistical association between our flood indicator and this value. We find a strong association (0.83), suggesting that our flood indicators are good proxies.

Figure 2 shows that flooding is a more recurrent phenomenon in southern and central regions. Floods may affect specific areas only, for example cities or districts as in 2005 and 2010; but floods commonly turn out to be national disasters as effects extend to several provinces or even entire regions. To illustrate, large scale floods hit Mozambique in 2006, 2007, 2008 and 2012, covering areas up to 350,000 sq. km. Economic damages are reported to be quite substantial. For example, the 2007 flood, recorded one of the worst natural disasters in Mozambique in the last 30 years, generated economic losses of around US$ 100 million (EM-DAT, 2013). On average, these large scale natural hazards affected about 30% of markets included in our sample.[13]

4.2.2 Drought events

To identify drought shocks, we construct two drought indicators. First, we follow Fisker (2014) in using predicted anomalies in the Normalized Difference Vegetation Index (NDVI).[14] By anomalies we mean the deviation from a long-run average for a specific month, and we predict the greenness using lagged anomalies in rainfall and temperature. NDVI is calculated as the ratio between near infrared radiation and visible red radiation; a higher index value is related to a greener land surface. NDVI data is obtained from the MODIS Terra satellite.[15] The link between anomalies in NDVI and climatic background variables for every month is modeled using up to 11 lags so that it is only what has happened during the preceding months is included. The estimations include monthly information on the NDVI, rainfall,[16] temperatures at night and temperatures at daytime[17] before aggregating to yearly averages. This leads to a satellite based drought-indicator with a spatial resolution of 0.25*0.25 degrees that takes greenness into consideration, but importantly leaves out all anthropogenic causes of changes in greenness. The technical aspects regarding the estimation of

[13] Flood damages can vary considerably depending on the type of the flood. For example, floodwater moving faster can damage road severely, implying substantial flood repair costs and in some cases, new road construction costs. In contrast, floodwater rising slowly and then falling slowly may have minor impacts, especially on paved roads (Chinowsky and Arndt, 2012). Unfortunately, the available data only allows us to distinguish intensity levels across different flood events but not within floods, which makes it difficult to formally test the effect of the duration/severity/magnitude of floods on market performance. Alternatively, we could have combined flood and rainfall data to identify wet cycles and then distinguish more severe flood events. However, a flood is a much more complex natural phenomenon, which responds to other parameters than only localized rainfall. For instance, floods in Mozambique may originate from very wet season in neighboring countries Zambia and Zimbabwe.

[14] From space it is possible to observe the surface of the earth and measure the light that is emitted at different wavelengths. Vegetation indexes such as the Normalized Difference Vegetation Index translate visible red and near infrared radiation into a decimal number between -1 and 1 which describes the greenness of a specified geographical area.

[15] It has been orbiting Earth daily since 2000.

[16] While greenness is best seen from above, rainfall is harder to measure using satellites. This study uses data from the Tropical Rainfall Measuring Mission (TRMM) which to our knowledge is the most precise and valid remote sensing estimate of rainfall for the relevant period. In terms of spatial extent and resolution, the TRMM data is not as good as our measures of greenness and land surface temperature. It includes pixels of 0.25 degrees, which seems sufficient for our purpose.

[17] Like NDVI, land surface temperature is measured from space globally using the MODIS Terra satellite, and again, the product in use has a spatial resolution of 0.05 degrees. Anomalies in both daytime and nighttime temperatures are included in the model. On average, it is expected that daytime temperatures affect greenness negatively since hotter means drier in most parts of the world. Nighttime temperatures are likely to affect greenness positively, however, since cold also becomes a serious constraint for plant growth in some areas.

predicted greenness is described in Fisker (2014). We define that a drought occurs if the average *predicted greenness* value falls at or below minus 1.0.[18]

Second, we use the Standardized Precipitation-Evapotranspiration Index (SPEI), a more commonly used drought index based on rainfall and temperature. The calculation of the SPEI is based on similar equations as the Standardized Precipitation index (SPI), but adds the component of evapotranspiration (Vincente-Serrano et. al, 2010). The SPEI is a multiscalar index based on long time series data of temperature and rainfall. Thus, the onset, duration and magnitude of drought conditions can be determined with respect to normal conditions defined over historical climate regularities. In particular, we use a 6 month time scale index with a 0.5 degrees spatial resolution based on monthly precipitation and potential evapotranspiration information back to 1901 from the Climatic Research Unit of the University of East Anglia. Contrary to the predicted NDVI described above, this index is based on observations from weather stations. This entails a number of advantages as well as drawbacks. A clear advantage is that, in the calculation of the index, it is possible to relate the climatic variation to a longer period of historical data. This generally increases the precision of the measure by allowing for a better understanding of the long-run average. In addition, close to weather stations, the measures of rainfall and temperature will probably be more precise than satellite observations. Two potential drawbacks arise when compared to the predicted NDVI: firstly, weather stations may be located far from each other, and the data for the area in between is roughly speaking an interpolation. This means that the error of the observed data increases with the distance to a weather station, which is most likely to be located near urban centers. Secondly, data derived from weather stations does not include greenness as a variable. This means that conditions that might affect the dry-ness of an area apart from rain and temperature are not captured by the index. Similar to the predicted NDVI, and following McKee et al. (1993; 1995), we define a drought event any time the SPEI value reaches an intensity of -1.0 or less.

The assumption is that a drought affects price dispersion smoothly over the agricultural season. The computation of the drought indexes on the basis of preceding months allow us to account for this dynamic by assuming a weaker effect during the sowing/planting season, which gradually become

[18] A similar classification is employed when using alternative drought indexes, for example, the Standardized Precipitation-evapotranspiration Index (SPEI). The NDVI has been standardized into a z-score to make it comparable with this index so that this classification also makes sense for the NDVI.

stronger until reaching the harvesting and commercialization period. Then, the effect vanishes gradually when reaching the onset of the next agricultural season.

Identification of wet and dry areas at the district level by the NDVI index is shown in Figure 3.

[INSERT FIGURE 3 ABOUT HERE]

A first observation is that droughts of different intensities occur unevenly across the country, which would ease crop risk sharing. Our index detects pronounced dry cycles in the south and north regions in 2005, central and southern areas in 2008 and the central region in 2012. Negative values of the drought index in 2005 and 2008 are consistent with the huge picks in maize prices observed in those years (see Figure A2). In particular, these droughts are recorded as one of the worst natural disasters in the last 30 years. According to official figures, an estimated of 1.4 million of people were affected by severe food shortage in 2005, and more than half million suffered food insecurity in 2008 (EM-DAT, 2013). Descriptive statistics for drought shocks identified by either the NDVI or SPEI are similar (see Table 1).

5 Estimation procedure

Spatial market integration has typically been tested by looking at the co-movements or long-run relationship between spatial prices. Vector autoregressive (VAR) models, including co-integration analyses have been extensively used to examine this relationship. In general, these methods have been criticized since they often assume stationary transaction costs, as well as unidirectional and/or continuous trade patterns, assumptions commonly violated in developing countries (Barrett and Li, 2002). Two alternative econometric approaches are intended to overcome these issues: the threshold autoregressive (TAR) and parity bounds models (PBM). The TAR models are a class of regime-switching models in which the different regimes are defined by whether the price differential is less than, equal to or greater than a critical threshold value. One of the drawbacks of the TAR model is that it is highly parameterized and often assumes fixed transaction costs (Fackler and Goodwin 2001). On the other hand, the PBM approach lies in the statistical identification of upper and lower bounds of transfer costs. Thus, markets are classified as efficient when the price differential is within those bounds. One drawback of the PBM model is that they are static models and the consistency of the results relies heavily on the validity of the distributional assumptions (Barrett, 2001). In this paper, we follow Aker (2010a; 2010b) to exploit both the temporal and spatial variation in the data, and apply a dyadic regression analysis to study the association between weather shocks (drought and flood events) and maize market performance.

5.1 Supply shock specification

We first assume that both droughts and floods affect directly price dispersion. This may be more consistent with a supply shock. We use the absolute value of inter-market price differences as our measure of market efficiency.[19] Let us define $Y_{ij,t} = |p_{it} - p_{jt}|$ as the absolute value of the price difference between market *i* and *j* at time *t*. We estimate the following equation:

$$Y_{ij,t} = \beta_0 + \beta_1 WF_{ij,t} + \beta_2 WD_{ij,t} + \beta_3 TC_{ij,t} + a_{ij} + \theta_t + u_{ij,t} \quad (3)$$

The absolute price dispersion between two markets is a function of transport costs between the market pair ij at time *t* denoted by $TC_{ij,t}$, a drought indicator $WD_{ij,t}$, and a flood indicator $WF_{ij,t}$ taking the value of 1 if a drought/flood event affected one/both markets *i* and *j* at time *t*, zero otherwise. The parameter a_{ij} denotes market pair fixed effects, reflecting time-invariant covariates that could be correlated with price dispersion and shocks. θ_t are time-varying unobserved factors and $u_{ij,t}$ corresponds to the market pair-year error term.[20] The parameters of interest are β_1 and β_2. Reliable transport costs data is particularly important as the impact of flood is supposed to be transmitted through an increase in transport costs. Unfortunately, as in many developing countries, data on transport costs is only available for a few market pairs at a relatively low frequency. Given this limitation, we first compute the monthly average of transport costs and use it as control. This seems a sensible strategy given that the panel structure of our model will take care on the cross-sectional variation in transport costs, primarily a function of distance between markets. Thus, the monthly average of transport costs will pick up reasonably well the temporal variation in transport costs.

[19] Other measures of price dispersion, such as the sample variance of prices, the coefficient of variation (CV), and the maximum and minimum (max-min) prices across markets over time have been also used in the literature before.
[20] For example, they include geographic location, urban status and market size.

5.2 Transport cost shock specification

Alternatively, we assume that while droughts affect price dispersion directly, floods do it through transportation costs. This corresponds to a supply shock due to a drought and a transport shock as a result of flooding. We here follow a different strategy to account for transport costs. We use existing information to predict transport cost values for each market pair along the study period. Thus, although TC is not fully observable for all the market pairs and months, it can be related to observable data through a function $TC = f(Z, WF, \delta)$. Where f is a known function, Z is a vector of observed characteristics affecting transportation costs such as distance, road quality and diesel prices and δ is a parameter vector to be estimated. We here assume that flood shocks (WF) also affect transport costs. Thus, for each observation ij, t we estimate $\widehat{TC}_{ij,t} = f(Z, WF, \hat{\delta})$. Pagan (1984) calls $\widehat{TC}_{ij,t}$ a generated regressor. Then, we remove flood indicators from equation (3) and include these estimates in the price dispersion equation as follows:

$$Y_{ij,t} = \beta_0 + \beta_1 WD_{ij,t} + \beta_2 \widehat{TC}_{ij,t}(WF_{ij,t}) + a_{ij} + \theta_t + u_{ij,t} \tag{4}$$

6 Results

6.1 Homogenous effects

6.1.1 Price dispersion and supply shock

Table 2 presents our baseline results. We here include both droughts and floods affecting directly price dispersion. Columns 1-2 show estimates by OLS. Here we include both time-variant and invariant covariates, and control for market fixed effects. Columns 3-6 report our main results. They are derived from the Fixed Effect (FE) estimator. While columns 3 and 4 control for mobile network, columns 5 and 6 include market pair time-trends, instead.[21] Column 7-8 presents the results of the model with a lagged dependent variable as control. This specification assumes that performance in period *t* depends on performance in period *t-1*. They are obtained by applying the Arellano-Bover/Blundell-Bond estimator (Arellano and Bover, 1995; Blundell and Bond, 1998).[22] All specifications include monthly and agricultural year season dummies as well a common time trend as controls.

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[21] We remove the mobile network variables because of their time-trend nature.

[22] This estimator assumes additional moment conditions to the Arellano and Bond (1991) estimator that are proved to enhance the efficiency and reduce the bias in the GMM estimator when ρ is close to one (Wooldridge, 2010). Furthermore, the use of first-differencing allows for a possible nonstationary process.

[INSERT TABLE 2 ABOUT HERE]

Since our specification is a time-series dyadic linear regression, the standard errors must be corrected for spatial and temporal dependence. We first cluster the standard errors at the market pair level, which allows for dependence between market pairs over time. Then, we use dyadic standard errors (Fafchamps and Gubert, 2007), which correct for spatial dependence, but do not allow for temporal independence.

Time-invariant controls in OLS estimations show expected results. Price dispersion is higher among markets that are more distant from each other. This result is expected since transport costs are a function of distance. There is also evidence that road infrastructure matters for spatial market efficiency. Markets connected by a paved road are more likely to equalize prices, and therefore are spatially more efficient. Better road infrastructure connecting markets may encourage trade flows from surplus to deficit zones, since transport costs are lower. Furthermore, better roads increase competition by reducing barriers to market entry. Distance and road quality are capturing the long term and fixed component of transport costs. We also control for a direct measure of transport costs that varies over time. In all specifications, we find that transportation costs increase price dispersion. Overall, a 1 MZN/kg increase in transport costs between markets increases price dispersion by 0.33 MZN/kg. The latter suggests that time-variant effects of transportation costs are also relevant to control for. We also find for the FE estimator that market price differences reduce when diesel prices augment. This may seem inconsistent with transport costs enhancing price differences. Nevertheless, a negative effect of diesel prices is not unreasonable since an increase in oil prices can be seen as a common shock, causing an increase in production costs simultaneously in all markets. However, this effect reverses when controlling for the lag of the dependent variable, which is more in line with a general escalations in the costs of food transportation. Finally, we find that mobile phone development reduces price dispersion. This has already been noticed in the literature before (Aker, 2010b).

We now turn to the discussion of the association between natural hazards and price dispersion. We find that price dispersion is lower during drought shock periods. This result is robust to the inclusion of other covariates, market fixed effects, market pair fixed effects, different drought indicators, a lagged of the dependent variable, as well as time dummy variables. This result is still significant to the use of dyadic standard errors. The negative relationship is evidence of markets performing well at the face of a supply shock. This is consistent with improvements in spatial price efficiency reported in Mozambique in the post-reform period (Tostao and Brorsen, 2005). This effect seems to be larger when both markets are affected. A supply shock occurring in both markets should produce a simultaneous increase in prices, leading to a more likely equalization of prices at high levels. The latter would imply a larger reduction in price gap. On average, price dispersion reduces around 95 MZN/kg after a drought affecting both markets, representing 8.4 percent decrease as compared with mean price dispersion. A small impact is not surprising since maize is a storable crop that can be saved and consumed after harvesting, which would attenuate price fluctuation. This value is similar to the 10 percent decrease found in Aker (2010a) for the millet market in Niger.

Regarding the effect of flood, we find that a flood occurring in one market affects significantly and positively price differences. A flood affecting both markets is not statistically significant; nevertheless, the effect remains positive. Although this result is robust to a set of covariates, markets fixed effects, market pair fixed effects, a lagged dependent variable, a series of time-dummies, this effect turns insignificant when including market pair time trends and correcting for spatial dependence. Inconclusive evidence of a direct effect of flood on prices dispersion may suggest that other mechanisms than supply shocks may be more important for interpretations.

6.1.2 Price dispersion and transport cost shock

We then estimate transport costs at the market pair level and replicate the above results by including these estimates. Table A1 displays transport cost regressions. In this model, we control for distance between markets, road quality, diesel prices, a dummy for the main commercialization period, market fixed effects and a series of time dummies. First, we assume that a flood has no effect on transport costs. Results are shown in column 1. Then, we include flood indicators as explanatory variables. Column 2 includes flood indicators informing whether or not one or two markets were affected. Column 3 adds our alternative flood block-road indicator. Results are intuitive: transport costs increase with distance, diesel prices and are lower among markets that are connected by a paved road. Floods also contribute to increase transport costs. A flood affecting one market and blocking the road between them are found to have a significant and positive effect on transport costs. On average, a flood affecting one market increases transport costs in 260 MZN/kg (33%), while a flood blocking the road leads to an augment of 122 MZN/kg (14%).

Table 3 shows the results for price dispersion with predicted transport costs for the market pairs. In column 1-4, we include predicted transport costs not explained by flood. In this specification, we keep flood indicators in the main equation, assuming a flood can still affect price dispersion directly. Columns 2 and 4 add the flood block-road indicator. Columns 5-8 use predicted transport cost values from regressions including flood indicators as controls. We here remove flood indicators and diesel prices from our model of price dispersion, assuming that these effects are captured through transport costs. Columns 5 and 7 use the values predicted by a flood affecting markets directly. Columns 6 and 8 employ values predicted by adding the flood block-road indicator. In all the specifications, we correct for spatial dependence using a bootstrapping-dyadic procedure suggested by Fafchamps and Söderbom (2014). We choose a bootstrapping technique here due to the inclusion of generated regressors in the price dispersion equation.[23]

[INSERT TABLE 3 ABOUT HERE]

Main findings remain. Price dispersion is lower in drought periods. This result is only significant when identifying droughts by the SPEI index, though. The coefficients of flood affecting one or both markets are statistically insignificant. However, our flood block-road indicator is negative and significant. A reduction in price dispersion after a flood blocking the road while markets remain unaffected seems contradictory with a food transport shock story. Comments regarding imprecisions in the identification of blocked road deserve some attention here. We cannot guarantee that indeed our flood block-road indicator is correctly informing on the operability of the road. Even so, it is highly likely that there may exist other tertiary or even vicinal roads, alternative to the main one, than can be used to potentially bypass a flood. Unfortunately, we do not observe that in our data with the required precision. Thus, a negative effect on price dispersion may respond to this imprecision. However, this alternative flood indicator does contribute to improve predictions of transport costs. Our estimates reveal that transport costs yield much better to explain price dispersion as they are predicted using flood indicators, and precision improves even more when adding the flood block-

[23] Results are fundamentally the same as computing the dyadic standard errors. Results are not shown in the paper but can be obtained from the authors under request.

road indicator. For example, marginal effects of transport costs are considerably high, close to 1, as flood events are not used to predict transport costs. The estimated coefficient lowers to values around 0.7 as including flood indicators affecting one or both markets, and reduces to 0.5 as adding the three flood indicators together. An average increase of 0.5 MZN/kg in price dispersion after a 1 MZN/kg increase in transport costs is more consistent with marginal effects found in settings where flooding is a relatively rare phenomenon (Aker, 2010a).

The latter is more in line with a specification in which flood effects on price dispersion are picked up indirectly through transportation costs. However, as discussed before, the supply shock effect can take longer to be transmitted into the markets since there is a gap between the main commercialization period and the months in which floods usually hit Mozambique. We exploit this timing to examine a potential supply shock. We assume that a supply shock will reflect stronger in prices since trade takes place. Results are shown in Table 4.

[INSERT TABLE 4 ABOUT HERE]

We find some evidence of a flood supply shock. Markets affected by a flood reduce their price gap along the commercialization period, and the magnitude of the effect becomes lower to the extent we reach the end of the agricultural season. However, this effect is only statistically significant the first two months.

6.2 Heterogeneous effects of floods

The results above suggest that the effect of floods is better captured through transport costs. That implies that floods affect price dispersion mainly via impacts on road operability and therefore on trade potentiality. Better road infrastructure can help minimize the impact of such a natural disaster. Thus, we expect that flood effects are conditioned on road characteristics. We explore this further in this section.

Table 5 reports the results for the interaction of flood indicators and road characteristics. Column 1 and 2 include interactions with distance; column 3 and 4 show interactions with a variable denoting a paved road connecting markets. All specifications include drought indicators, transport costs, diesel prices, monthly and year dummy variables as controls.

[INSERT TABLE 5 ABOUT HERE]

The results suggest some evidence that the impact of floods on market performance is conditioned on distance and road characteristics. First, we note that the increase in price dispersion is larger among closer markets. This effect is only significant when both markets are affected, though. Neighboring markets have more similar prices and trade more since transport costs are lower. Thus, any shock that disturbs their connectivity may have a stronger impact on their price differential.

Second, we find that the effect of floods on price dispersion is lower among markets connected by a paved road. This association is also negative and significant when both markets are affected. This suggests that flood effects can be attenuated as having better road infrastructure since flooding is more likely to cause stronger impacts on unpaved roads. This is relevant for the Mozambican economy given the current poor road infrastructure and a higher expected frequency and severity of floods due to climate change (Chinowsky and Arndt, 2012).

7 Conclusions

Markets that are spatially more integrated enjoy the advantages of price transmission and higher product availability. Furthermore, spatially efficient markets are more resilient to natural disasters, attenuating product scarcity and fluctuating prices. This paper intends to examine the relationship between weather shocks and agricultural market efficiency in Mozambique. For this purpose, we estimate dyadic regression equations using monthly maize prices, transport costs and weather shock indicators derived from satellite, rainfall and temperature data.

We found that the effect depends on the type of weather shocks. While price differences reduce during drought periods, price dispersion increases after a flood. A reduction in price dispersion coming after drought periods suggests a supply shock effect given by a strong association between rainfall availability and agricultural production. In contrast, an indirect positive association between floods and price dispersion is more consistent with a shock in transport cost. Results also revealed a potential supply shock after a flood. Price gap between flooded markets narrows along the commercialization period. Finally, we uncovered some heterogeneity in the results. Floods were found to raise price dispersion more among markets that are closer to each other and connected by poorer road infrastructure.

Our results are consistent with previous literature finding a substantial number of markets in autarky in Mozambique, that is, where transport costs exceed price differential (Tostao and Brorsen, 2005; Cirera and Arndt, 2008). Although this does not imply inefficiency, since arbitrage is not profitable, it is commonly associated with lack of spatial integration. Poor road accesses already make transport costs substantially high in Mozambique. We found that transport costs become even more prohibited during flood periods, exacerbating this lack of integration.

Some caveats with respect to our results deserve some comments. First, we lack of precise information on other potential factors that were ongoing during the study period and that may have enhanced agricultural market development. For example, road improvements and the adoption of new technology for collecting price information can have important implications for market performance (Cirera and Arndt, 2008; Aker, 2010b). Furthermore, demand-side factors such as changes in market size and income levels are also supposed to drive price dispersion. Nevertheless, to the extent that these processes do not change fundamentally and/or develop gradually over time, the inclusion of market-pair fixed effects and market-pair trends may suffice to pick up these changes. Special mention deserves substantial investments undergoing during the study period to support the sustainable development of the road transport-infrastructure network along Mozambique and their neighboring countries. Specifically, the 10th EDF Country Strategy Paper and National Indicative Program (CSP/NIP) for Mozambique committed €130, 62 million to the transport infrastructure sector and regional integration for the period 2008-2013. One of the emblematic projects funded by this program was the construction of the Zambezi Bridge, opened in August of 2009. Certainly, this bridge connecting the north with rest of the country led to promoting north-south trade. More cautious analysis is needed to evaluate the contribution of these road rehabilitations projects in enhancing spatial market efficiency. Second, food aid programs are usually implemented during water shortage food periods, which are more likely to arise after natural disasters. These programs help reduce price fluctuations by stabilizing food supply. If these programs were important during the period, we may be underestimating the effect of weather shocks. Yet, our estimates can be considered as lower bound impacts. Finally, markets near borders may also have substantial trade with neighboring countries, implying that they may be more spatially integrated with international markets. For example, surplus production in the north is regularly exported to Malawi. Similarly, South Africa is the main supplier of white maize grain to southern Mozambique, a maize deficit region. However, in spite of this substantial trade, empirical evidence shows a weak price transmission of maize prices between Mozambique and South Africa, suggesting limited spatial efficiency between domestic and international markets in Mozambique (Acosta, 2012).[24]

Despite these limitations, an important implication of our results is that markets work relatively efficient during supply shock periods in Mozambique. However, it does not imply that markets are fully integrated. Maximizing welfare implies not only the achievement of market efficiency but also the minimization of transaction costs, which are traditionally assumed exogenous. In Mozambique, there still persist substantial social inefficiencies due to trade barriers and excessive transaction costs, exacerbated by poor road infrastructure and a high incidence of flood shocks. Climate change, which is expected to increase the frequency of extreme weather events, demands better efforts to enhance resilience to supply and food transport shocks. Particularly, the increased frequency and intensity of floods will potentially lead to more rapid deterioration of road stocks and therefore an increase in maintenance costs (Chinoswsky and Arndt, 2012). Further developments in the functioning of markets and investments in resilient and reliable road infrastructure are necessary to continue improving spatial arbitrage within Mozambique and between Mozambique and its neighbors, and strengthening resilience to natural shocks. Investments in other transport alternatives, such as railways and maritime transport, should also be promoted.

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[24] A highly prohibitive import tariff and the structure of a value added tax (VAT) are some of the barriers that limit a more efficient price transmission between southern Mozambique and South Africa. The 17% VAT seems to be particularly detrimental for maize grain market efficiency for two reasons. First, the tax is charged on maize grains, but not on rice and wheat, generating a clear disadvantage for this product. Second, maize meals are exempted from VAT, but not maize grains, discouraging sales of imported maize grain in Mozambique. Thus, most of the imports of maize grain are carried out by industrial millers. In fact, evidence suggests that maize grain for sale at retail in Maputo is almost entirely domestic, in spite of a potential arbitrage of importing from South Africa (Tschirley et al., 2006). Other reasons include complex import procedures, and some aspects related to the South African marketing system which emerge as important impediments for many small traders operating informally.

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Tables

Table 1. Descriptive statistics.

Variables	Observations	Mean	St. dev.	Min	Max
Absolute price difference per kilo (000 MZM)	27,000	1.13	0.97	0.00	8.80
Maize price per kilo (000 MZN)	27,000	4.80	1.89	1.42	13.85
Transport cost per kilo (000 MZN)	27,000	0.87	0.16	0.55	1.33
Diesel price per liter (000 MZN)	27,000	22.98	4.21	14.07	30.24
Distance (kilometers)	27,000	629.14	364.07	4.01	1660.93
Mobile network in one market	27,000	0.25	0.44	0.00	1.00
Mobile network in both markets	27,000	0.69	0.46	0.00	1.00
1 if road connecting *i* and *j* is paved	27,000	0.57	0.50	0.00	1.00
1 if one market hit by a flood	27,000	0.03	0.17	0.00	1.00
1 if both markets hit by a flood	27,000	0.01	0.10	0.00	1.00
1 if the road was blocked	27,000	0.05	0.22	0.00	1.00
1 if one market hit by a drought (NDVI)	27,000	0.22	0.42	0.00	1.00
1 if both markets hit by a drought (NDVI)	27,000	0.07	0.25	0.00	1.00
1 if one market is by a drought (SPEI6)	27,000	0.27	0.44	0.00	1.00
1 if both markets hit by a drought (SPEI6)	27,000	0.06	0.24	0.00	1.00

Note: Values are deflated by the consumer price index (base=2005).

Table 2. Estimated effects of drought and flood on price dispersion.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Flood (one market)	0.083**	0.081*	0.072**	0.071**	0.029	0.025	0.118***	0.113***
	(0.035)	(0.035)	(0.036)	(0.034)	(0.036)	(0.036)	(0.033)	(0.034)
Flood (both markets)	0.009	0.014	0.045	0.047	0.028	0.025	-0.031	-0.033
	(0.058)	(0.058)	(0.058)	(0.058)	(0.053)	(0.052)	(0.048)	(0.048)
Drought NDVI (one market)	-0.045**		-0.039**		-0.036**		0.028	
	(0.017)		(0.018)		(0.018)		(0.019)	
Drought NDVI (both markets)	-0.080***		-0.086***		-0.107***		-0.047*	
	(0.026)		(0.026)		(0.026)		(0.025)	
Drought SPEI6 (one market)		-0.043***		-0.053***		-0.039***		-0.028*
		(0.015)		(0.015)		(0.015)		(0.015)
Drought SPEI6 (both markets)		-0.125***		-0.101***		-0.106***		-0.107***
		(0.025)		(0.025)		(0.025)		(0.025)
Transport cost (MZM/kilo)	0.332***	0.321***	0.334***	0.323***	0.334***	0.326***	0.309***	0.279***
	(0.051)	(0.051)	(0.051)	(0.050)	(0.052)	(0.051)	(0.063)	(0.059)
Mobile network (one market)	-0.113***	-0.119***	-0.075*	-0.079*				
	(0.037)	(0.038)	(0.043)	(0.042)				
Mobile network (both markets)	-0.235***	-0.250***	-0.215***	-0.229***				
	(0.044)	(0.045)	(0.045)	(0.046)				
Diesel price (MZN$/liter)	-0.004	-0.005*	-0.004	-0.005*	-0.004	-0.005*	0.011***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Distance (km)	0.001***	0.001***						
	(0.00001)	(0.00001)						
1 if paved road	-0.177***	-0.177***						
	(0.049)	(0.049)						
Lagged dependent variable							0.441***	0.440***
							(0.011)	(0.011)
Constant	0.343***	0.372***	0.831***	0.845***	0.734***	0.733***	0.081	0.108*
	(0.082)	(0.081)	(0.081)	(0.079)	(0.072)	(0.069)	(0.066)	(0.061)
Dyadic s.e.								
Flood (one market)	0.056	0.081	0.073	0.071	0.059	0.057		
	(0.0742)	(0.076)	(0.076)	(0.075)	(0.079)	(0.079)		
Flood (both markets)	0.018	0.014	0.045	0.047	0.026	0.027		
	(0.093)	(0.091)	(0.094)	(0.092)	(0.092)	(0.091)		
Drought NDVI (one market)	-0.044		-0.039		-0.046			
	(0.047)		(0.047)		(0.047)			
Drought NDVI (both markets)	-0.081		-0.090*		-0.099*			
	(0.054)		(0.054)		(0.053)			
Drought SPEI6 (one market)		-0.043		-0.053*		-0.047*		
		(0.028)		(0.028)		(0.029)		
Drought SPEI6 (both markets)		-0.125**		-0.101**		-0.097*		
		(0.052)		(0.052)		(0.053)		
Market fixed effect	Yes	Yes	No	No	No	No	No	No
Market pair fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market pair time trend	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.219	0.220	0.065	0.066	0.120	0.120		
Observations	27,000	27,000	27,000	27,000	27,000	27,000	26,700	26,700
Number of market pairs	300	300	300	300	300	300	300	300

Note: Columns (1), (3), (5) and (7) include NDVI drought indicators. Columns (2), (4), (6) and (8) use the SPEI index. Columns (1) – (2) display OLS estimations. Column (3-4) presents results of the FE model. They include mobile network controls. Columns 5-6 show FE estimations with market pair time trends. We here remove mobile network controls. Columns 7-8 present the Arellano-Bover/Blundell-Bond estimator. The dependent variable in all the estimations is the price differential between two markets. Standard errors clustered by market pair are in parentheses. Cross-sectional dyadic standard errors are also provided below. Missing values in the dyadic s.e. denote that this specification cannot be used with the specific standard error correction. All prices are deflated by the Mozambican Consumer Price Index (CPI). *** p<0.01, ** p<0.05, * p<0.1

Table 3. Estimated effects of drought and flood on price dispersion with predicted transaction costs.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Flood (one market)	0.011	-0.032	0.001	-0.037				
	(0.072)	(0.076)	(0.072)	(0.076)				
Flood (both markets)	-0.002	-0.036	-0.005	-0.039				
	(0.146)	(0.146)	(0.142)	(0.142)				
Flood (block-road)		-0.195**		-0.198**				
		(0.070)		(0.068)				
Drought NDVI (one market)	-0.039	-0.037			-0.042	-0.045		
	(0.056)	(0.056)			(0.056)	0.056		
Drought NDVI (both markets)	-0.080	-0.078			-0.087	-0.092		
	(0.076)	(0.076)			(0.075)	(0.075)		
Drought SPEI6 (one market)			-0.052	-0.053			-0.054	-0.055
			(0.034)	(0.033)			(0.034)	(0.034)
Drought SPEI6 (both markets)			-0.101*	-0.101*			-0.104*	-0.108*
			(0.055)	(0.054)			(0.056)	(0.058)
Predicted transport cost (MZM/kilo)	0.933***	1.026***	0.949***	1.040***	0.684***	0.487***	0.695***	0.498***
	(0.2588)	(0.263)	(0.247)	(0.252)	(0.202)	(0.186)	(0.194)	(0.179)
Constant	-0.128	-0.20*	-0.169	-0.526***	0.189***	0.384***	0.156***	0.349***
	(0.104	0.108)	(0.105)	(0.127)	(0.087)	(0.081)	(0.084)	(0.077)
Market pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market pair time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.122	0.124	0.123	0.124	0.121	0.120	0.122	0.120
Observations	27,000	27,000	27,000	27,000	27,000	27,000	27,000	27,000
Number of market pairs	300	300	300	300	300	300	300	300

Note: Columns (1), (2), (5) and (6) include droughts indicators identified by the NDVI index. Columns (3), (4), (7) and (8) use the SPEI index. Columns (1) – (4) display estimations with predicted transport costs without flood indicators. Columns (2) and (4) include the flood block-road indicator in the main equation. Columns (5)-(8) show results with transport costs predicted by flood indicators. Columns (5) and (7) only use the flood indicators informing whether one or both markets were affected to predict transport costs. Columns (6) and (8) include also the flood block-road indicator to predict transport costs. The dependent variable in all the estimations is the price differential between two markets. We use the FE estimator in all the models. Cross-sectional-dyadic bootstrapped standard errors are in parentheses. All prices are deflated by the Mozambican Consumer Price Index (CPI). *** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimated effects of flood supply shock on price dispersion with predicted transport costs.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Flood (one market) (May)	-0.087				
	(0.085)				
Flood (both markets) (May)	-0.236*				
	(0.131)				
Flood (one market) (May-Jun)		-0.103			
		(0.074)			
Flood (both markets) (May-Jun)		-0.198*			
		(0.106)			
Flood (one market) (May-Jul)			-0.116		
			(0.083)		
Flood (both markets) (May-Jul)			-0.146		
			(0.113)		
Flood (one market) (May-Aug)				-0.091	
				(0.074)	
Flood (both markets) (May-Aug)				-0.133	
				(0.104)	
Flood (one market) (May-Sep)					-0.096
					(0.065)
Flood (both markets) (May-Sep)					-0.132
					(0.102)
Predicted transport cost (MZM/kilo)	0.493***	0.499***	0.509***	0.516***	0.529***
	(0.179)	(0.179)	(0.179)	(0.179)	(0.179)
Constant	0.380***	0.377***	0.369***	0.356***	0.346***
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
Drought indicators	Yes	Yes	Yes	Yes	Yes
Market pair fixed effects	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Market pair time trend	Yes	Yes	Yes	Yes	Yes
R-squared	0.121	0.121	0.121	0.121	0.1214
Observations	27,000	27,000	27,000	27,000	27,000
Number of market pairs	300	300	300	300	300

Note: Columns (1)-(5) display estimations with transport costs predicted by the three flood indicators. We control for droughts identified by the SPEI index. The dependent variable in all the estimations is the price differential between two markets. We use the FE estimator in all the models. Cross-sectional-dyadic bootstrapped standard errors are in parentheses. All prices are deflated by the Mozambican Consumer Price Index (CPI). *** p<0.01, ** p<0.05, * p<0.1

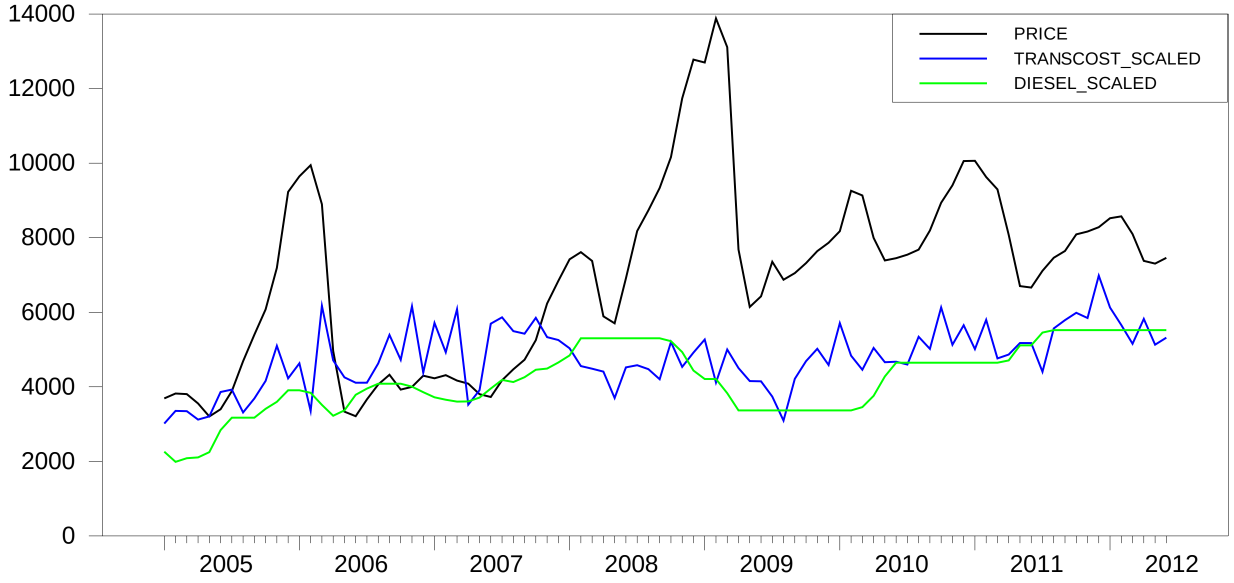
Table 5. Heterogeneous effects of flood on price dispersion.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Flood (one market)	0.219*	0.194	0.093	0.062
	(0.130)	(0.132)	(0.093)	(0.096)
Flood (both markets)	0.314***	0.293**	0.221	0.197
	(0.116)	(0.118)	(0.160)	(0.161)
Flood (block-road)		-0.211*		-0.157*
		(0.113)		(0.088)
Flood (one)*distance	-0.0002	-0.000286		
	(0.0002)	(0.000227)		
Flood (both)*distance	-0.001***	-0.001***		
	(0.0002)	(0.0002)		
Flood (block-road)*distance		0.000		
		(0.0001)		
Flood (one)*paved road			-0.064	-0.062
			(0.107)	(0.107)
Flood (both)*paved road			-0.301*	-0.301*
			(0.156)	(0.156)
Flood (block-road)*paved road				0.025
				(0.081)
Constant	0.730***	0.729***	0.731***	0.728
	(0.069)	(0.069)	(0.069)	(0.069)
Other covariates	Yes	Yes	Yes	Yes
Drought indicators	Yes	Yes	Yes	Yes
Market pair fixed effects	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Market pair time trend	Yes	Yes	Yes	Yes
R-squared	0.121	0.121	0.120	0.121
Observations	27,000	27,000	27,000	27,000
Number of market pairs	300	300	300	300

Note: Columns (1)-(2) display interactions between flood indicators and distance. Columns (3)-(4) show interactions between flood indicators and paved road. Other covariates include monthly average of transport costs and diesel prices. We control for droughts identified by the SPEI index. The dependent variable in all the estimations is the price differential between two markets. We use the FE estimator in all the models. Cross-sectional dyadic standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

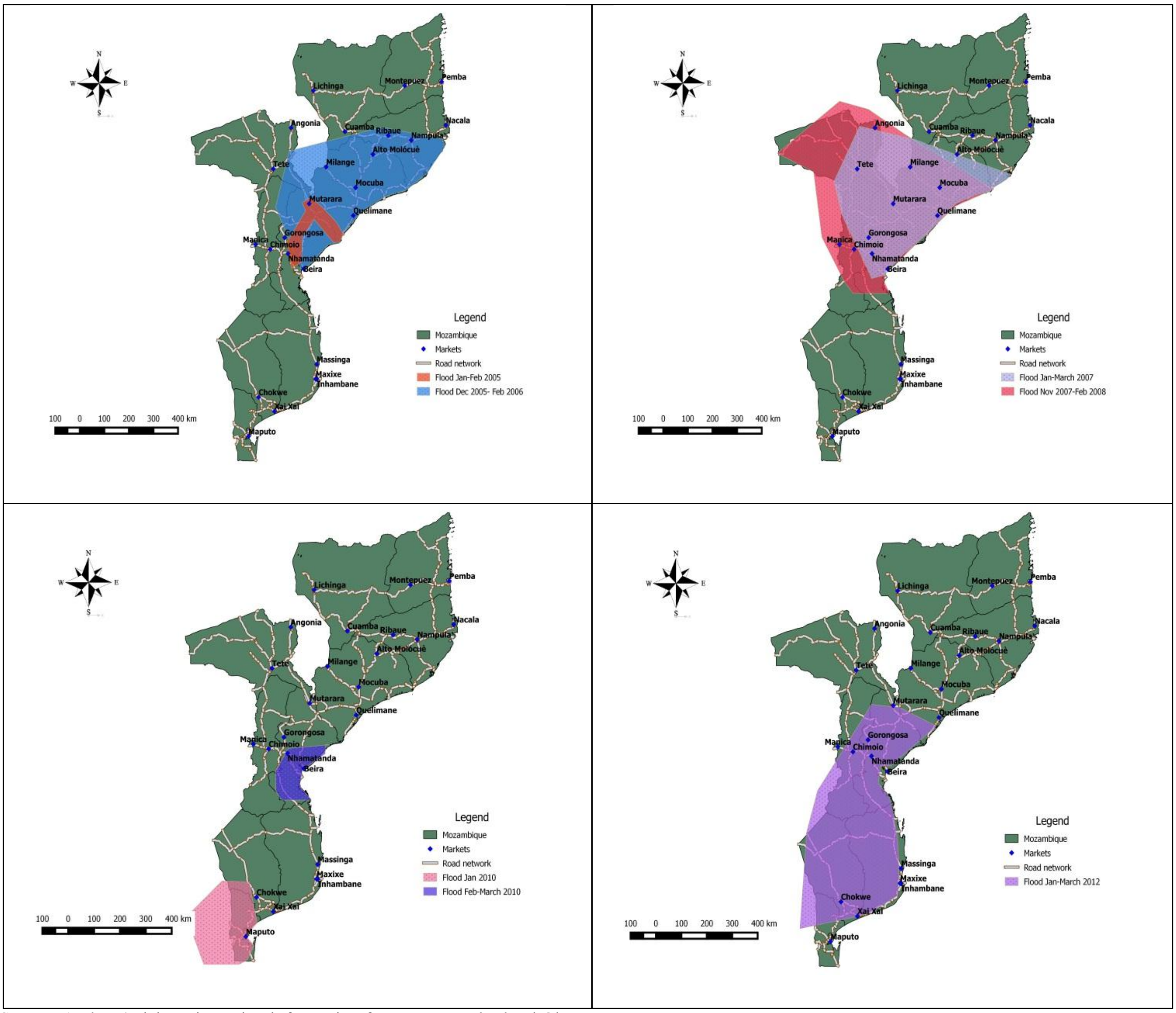
Figures

Figure 1. Evolution of maize price, transport cost and diesel price in Mozambique.



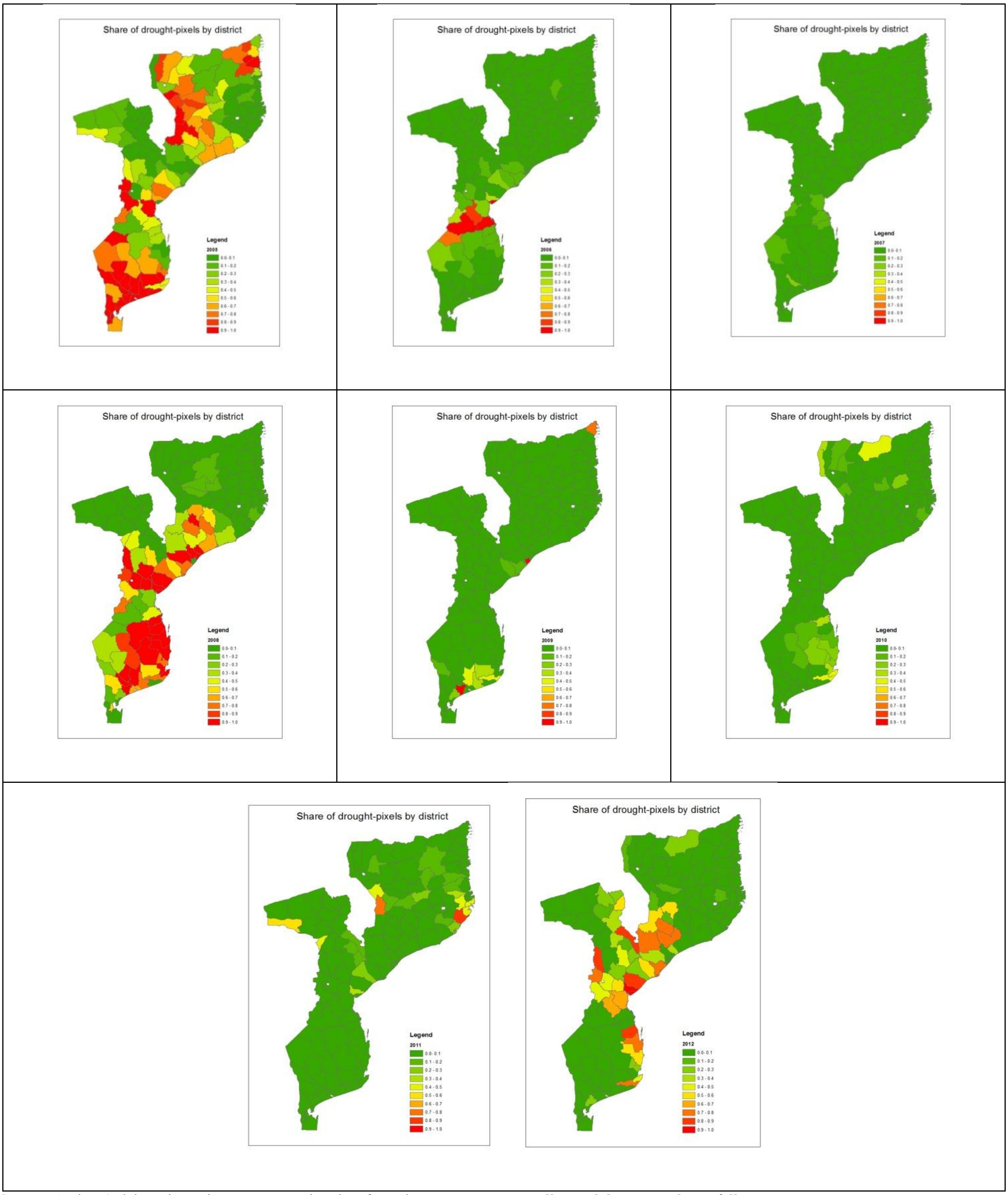
Source: Authors' elaboration using SIMA data and information from INIA

Figure 2. Flood events and affected markets in Mozambique. Period 2005-2012.



Source: Authors' elaboration using information from Dartmouth Flood Observatory

Figure 3. Drought identification by the NDVI index in Mozambique. Period 2005-2012.



Source: Authors' elaboration using remote sensing data from the MODIS Terra satellite and the Tropical Rainfall Measuring Mission (TRMM).

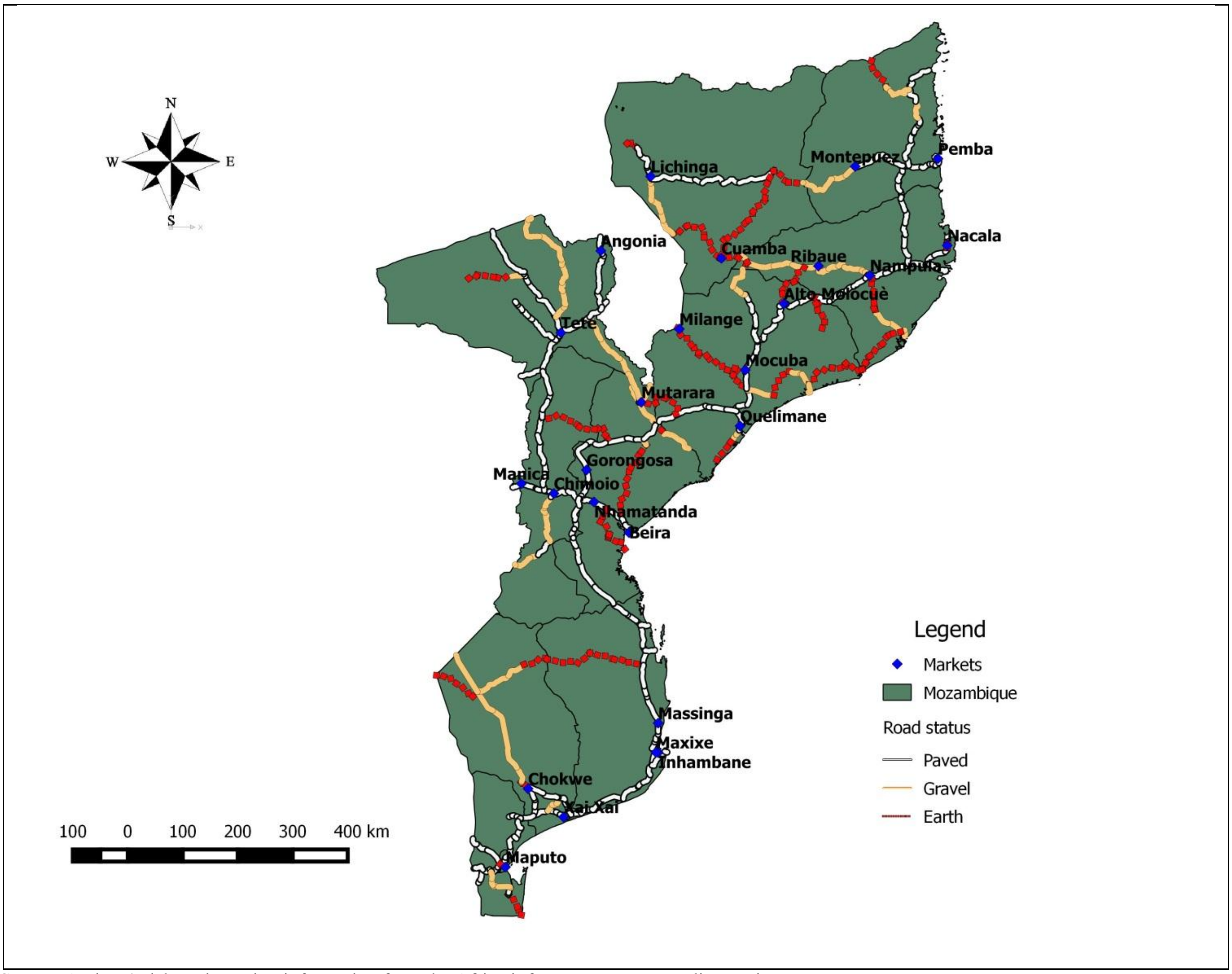
Appendix A: Additional Tables and Figures.

Table A1. Predictions of transport costs.

Variables	**(1)**	**(2)**	**(3)**
Flood (one market)		0.221	0.260*
		(0.156)	(0.159)
Flood (both markets)		-0.0319	-0.00864
		(0.0847)	(0.0842)
Flood (block-road)			0.122**
			(0.0582)
Distance (km)	0.00115***	0.00115***	0.00114***
	(4.75e-05)	(4.67e-05)	(4.64e-05)
1 if paved road	-0.850**	-0.825**	-0.817**
	(0.395)	(0.371)	(0.372)
Diesel price (MZM/liter)	0.0241***	0.0246***	0.0253***
	(0.00603)	(0.00611)	(0.00647)
1 if commercialization period	-0.0421	-0.0420	-0.0430
	(0.0409)	(0.0410)	(0.0411)
Constant	0.676	0.642*	0.623
	(0.411)	(0.387)	(0.390)
Market fixed effects	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes
Time trend	Yes	Yes	Yes
R-squared	0.681	0.683	0.685
Observations	1,383	1,383	1,383
Number of market pairs	116	116	116

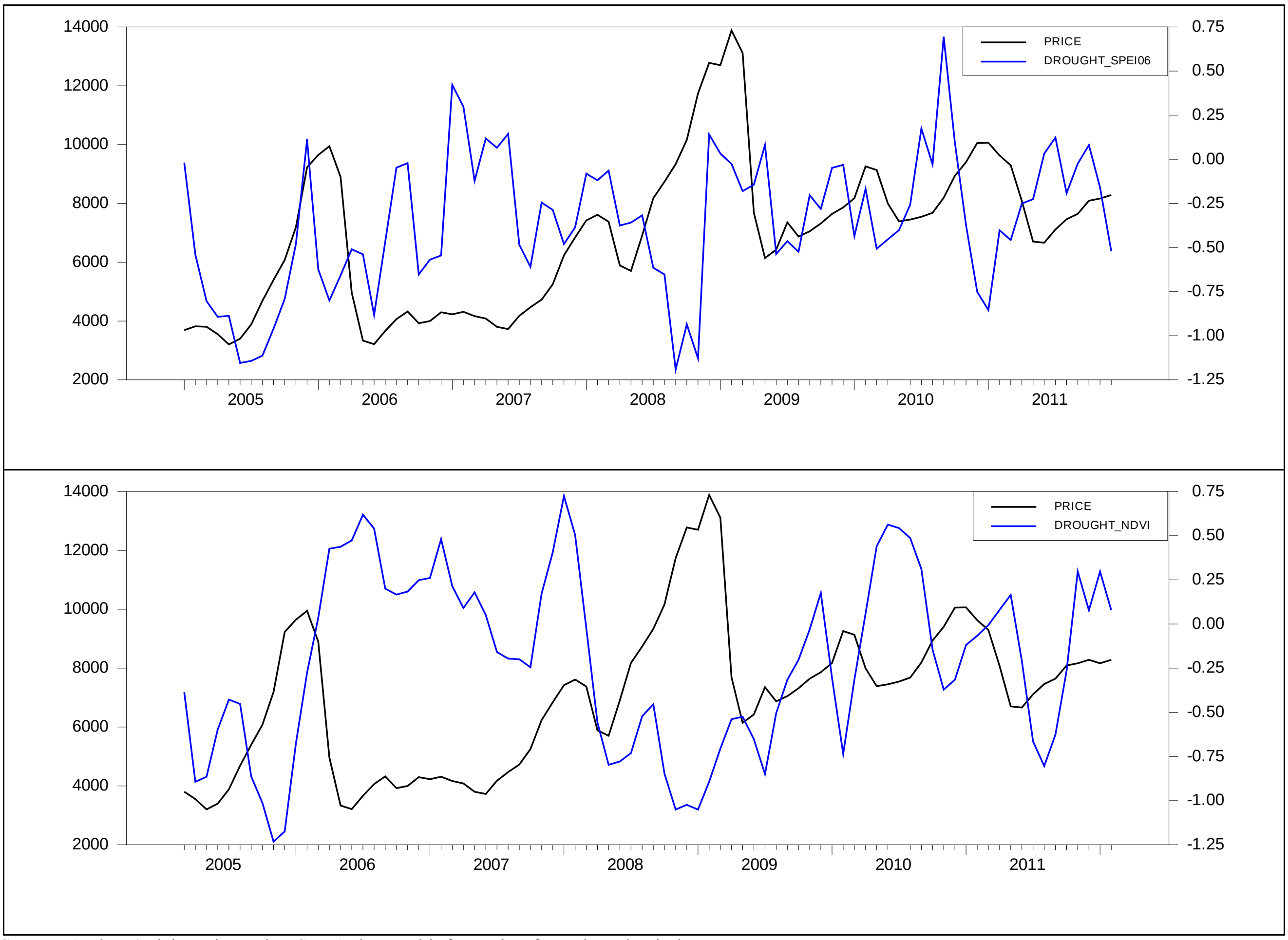
Note: Columns (1) shows estimations of transport costs without flood indicators. Column (2) adds flood indicators informing whether one or two markets were affected. Column 3 includes the flood block-road indicator. The dependent variable in all the estimations is transport costs between two markets. We use the OLS estimator in all the models. Standard errors clustered by market pairs are in parentheses. All prices are deflated by the Mozambican Consumer Price Index (CPI). *** p<0.01, ** p<0.05, * p<0.1

Figure A1. Road network by road status classification in Mozambique.



Source: Authors' elaboration using information from the Africa infrastructure country diagnostic.

Figure A2. Drought indexes and monthly average maize price.



Source: Authors' elaboration using SIMA data and information from droughts indexes.