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Fertilizer Quality and Its Impacts on Technical Efficiency and Use Intensity in the North China Plain

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Executive Summary

There has been a significant increase in agricultural output in the past 50 years. A major factor of this growth is the rise in input use such as fertilizer, especially during the beginning of this period. However, the trend is not uniform throughout the world. Even though there are still regions where fertilizer can contribute greatly to the increase in yield, this input is so overused in some other places that its marginal productivity is no longer significant. In this case, not only is it a waste of valuable resources, it also leads to environmental degradation and pollution that is detrimental to human health. To make matters worse, the quality of the agricultural input itself has been of increasing concern lately. It includes problems such as normal seed being sold as hybrid seed, pesticide that is mixed with less effective chemicals, or fertilizer which contains less nutrient than that labeled on the package. We focus our research on the North China Plain, a region with both fertilizer overuse and fertilizer quality problems. The issue of low fertilizer quality is however not confined to this region only, as recent news reports have indicated that substandard or fake agricultural input is a problem in other countries as well, for example Bangladesh, Cambodia, Nigeria, Tanzania, and Vietnam. In addition, although the analysis presented in this dissertation concentrates on fertilizer, some of the methodology can also be extended to examine the impact of other agricultural inputs with questionable quality, such as seed and pesticide. The main theme of our study is split into three subtopics: efficiency, wealth effect, and use intensity, with each of them focusing on a different aspect of the impact from low quality fertilizer.

The study begins by making a methodological contribution in analyzing the effects of low quality fertilizer on the estimation of production functions and technical efficiency. We incorporate a fertilizer quality term into the stochastic frontier model and derive an expression that captures the potential bias if

the quality term is ignored. In order to put a number to these expressions, and to examine the magnitude of the bias in percentage terms, we estimate a production function for the Hebei province using a panel dataset provided by the Research Center for Rural Economy (RCRE) of China. The data span five years and include more than 800 households per year. However, the dataset does not contain information on input quality. So we use Monte Carlo simulation to generate the fertilizer quality term under different scenarios. The first scenario is that the households who have better quality fertilizer one year will also have better quality fertilizer in the other four years. Another scenario captures the situation in which the assignment of fertilizer quality is totally random, and that a household could be using good quality fertilizer one year and then bad quality fertilizer the next. In other words, the buyers have no idea at all about the quality of the fertilizer, as they are mainly smallholder farmers and have neither the buying power nor the equipments to test for the true contents of the input. The results show that ignoring the lower fertilizer quality could switch the sign of the partial elasticity of fertilizer, and overestimate the overall technical efficiency by 16 to 30 percent. We also repeat the same Monte Carlo simulation procedure for robustness testing with different distribution assumptions, such as exponential and gamma distributions, and find that the main results of the study remain consistent. That means the effectiveness of fertilizer and the overall technical efficiency are both overestimated if one ignored the lower fertilizer quality in the analysis.

The second part of our study focuses on how the wealth level of a farmer affects fertilizer use. This is a common theme in the literature, but the conclusions reached on the direction of this wealth effect are mixed. The three outcomes of positive, insignificant, and negative have all been presented as the results in different papers. We provide an analytical framework which shows that all the three possible findings are theoretically consistent when there is uncertainty. This uncertainty could be due to doubts on the input quality in regions affected by fertilizer quality problems. At places where the use of chemical fertilizer is not so common, the uncertainty could also be caused by doubts on the effectiveness of fertilizer. Our theoretical model is based on the expected value-variance method, which captures the decision making process when there is uncertainty in the quality of input. We add two budget constraints that reflect the situation we analyze. First is affordability, which means that the wealthier farmers can afford to buy more fertilizer. The second constraint exists because farmers who are poor are less able to cope with a big loss in output, which might happen if the fertilizer is of very low quality. So the poorer farmers apply more fertilizer to compensate for any potential lack of quality in the fertilizer. We then solve for the first order conditions of the model, and use comparative statics to examine how a marginal change in wealth affects the level of fertilizer use. We also construct a wealth index through principal component analysis and carry out an empirical study using the RCRE data for one rich province, Hebei, and one poor province, Yunnan. As the dataset does not contain information on farmer's risk behavior, we cannot test the interaction between wealth and risk preference. However, the regression results do support the derivation of the theoretical model that the direction of the wealth effect is not fixed and can be different between regions of different wealth levels. In addition, the results show that the direction can even change within the same region as we move from low wealth farmers to high wealth farmers.

The final part of our study examines how the quality of fertilizer affects use intensity. For the measurement of fertilizer quality, we differentiate between perceived quality and true quality. The former reflects what the farmers think is the quality of their fertilizer, and the latter is based on lab testing of the fertilizer content. We use comparative statics on a production model to examine how a marginal change in perceived quality and true quality affects the intensity of fertilizer use. The derivation from the theoretical model shows that lower perceived quality leads to higher fertilizer use intensity. True quality only affects use intensity through perceived quality. If the correlation between the two quality variables is positive, then the effect of true quality is the same as the effect of perceived quality, which means that higher true quality reduces fertilizer use intensity. The direction of the effect is reversed if the correlation between true and perceived quality is negative. For the empirical analysis of this part of the study, we conduct a separate household survey in the Hebei province at the end of 2012. We ask for data on household characteristics and farmer's perception of the quality of their main fertilizer. During the survey, we also collect a sample of their main fertilizer and have the fertilizer analyzed for their true nitrogen content and phosphorus availability. Test results reveal that on average a fertilizer sample contains only 71 percent of the nitrogen share that is labeled on the fertilizer package. In addition, there is no significant correlation between perceived and true quality. As predicted by the theoretical model, regression analysis shows that perceived quality has a negative effect on fertilizer use intensity, which means that farmers apply more fertilizer if they think that their fertilizer is bad, in order to compensate for the low quality. The effect of true quality on use intensity is insignificant, which is an expected outcome because there is no significant correlation between perceived and true quality, and theoretical derivation has indicated that true quality only affects use intensity through perceived quality.

The main contribution of this dissertation is that despite the widespread problem of fertilizer quality, we believe we are the first to examine its impact both theoretically and empirically on efficiency and use intensity. The theoretical contribution includes deriving the bias that exists if one were to ignore the quality aspect in the estimation of production functions and technical efficiency, especially if the research area is located at one of the places with fertilizer quality problems, such as China and the other affected countries. We also provide a theoretical framework that reconciles the different findings in the literature on the direction of wealth effect on fertilizer use. It offers a consistent explanation on why the wealth effect can be different when we are looking at regions or farmers of different wealth levels. Empirically, the dissertation quantifies the magnitude of estimation bias in input elasticity and technical efficiency in our research region of North China Plain. It also supports our theoretical derivation and shows that the direction of wealth effect is not fixed across farmers of different wealth levels. Finally, the integration of fertilizer testing into a household survey allows us to look closer at the link between perceived and true fertilizer quality, as well as how they affect the fertilizer use intensity of the farmers. However, the lack of risk behavior information in our dataset means that we cannot examine the role of risk empirically. It would be useful to analyze the interaction between wealth effect and risk preference when such dataset is available. In addition, our household survey on perceived and true fertilizer quality has a small sample size of only 100 households. It would help to shed more light on the situation if in the future there is similar integration of household survey and fertilizer testing that covers a bigger sample size and over a period of time to allow for panel data analysis. It would also be interesting to repeat the same study at another place where fertilizer use is not so common, in order to see how the impact of fertilizer quality differs between a region with low fertilizer intensity and our research area, which has a very high fertilizer usage.

The worsening fertilizer quality issue in the North China Plain is of great concern because - as this dissertation research shows - it leads to an increase in fertilizer use, which is already excessive in the area. This is not only a waste of valuable resources reducing economic efficiency but also causes environmental and health problems, e.g. through pollution of ground water. The currently implemented policy of subsidizing the fertilizer manufacturers is a double whammy in this regard because by keeping the price of the product low, it encourages the usage of an input that is already overused. It also makes the quality control of the fertilizer in the market more difficult, with the presence of so many small scale producers that are inefficient. In view of these deficiencies, it would be better to shift the policy focus from price reduction to quality improvement. A suggestion is to facilitate the award of quality labels to satisfactory products with regular third-party testing of the fertilizer to ensure that its quality does not deteriorate after receiving the label. The honest producers in the industry could also help set up a sector-wide monitoring body to prevent their image from being tarnished by the less responsible manufacturers. An additional recommendation is to increase the resources and staff available to extension service in order to increase the information flow between policymakers and farmers.

Zussamenfassung

In den letzten 50 Jahren ist die landwirtschaftliche Produktion deutlich gestiegen. Besonders zu Beginn diese Zeitraums war die zunehmende Nutzung von Produktionsmitteln wie Düngemittel ein bedeutender Treiber dieses Wachstums. Global verlief dieser Trend jedoch nicht einheitlich. Während es noch Regionen gibt, in denen Düngemittel maßgeblich zu einem Ertragsanstieg beitragen können, ist dieses Produktionsmittel in anderen Regionen so überbeansprucht, dass dessen Grenzproduktivität nicht länger bedeutend ist. In diesem Fall ist dies nicht nur eine Ressourcenverschwendung, sondern führt auch zu Umweltbelastung und -verschmutzung, die sich schädlich auf die menschliche Gesundheit auswirkt. Zudem gibt die Qualität der landwirtschaftlichen Produktionsmittel jüngst Anlass zur Besorgnis. Das beinhaltet den Verkauf von normalem Saatgut als Hybridsaatgut, Pestizide, die mit weniger wirksamen Chemikalien gemischt werden, oder Düngemittel, die weniger Nährstoffe enthalten als auf der Packung angegeben. Wir fokussieren unsere Forschungsarbeit auf die Nordchinesische Ebene, eine Region mit übermäßiger Nutzung und Qualitätsproblemen bei Düngemitteln. Die minderwertige Qualität der Düngemittel beschränkt sich jedoch nicht nur auf diese Region. So haben jüngste Berichte darauf hingewiesen, dass minderwertige landwirtschaftliche Produktionsmittel auch in anderen Ländern wie zum Beispiel Bangladesch, Kambodscha, Nigeria, Tansania und Vietnam ein Problem darstellen. Obwohl diese Dissertation sich auf Düngemittel fokussiert, kann ein Teil der verwendeten Methoden ausgebaut und dazu verwendet werden, die Auswirkungen anderer landwirtschaftlicher Produktionsmittel mit fragwürdiger Qualität, wie Saatgut und Pestizide, zu untersuchen. Das Thema dieser Arbeit ist in drei Unterthemen aufgeteilt: Effizienz, Wohlstandseffekte und Nutzungsintensität, drei unterschiedliche Aspekte der Auswirkungen von Düngemitteln mit mangelnder Qualität.

Diese Studie beginnt mit der Analyse der Auswirkungen von minderwertigen Düngemitteln auf die Bestimmung der Produktionsfunktion und der technischen Effizienz. Wir integrieren einen Term für Düngerqualität in das Stochastic-Frontier-Modell und erlangen durch mathematische Operationen am Modell einen Ausdruck, der den möglichen Bias erfasst, wenn der Term für die Qualität ignoriert wird. Um diese Gleichungen mit Zahlen zu füllen und um das Ausmaß der Verzerrung prozentual darzustellen, schätzen wir mithilfe eines Paneldatensatzes, welcher vom Forschungszentrum für Ländliche Entwicklung in China (RCRE) zur Verfügung gestellt wurde, eine Produktionsfunktion für die Provinz Hebei. Die Daten umfassen einen Zeitraum von fünf Jahren und beinhalten mehr als 800 Haushalte pro Jahr. Der Datensatz enthält jedoch keine Information zur Qualität der Produktionsmittel. Wir wenden deshalb eine Monte-Carlo-Simulation an, um die Qualitätsvariable für Düngemittel bei verschiedenen Szenarien zu berechnen. Das erste Szenario besteht darin, dass Haushalte, die im ersten Jahr Düngemittel mit besserer Qualität anwenden, dieses auch in den folgenden vier Jahren zur Verfügung haben. Ein anderes Szenario bildet den Fall ab, dass die Qualität der Düngemittel zufallsverteilt ist, das heißt, dass ein Haushalt in einem Jahr gutes Düngemittel und im nächsten Jahr schlechtes Düngemittel nutzen kann. Bei diesem Szenario, kennen die Haushalte die Qualität des Düngemittels nicht, da sie hauptsächlich Kleinbauern sind und weder die notwendige Kaufkraft noch die Ausstattung besitzen, um den wahren Gehalt des Düngers zu testen. Die Ergebnisse zeigen, dass im Falle, dass die mindere Qualität des Düngemittels nicht berücksichtigt wird, das Vorzeichen der partiellen Elastizität umgekehrt und die gesamte technische Effizienz um 16 bis 30 Prozent überschätzt wird. Um die Ergebnisse auf Robustheit zu testen, wiederholen wir dieselbe Monte-Carlo-Simulation mit verschiedenen Annahmen, wie exponentielle und Gammaverteilungen, und stellen fest, dass die Hauptergebnisse der Studie durchweg konsistent bleiben. Das heißt, dass die Effektivität des Düngemittels und die gesamte technische Effizienz überschätzt werden, wenn die mindere Qualität des Düngemittels in der Analyse ignoriert wird.

Der zweite Teil dieser Forschungsarbeit konzentriert sich auf die Auswirkungen des Wohlstandsniveaus eines Landwirts auf den Einsatz von Düngemitteln. Dies ist eine verbreitete Fragestellung in der Literatur, werden bezüglich der Richtung des Wohlstandseffekts unterschiedliche Schlussfolgerungen getroffen. Es wurden in unterschiedlichen Artikeln sowohl positive, nicht signifikante als auch negative Effekte dargestellt. Wir stellen einen analytischen Rahmen bereit, der zeigt, dass alle drei Resultate unter Unsicherheit theoretisch folgerichtig sind. In Regionen, in denen Qualitätsprobleme bei Düngemitteln vorherrschen, kann diese Unsicherheit durch Zweifel über die Qualität der Produktionsmittel entstehen. In Regionen, in denen der Einsatz von Mineraldünger nicht sehr verbreitet ist, kann die Unsicherheit auch auf Zweifel über die Effektivität der Düngemittel zurückgeführt werden. Unser theoretisches Modell basiert auf der Erwartungswert-Varianz-Methode, welche den Entscheidungsfindungsprozess unter Unsicherheit über die Qualität des Produktionsmittels erfasst. Wir fügen zwei Budgetbeschränkungen hinzu, die diese Situation widerspiegeln. Die erste Budgetbeschränkung ist Bezahlbarkeit, das heißt, dass wohlhabendere Landwirte sich mehr Düngemittel leisten können. Die zweite Beschränkung stellt dar, dass arme Landwirte weniger in der Lage sind, mit einem großen Ernteverlust zurechtzukommen. Dazu kann es kommen, wenn die Qualität des Düngemittels sehr schlecht ist. Um den möglichen Qualitätsmangel bei Düngemitteln zu kompensieren, verwenden ärmere Landwirte deshalb mehr Dünger. Wir lösen dann die Hauptbedingung des Modells und nutzen komparative Statik, um zu untersuchen, wie eine marginale Änderung des Wohlstandsniveaus die Nutzung von Düngemitteln beeinflusst. Wir erstellen einen Wohlstandsindex mit der Principal-Component-Analyse und führen eine empirische Studie mithilfe der RCRE-Daten für Hebei, eine wohlhabende Provinz, und Yunnan, eine arme Provinz, durch. Da der Datensatz keine Information zum Risikoverhalten der Landwirte enthält, können wir die Wechselwirkung zwischen Wohlstand und Risikopräferenz nicht berücksichtigen. Die Regressionsergebnisse stützen jedoch die Ableitung des theoretischen Modells, welches besagt, dass die Richtung der Wohlstandswirkungen nicht einheitlich ist und sich zwischen Regionen mit unterschiedlichen Wohlstandsniveaus unterscheiden kann. Desweiteren zeigen die Ergebnisse, dass sich die Auswirkungen zwischen Landwirten mit geringem und hohem Wohlstandsniveau sogar innerhalb einer Region ändern können.

Der letzte Teil dieser Studie untersucht, wie sich die Düngerqualität auf die Nutzungssintensität auswirkt. Zur Messung der Düngerqualität unterscheiden wir zwischen wahrgenommener und tatsächlicher Qualität. Die wahrgenommene Qualität reflektiert die Meinung des Landwirts bezüglich der Qualität des Düngemittels, während die tatsächliche Qualität des Düngerinhalts mit Hilfe von Labortests bestimmt wurde. Mittels komparativer Statik untersuchen wir, wie sich eine marginale Veränderung in der wahrgenommenen und tatsächlichen Qualität auf die Nutzungsintensität des Düngers auswirkt. Abgeleitet vom theoretischen Modell führt eine geringer wahrgenommene Qualität zu einer höheren Düngemittelnutzungsintensität. Die tatsächliche Qualität beeinflusst die Nutzungsintensität lediglich durch die wahrgenommene Qualität. Wenn die Korrelation zwischen beiden Qualitätsvariablen positiv ist, entspricht der Einfluss der tatsächlichen Qualität gleich dem Einfluss der wahrgenommenen Qualität, was bedeutet, dass eine höhere tatsächliche Qualität die Nutzungsintensität von Düngemittel reduziert. Die Richtung des Effekts kehrt sich um, wenn die Korrelation zwischen tatsächlicher und wahrgenommener Qualität negativ ist. Zur empirischen Analyse dieses Teilaspekts der Studie führten wir Ende 2012 eine gesonderte Haushaltsbefragung in der Provinz Hebei durch. Wir erhoben Daten zu Haushaltscharakteristika und zur Wahrnehmung der Landwirte hinsichtlich der Qualität ihres wichtigsten Düngers. Während der Befragung nahmen wir ebenfalls eine Probe ihres Hauptdüngers und ließen Stickstoffgehalt und Phoshorverfügbarkeit analysieren. Die Testergebnisse zeigen, dass eine Düngerprobe durchschnittlich nur 71 Prozent der auf der Düngemittelpackung gekennzeichneten Menge an Stickstoff enthält. Desweiteren besteht keine signifikante Korrelation zwischen tatsächlicher und wahrgenommener Qualität. Die Regressionsanalyse zeigt, wie durch das theoretische Modell prognostiziert, dass die wahrgenommene Qualität einen negativen Einfluss auf die Düngemittelnutzungsintensität hat. Dies bedeutet, dass Landwirte, die glauben, dass ihr Düngemittel schlecht ist, mehr Dünger anwenden, um die minderwertige Qualität zu kompensieren. Der Einfluss der tatsächlichen Qualität auf die Nutzungsintensität ist unwesentlich, was zu erwarten war, da zwischen wahrgenommener und tatsächlicher Qualität keine signifikante Korrelation besteht und die theoretische Ableitung bereits besagt, dass die tatsächliche Qualität die Nutzungsintensität nur durch die wahrgenommene Qualität beeinflusst.

Der Hauptbeitrag dieser Dissertation ist, dass wir den Einfluss von Düngemittelqualität auf die Effizienz und Nutzungsintensität sowohl theoretisch als auch empirisch untersuchen. Dies wurde trotz dem weitverbreiteten Problem der Düngerqualität bisher noch nicht erforscht. Der theoretische Beitrag umfasst das Ermitteln des Bias, der aus der Vernachlässigung des Qualitätsaspekts in der Schätzung der Produktionsfunktionen und der technischen Effizienz besteht. Dies ist insbesondere dann der Fall, wenn Düngerqualität im Forschungsgebiet ein Problem darstellt, wie etwa in China oder in anderen betroffenen Ländern. Wir präsentieren außerdem ein theoretisches Rahmenwerk, das die verschiedenen Erkenntnisse in der Literatur zur Richtung des Wohlstandseffekts auf Düngemittelnutzung zusammenführt. Es liefert eine konsistente Erklärung dafür, warum der Wohlstandseffekt unterschiedlich sein kann, wenn wir Regionen oder Landwirte mit unterschiedlichem Wohlstandsniveau betrachten. Der empirische Beitrag diese Dissertation besteht darin, die Größe der Schätzverzerrung bei der Elastizität der Produktionsmittel und der technischen Effizienz für unsere Forschungsregion, die Nordchinesische Ebene, quantitativ zu bestimmt. Dies stützt auch unsere theoretische Ableitung und zeigt, dass die Richtung des Wohlstandseffekts für Landwirte mit unterschiedlichem Wohlstandsniveau nicht konstant ist. Schließlich ermöglicht uns das Einbeziehen von Düngemitteltests in die Haushaltsbefragung sowohl den Zusammenhang zwischen wahrgenommener und tatsächlicher Düngerqualität genauer zu betrachten als auch zu sehen, wie diese die Nutzungsintensität von Dünger beeinflussen. Da in unserem Datensatz jedoch Informationen zum Risikoverhalten fehlen, können wir die Rolle von Risiko nicht empirisch untersuchen. Wenn ein solcher Datensatz vorhanden wäre, wäre es nützlich die Wechselwirkung zwischen Wohlstandseffekt und Risikopräferenz zu analysieren. Außerdem ist die Stichprobengröße unserer Haushaltsbefragung zu wahrgenommener und tatsächlicher Düngerqualität mit nur 100 Haushalten klein. Es würde mehr Aufschluss über die Situation geben, wenn in der Zukunft Düngemitteltests in ähnlicher Weise in eine Haushaltsbefragung einbezogen würden. Dabei sollte die Haushaltsbefragung eine größere Stichprobe als auch einen Zeitraum abdecken, um Analysen von Paneldaten zu ermöglichen. Außerdem wäre es interessant, dieselbe Studie in einer anderen Region, in der Nutzung von Dünger nicht so verbreitet ist, zu wiederholen, um zu sehen, wie sich der Einfluss von Düngerqualität zwischen Regionen mit niedriger Düngemittelintensität und unserem Forschungsgebiet mit hohem Düngemitteleinsatz unterscheidet.

Die Verschlechterung der Düngemittelqualität in der Nordchinesischen Ebene bereitet Anlass zur Sorge, da sie - wie diese Dissertation zeigt - zu einem Anstieg des Düngemitteleinsatzes, welcher in diesem Gebiet schon extrem hoch ist, führt. Dies bedeutet nicht nur eine Verschwendung wertvoller Ressourcen, sondern verursacht auch Umwelt- und gesundheitliche Probleme. Die derzeitige Subventionierung der Düngemittelherstellung ist dabei ein doppeltes Dilemma, da ein Niedrighalten des Produktpreises die Nutzung eines Produktionsmittels, welches bereits schon übermäßig eingesetzt wird, zusätzlich begünstigt. Das Vorhandensein von vielen Kleinproduzenten, die ineffizient wirtschaften, erschwert darüber hinaus die Qualitätskontrolle von Düngemitteln im Markt. Angesichts dieser Unzulänglichkeiten wäre es besser, den Fokus der Politikmaßnahmen von Preisreduktion auf Qualitätsverbesserung zu verlagern. Ein Vorschlag wäre, die Vergabe von Qualitäts-Gütesiegeln an zufriedenstellende Produkte zu fördern, wobei regelmäßige Tests von Seiten unabhängiger Dritter erfolgen sollten, um eine Verschlechterung der Qualität nach Erhalt des Siegels zu verhindern. Verantwortungsbewusste Produzenten der Branche könnten auch dabei helfen, ein sektorweites Überwachungsorgan zu bilden, um zu verhindern, dass ihr Image durch weniger verantwortungsvolle Hersteller getrübt wird. Ein weiterer Vorschlag wäre die Aufstockung von Ressourcen und Personal im neutralen Beratungsdienst, um den Informationsfluss zwischen politischen Entscheidungsträgern und Landwirten zu verbessern.

List of Abbreviations

CAU	China Agriculture University
CD	Cobb-Douglas
CE	certainty equivalent
EVV	expected value - variance
FAO	Food and Agriculture Organization of the United Nations
FE	fixed effects
ID	identifier
IFPRI	International Food Policy Research Institute
IV	instrumental variable
KMO	Kaiser-Meyer-Olkin
ML	maximum likelihood
NCP	North China Plain
NPK	nitrogen-phosphorus-potassium
PCA	principal component analysis
RCRE	Research Center for Rural Economy
SFA	stochastic frontier analysis
SSB	State Statistical Bureau
TL	translog

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Chapter 1

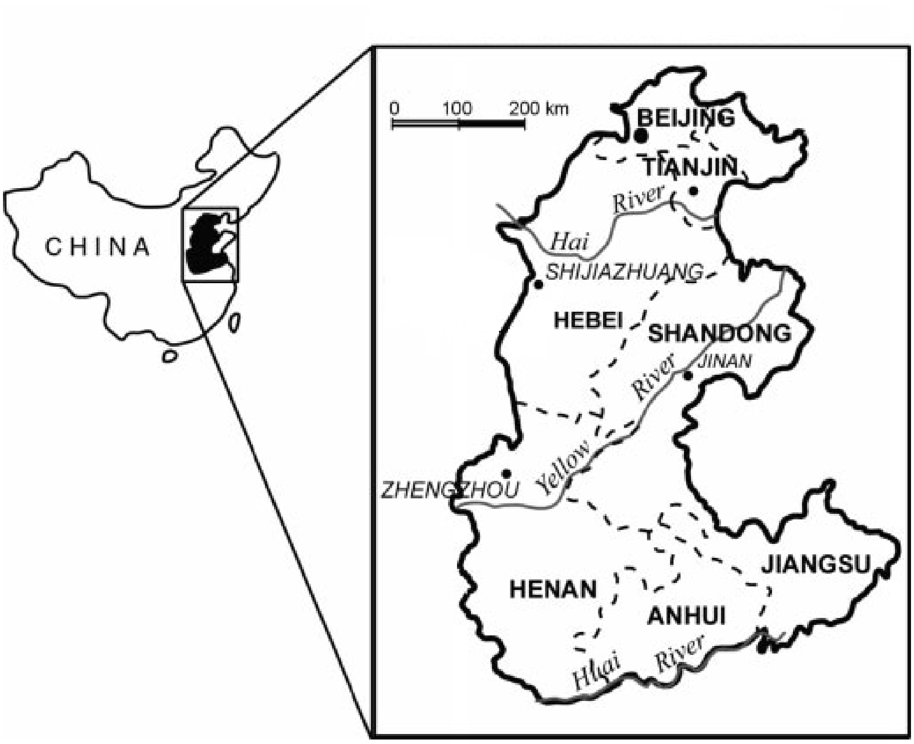
Introduction

1.1 Background information

The world population was around three billion in the 1960s. Over the next 50 years, the figure more than doubled and reached seven billion. This annual growth rate of 1.7 percent has been outpaced by the rise of total agricultural output at 2.3 percent per year, which has helped to reduce the proportion of people suffering from hunger (Wik et al., 2008). In the beginning, the growth in agricultural output has been largely due to the increase of input use, which includes resources such as land and water, as well as labor, capital and chemicals. During the 10 year period from 1960, the rise in input contributed 82 percent of the output growth with the rest coming from improvement in total factor productivity. The importance of these two components shifted over the years. The contribution of input dropped to 64 percent in the 1970s and 1980s, and reduced further to 29 percent over the following 20 years, with an increase in productivity accounting for the bulk of agricultural output growth (Fuglie, 2010). This trend is however not uniform throughout the world. According to the 2012 Global Food Policy Report by the International Food Policy Research Institute (IFPRI), the switch from input intensification to productivity growth took place around 1980 in high-income countries, which helped to maintain output level despite the decrease in resource use. The growth in labor productivity also outpaces that of land productivity following the drop in agricultural labor and the rise in average farm size. The switch comes later for many developing countries at around 2000, but China and Brazil have managed to maintain high productivity growth for the past two decades (Fuglie and Nin-Pratt, 2013).

Fan (1991) separates the growth promoting factors of Chinese agriculture into three components, which are input, technology, and efficiency. He finds that from 1960s to mid 1980s, 58 percent of the output growth is due to the increase in input use, especially chemical fertilizer. Technological advancement and greater efficiency account for 16 percent and 26 percent of the growth, respectively. Fan and Pardey (1997) extend the study period to mid 1990s and include more components, such as research and development, into consideration. In this case, input intensification accounts for 46 percent of output increase, with almost half of it coming from fertilizer alone. Agricultural research is responsible for 20 percent of growth, while the contributions from institutional and market reforms amount to 18 percent. Lin (1987), Lin (1992), and Young (2000) provide more explanation on the process of change in the Chinese agricultural institutions. For the topic of increasing agricultural input use in China, especially chemical fertilizer and its impact, more studies can be found in Huang and Rozelle (1995), Wang et al. (1996), and Zhen et al. (2006). Other than the research done at the country level, Fuglie and Nin-Pratt (2013) find that productivity growth can vary quite a bit even within a country itself. For example, they find that the growth in total factor productivity has been very strong along the coast in Northeast, East, and Southeast China. However, the performance is weaker in the interior parts of the country.

When agricultural growth began to take off in China in the 1980s, the region with the highest grain output growth was the North China Plain (NCP) at 55.5 percent, followed by the Northeast at 53.2 percent. Fertilizer application in that region also almost doubled from 1980 to 1990. Comparatively, southwestern China had a lower increase in fertilizer use at about 60 percent (Zhang and Carter, 1997) over the same time period. NCP is located in the eastern coastal region of China and covers a big part of the provinces of Hebei, Henan, Shandong, and the northern parts of Jiangsu and Anhui provinces. It is one of the most important agricultural regions in China, contributing to a quarter of the total grain yield of the country, with the main crops being summer maize and winter wheat (Zhen and Routray, 2002). Due to the intensification of agriculture and the increasing demand for irrigation, the decline of groundwater level has been a serious problem in this region (Sun et al., 2011). From 1983 to 1993, the average water table lowers by 0.429 meter per

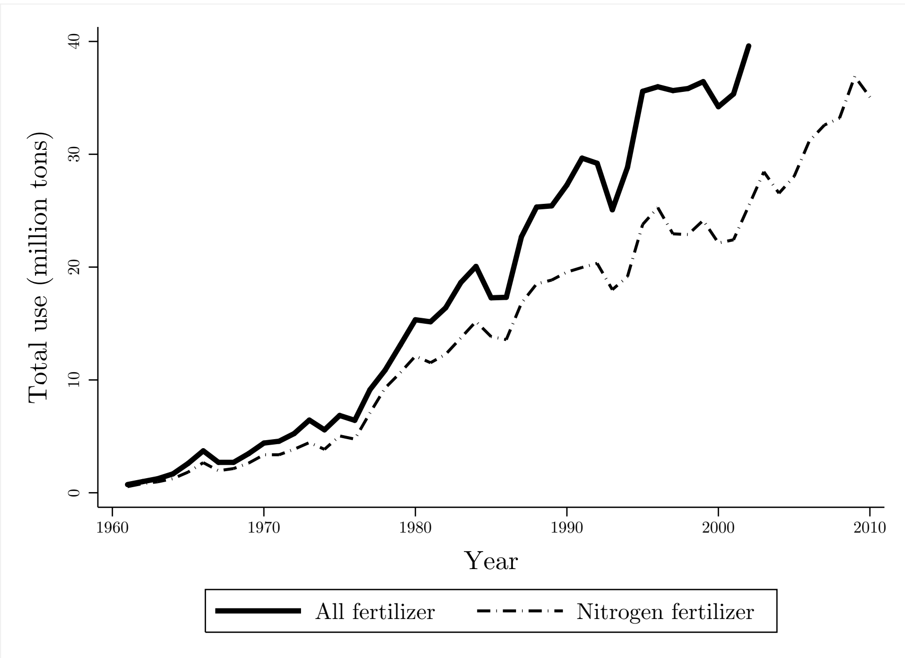


Source: Kendy et al. (2004)

Figure 1.1: Location of the North China Plain

year from 7.23 meter to 11.52 meter beneath the surface (Liu et al., 2001). In addition to water shortage, the degradation of water quality is another problem faced by the region. In a comprehensive five-year study conducted by the China Academy of Geological Sciences from 2006 to 2011, a total of 7,451 groundwater samples were collected in the NCP and tested. The results show that only 25 percent of the samples are safe for direct human consumption, which is lower than the national average of 45 percent (Jiang and Jiang, 2013). One of the causes is the overuse of chemical fertilizer, as Chen et al. (2005) and Hu et al. (2005) show that nitrate pollution in groundwater is a problem in the region. In a case study conducted by Zhen et al. (2005) in a county of the NCP, 16 out of the 20 well water samples and 19 out of the 20 vegetables samples collected contain a higher nitrate concentration than the maximum level deemed safe for human consumption. The authors also find significant and positive correlation between the amount of nitrogen fertilizer used and the nitrogen concentration in groundwater. This contamination of both food and drinking water could be dangerous to the people living in the region, as the review of evidence by Fraser et al. (1980) indicates that nitrate ingestion could be a factor that raises gastric cancer rate.

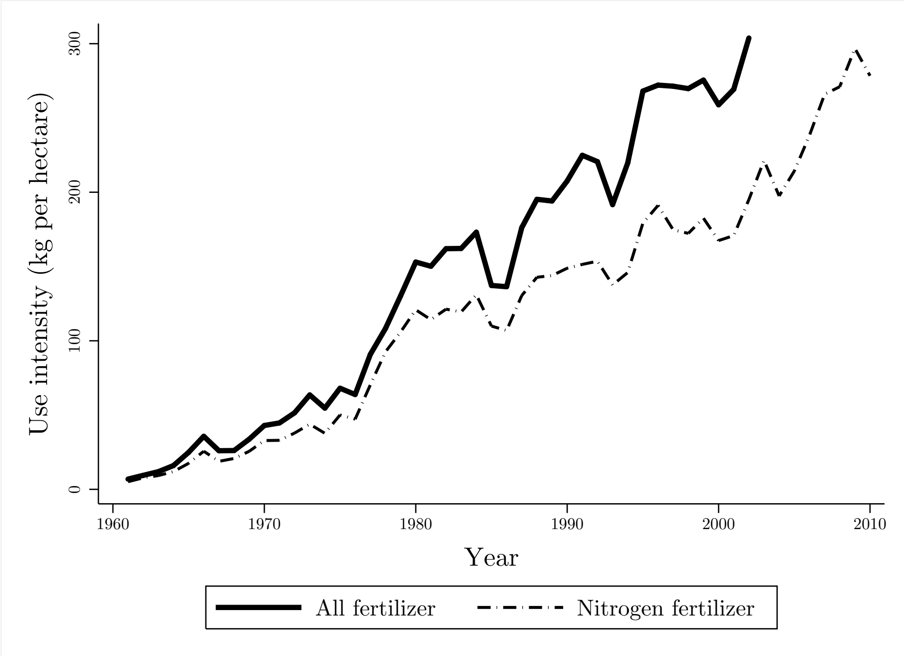
As mentioned by Fan (1991), chemical fertilizer was a huge factor in the fast agricultural growth up to the 1980s. Its impact has however diminished greatly since then. Tian and Wan (2000) shows that in the mid 1990s, even though the output elasticity of fertilizer was still quite high in wheat production with a value of 0.3, the impact on maize was already very small at 0.035. In a review of other studies by Chen et al. (2003), we can see that the marginal effect of fertilizer is quite small or negative, while Zhen et al. (2006) find that nitrogen use is not a significant factor in determining crop yield. Piotrowski (2009) comes to the conclusion that the marginal effect of fertilizer is not statistically significant in wheat production. This is contradictory to the earlier finding by Tian and Wan (2000) on wheat. However, the study by Piotrowski was conducted in mid 2000s, a difference of 10 years from that of Tian and Wan. So it is possible that fertilizer has since lost its marginal effectiveness in wheat production as well. Despite the reduction in the impact of fertilizer, the use intensity of this input remains very high in China. As illustrated in Figures 1.2



Source: FAO (2011)

Figure 1.2: Total fertilizer use in China from 1960 to 2010

and 1.3, other than a few short-term dips in some years, both total fertilizer



Source: FAO (2011) and own calculation

Figure 1.3: Fertilizer use intensity in China from 1960 to 2010

use and fertilizer intensity per unit of land are on a growing trend from 1960 to 2010. This rise applies to nitrogen fertilizer as well as the sum of all fertilizer.

A reason for this high application rate is the favorable policy towards fertilizer producers that helps to drive the price down and encourages fertilizer usage. There is no direct subsidy to farmers for fertilizer use. However, according to a report on the real cost of nitrogen fertilizer in China, both the energy and transportation costs of fertilizer manufacturers are subsidized. In the case of transportation, these manufacturers pay on average 70 percent less than those from other chemical industries. They are also not required to pay the value added tax, which has a standard rate of 17 percent. In a cross-country comparative study, the same report also mentions that there are almost 1,000 different manufacturers of nitrogen fertilizer in China, with an annual average production of 20,000 tons. Among them, only 26 are big manufacturers who produce more than 300,000 tons, while there are 800 of them who produce less than the industrial average of 20,000 tons per year. In comparison, other big producing countries such as Russia has about 35 nitrogen fertilizer manufacturers in total and USA has about 50. Their average annual production levels are 400,000 tons and 300,000 tons, respectively. The favorable conditions for the fertilizer manufacturers in China mean that even the small-scale producers who have low expertise and are inefficient can also survive in the industry (Cheng et al., 2010). In addition, the big number of manufacturers makes quality control of the products in the market even more difficult.

1.2 Fertilizer quality

In 2008, the Chinese authority found 29.4 million U.S. dollars worth of fake or poor quality agricultural inputs such as fertilizers and seeds in the country (Han, 2009). There are signs that the problem has worsened, as in 2011, the value was already at 23.5 million U.S. dollars from the first six months of the year alone (Wang, 2011). On the level of household survey, Boeber et al. (2009) analyzed 14 samples of fertilizer from five villages in the southern part of Hebei province. They find that 12 of them have less nitrogen than that labeled on the package with the average reduction at about 20 percent. We conducted a survey ourselves in the same province in 2012 and collected fertilizer samples from the households. After having their contents tested in a lab, we arrange the results of all these samples in an ascending quality order and show them in Figure 1.4. They correspond to 86 surveyed households. As we can see, the fertilizer from most of the surveyed households does not have the full nitrogen amount as labeled on the package. The average sample contains only 71 percent of the labeled nitrogen, which means that 29 percent of the nitrogen content is missing.

This fertilizer quality issue is not confined to China alone and the same incident has been reported in other countries of various regions as well. According to a study by the Soil Research Development Institute in Bangladesh, the percentage of questionable fertilizer in the country ranges from almost zero for urea to a very high 87 percent for the nitrogen-phosphorus-potassium (NPK) composite fertilizer (Zahur, 2010). In Tanzania, the Ministry for Agriculture, Food Security and Cooperatives found fertilizer samples that have been mixed with cement and salt. The costs of cement and salt are five to more than ten times lower than that of fertilizer, so it is a lucrative business for the counterfeiters (Mwakalebela, 2012). A country-wide inspection in Vietnam, in which 850 fertilizer samples were collected from 17 cities and provinces, shows that almost half of the tested samples do not meet the quality standards (Viet

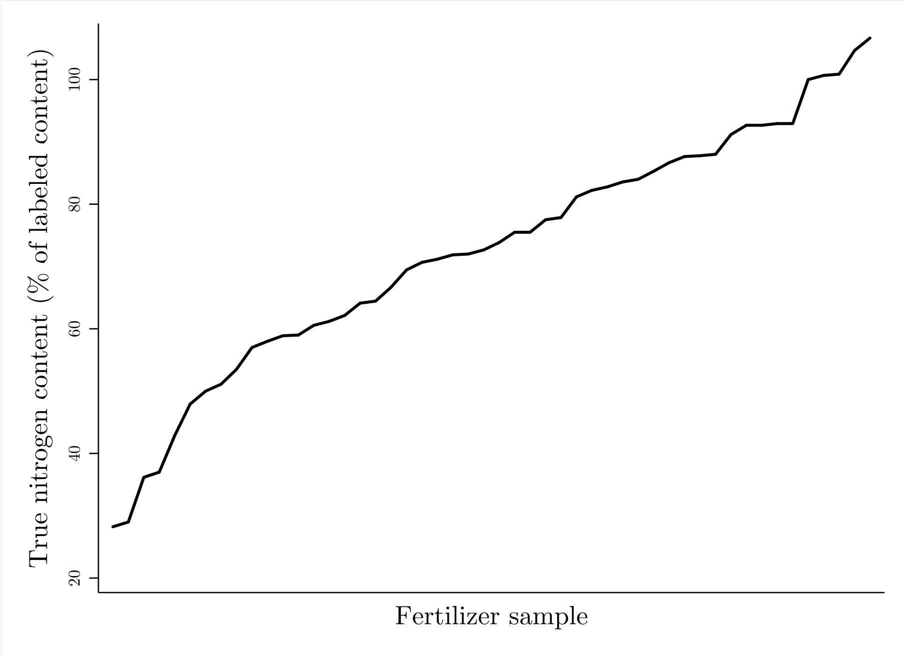


Figure 1.4: Percentage of labeled nitrogen content that is found in the fertilizer of Disituan, Hebei province

Nam News, 2010). Similar problems on fertilizer quality have also been found in Cambodia (Hamaguchi, 2011) and Nigeria (Liverpool-Tasie et al., 2010).

1.3 Conceptual framework and outline of the dissertation

In view of the widespread issue, this dissertation research focuses on agricultural input quality, notably fertilizer, and its effects on efficiency, wealth, and use intensity.

Research topic 1. *Efficiency*

Question 1.1. How does fertilizer quality affect the estimation of production function and output elasticity of fertilizer?

Question 1.2. What is the impact of fertilizer quality on technical efficiency?

Research topic 2. *Wealth*

Question 2.1. How does the difference in wealth level among the farm households affect their fertilizer use decisions?

Question 2.2. What is the impact of fertilizer quality on this wealth effect?

Research topic 3. *Use intensity*

Question 3.1. What is the link between the perceived fertilizer quality by farmers and the true nutrient content?

Question 3.2. How do these two different measurements of fertilizer quality affect use intensity?

In the earlier section of this chapter, we write about how efficiency contributes to agricultural growth, which then leads to economic growth in general (Fan et al., 2003). It emphasizes the importance of our first topic, the study on efficiency. Regarding the second topic, there are studies showing that income inequality in rural China is increasing, and has worsened in the second half of 1990s (Benjamin et al., 2005; Ravallion and Chen, 2007). However, Rozelle (1994) and Ravallion and Chen (2007) find that the growth of the agriculture sector has helped to reduce income inequality. Being able to identify the direction of wealth effect in fertilizer use is important for the research on equity. For example, if the wealth effect is positive, it means that the rich is using more of the input than the poor. Assuming that a higher level of input leads to greater output and income, this increases the gap between the rich and the poor. Thus, there is a rise in income inequality, or in other words, a reduction in equity. Finally on the topic of environment, Section 1.1 mentions the leaching of fertilizer into groundwater causes nitrate pollution and health issues. There are also studies showing the negative impact of fertilizer overuse on the environment in China (He et al., 2007; Zhang et al., 2008a,b; Shen et al., 2009; Liu et al., 2013). Therefore, the three aspects that we look at (efficiency, wealth, and use intensity) form a part of the ideal of economic growth, equity, and environment protection. The conceptual framework is summarized and illustrated in Figure 1.5. Among the different types of agricultural inputs, recent news reports indicate that besides fertilizer, there are problems with the quality of other purchased inputs as well, such as seed (Wang, 2011; Tambwe, 2013) and pesticide (Fishel, 2009; Henshaw, 2011). Even though we focus on fertilizer in our analysis, some of the methodology presented here can also be used to study the impact of questionable quality in other inputs.

For each of the three topics of our research, we start by constructing a theoretical model that captures the problem at hand, and postulates empirically

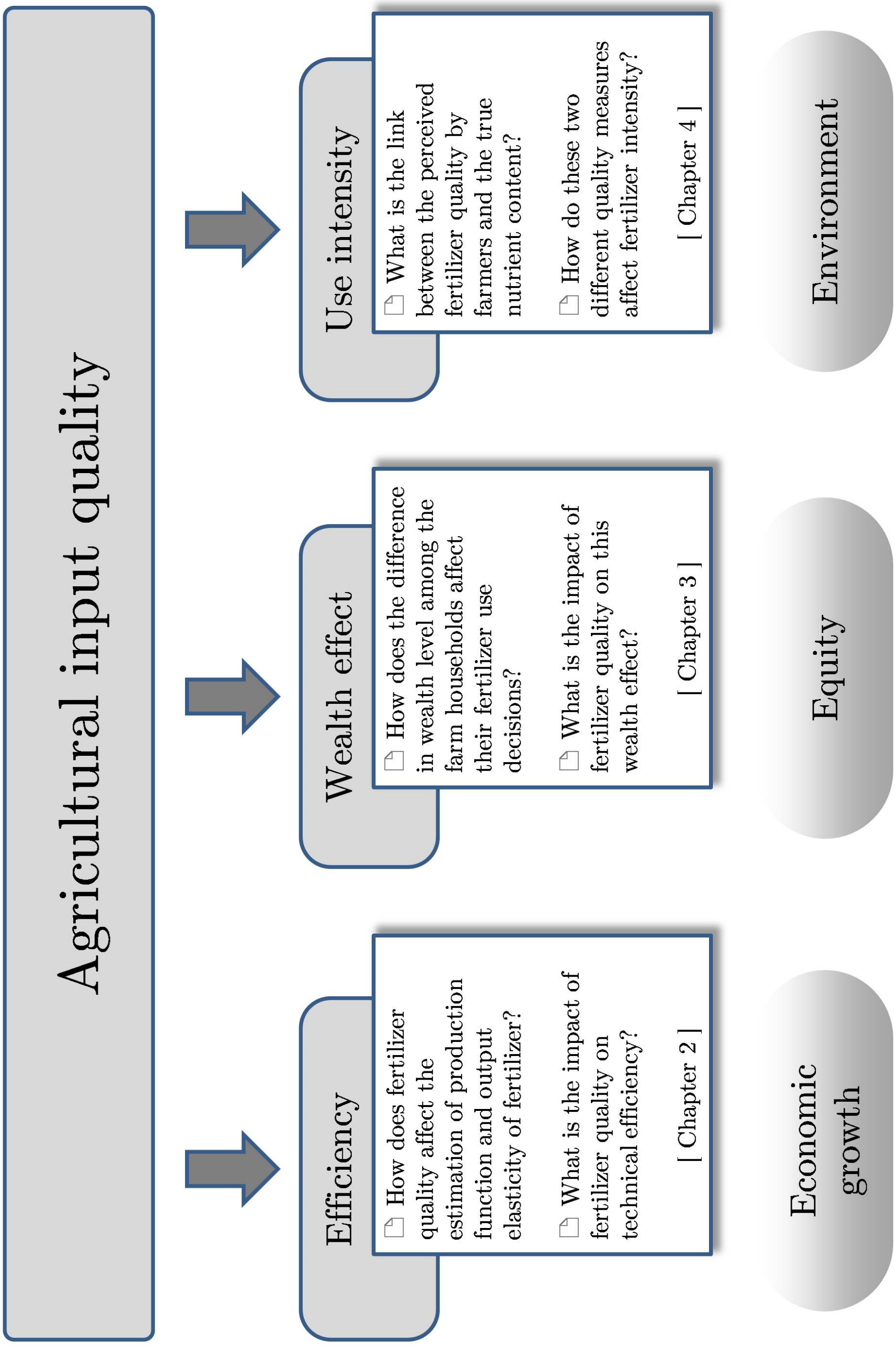


Figure 1.5: Conceptual framework of the dissertation

testable hypotheses. These models are based on theoretical work by others but with elements added to reflect the situation of our study. We then construct an econometric model to test the theory-driven hypotheses. Both the theoretical derivation and empirical results help to further our understanding of the issue. There are two main datasets for the empirical section of our research. The first is a panel dataset of a household survey in Hebei province conducted by the Research Center for Rural Economy (RCRE) of China. It covers a period of five years from 2004 to 2008 with about 800 households for each year (Ministry of Agriculture, 2010). The second is a survey of 100 households that we conducted in 2012 in the Quzhou county of Hebei province.

On the issue of efficiency, we are interested in the question on how the reduction in fertilizer quality affects both the estimation of output elasticity for fertilizer, as well as technical efficiency of the production as a whole. In Chapter 2, we incorporate the fertilizer quality term into the stochastic frontier model of Aigner et al. (1977), and derive an expression that capture the estimation bias in output elasticity and technical efficiency if we were to ignore the lower fertilizer quality. For the empirical analysis, we apply the method by Battese and Coelli (1995) on the RCRE data to estimate a maize production function of Hebei province. As the RCRE dataset does not have information on fertilizer quality, we use Monte Carlo simulation to generate the quality variable for different scenarios, such as whether the distribution of fertilizer quality is household-specific over the years or totally random. We then examine the impact of fertilizer quality on output elasticity and technical efficiency under each of these scenarios.

Analysis on how the wealth levels of farmers affect their fertilizer use decisions is a common theme in the literature (Kaliba et al., 2000; Lamb, 2003; Abdoulaye and Sanders, 2005; Ariga et al., 2008). However, the direction of this wealth effect is not clear, as some studies find that the effect is positive (Lamb, 2003; Abdoulaye and Sanders, 2005), while others conclude that it is insignificant (Kaliba et al., 2000) or negative (Ariga et al., 2008). We analyze this issue in Chapter 3 from another, new angle, by including uncertainty into the decision making. Where does the uncertainty come from? In our research region where fertilizer use is very common, this uncertainty could be due to the true content of fertilizer not matching that labeled on the package. Poor quality fertilizer creates uncertainty because farmers are not sure whether the fertilizer they use is good or bad. At other places with less widespread fertilizer use, farmers might not be that familiar with the input. This leads to uncertainty as well because the farmers have doubts on the effectiveness of chemical fertilizer. We first construct a model based on Robison and Barry (1987) and derive the direction of wealth effect theoretically. We then examine the hypothesized effect empirically using the RCRE data and by constructing a wealth index with the methodology of Henry et al. (2003) and Zeller et al. (2006).

We study the impact of fertilizer quality on use intensity in Chapter 4. For this part, we differentiate between the fertilizer quality as perceived by farmers and the true quality that is based on lab testing of fertilizer samples. The theoretical model for this chapter follows Zellner et al. (1966). Using comparative statics, we derive the marginal change on fertilizer use when perceived quality shifts. We then repeat the same procedure for true quality. In the empirical analysis, we conduct a survey in the Hebei province to collect the data we need. During the survey, we ask the farmers about the quality of their main fertilizer based on own perception. We also collect fertilizer samples from them and send these samples to a lab to have their contents tested. We are interested in finding out whether the perceived quality and the true quality are linked, and how each of them affects fertilizer use intensity.

Finally in Chapter 5, we discuss in general our findings from Chapters 2, 3, and 4. The dissertation concludes with implications for research and policy.

1.4 References

Abdoulaye, T. and Sanders, J. H. (2005). Stages and determinants of fertilizer use in semiarid African agriculture: The Niger experience. *Agricultural Economics*, 32(2):167–179.

Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1):21–37.

Ariga, J., Jayne, T. S., Kibaara, B., and Nyoro, J. K. (2008). Trends and patterns in fertilizer use by smallholder farmers in Kenya, 1997-2007. Food security collaborative working paper no. 55169, Department of Agricultural, Food, and Resource Economics, Michigan State University.

Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2):325–332.

Benjamin, D., Brandt, L., and Giles, J. (2005). The evolution of income inequality in rural China. *Economic Development and Cultural Change*, 53(4):769–824.

Boeber, C., Kuehl, Y., and Rumbaur, C. (2009). Land degradation in the North China Plain (NCP): Recent evidence, farmers concerns and policy implications. In *International Association of Agricultural Economists conference*, Beijing, China.

Chen, A. Z., Huffman, W. E., and Rozelle, S. (2003). Technical efficiency of Chinese grain production: A stochastic production frontier approach. In *American Agricultural Economics Association annual meeting*, Montreal, Canada.

Chen, J., Tang, C., Sakura, Y., Yu, J., and Fukushima, Y. (2005). Nitrate pollution from agriculture in different hydrogeological zones of the regional groundwater flow system in the North China Plain. *Hydrogeology Journal*, 13(3):481–492.

Cheng, C., Shi, Y., and Wen, T. (2010). The real cost of nitrogen fertilizer. Technical report, School of Agriculture and Rural Development, Renmin University of China.

Fan, S. (1991). Effects of technological change and institutional reform on production growth in Chinese agriculture. *American Journal of Agricultural Economics*, 73(2):266–275.

Fan, S. and Pardey, P. G. (1997). Research, productivity, and output growth in Chinese agriculture. *Journal of Development Economics*, 53(1):115–137.

Fan, S., Zhang, X., and Robinson, S. (2003). Structural change and economic growth in China. *Review of Development Economics*, 7(3):360–377.

FAO (2011). FAOSTAT database. Food and Agriculture Organization of the United Nations. Available at http://faostat.fao.org/. Accessed July 1, 2013.

Fishel, F. M. (2009). The global increase in counterfeit pesticides. Institute of Food and Agricultural Sciences, University of Florida. Available at http://edis.ifas.ufl.edu/pdffiles/PI/PI21000.pdf. Accessed July 1, 2013.

Fraser, P., Chilvers, C., Beral, V., and Hill, M. J. (1980). Nitrate and human cancer: A review of the evidence. *International Journal of Epidemiology*, 9(1):3–12.

Fuglie, K. and Nin-Pratt, A. (2013). Agricultural productivity: A changing global harvest. In *2012 Global Food Policy Report*, chapter 2, pages 15–27. International Food Policy Research Institute (IFPRI).

Fuglie, K. O. (2010). Total factor productivity in the global agricultural economy: Evidence from FAO data. In Alston, J. M., Babcock, B. A., and Pardey, P. G., editors, *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, chapter 4, pages 63–95. The Midwest Agribusiness Trade Research and Information Center, Iowa.

Hamaguchi, T. (2011). Awareness raising activities on proper selection and use of chemical fertilizers have been started. Japan International Cooperation Agency. Available at http://www.jica.go.jp/project/english/cambodia/006/news/general/110617.html. Accessed July 1, 2013.

Han, P. (2009). China cracks down on shoddy fertilizers, seeds. Chinese Government's Official Web Portal. Available at http://english.gov.cn/2009-01/06/content_1196983.htm. Accessed July 1, 2013.

He, C.-E., Liu, X., Fangmeier, A., and Zhang, F. (2007). Quantifying the total airborne nitrogen input into agroecosystems in the North China Plain. *Agriculture, Ecosystems & Environment*, 121(4):395–400.

Henry, C., Sharma, M., Lapenu, C., and Zeller, M. (2003). *Microfinance Poverty Assessment Tool*. Technical Tools Series No. 5. The World Bank and Consultative Group to Assist the Poor, Washington, DC.

Henshaw, C. (2011). Fake pesticides are a growing danger. Wall Street Jounal. Available at `http://www.sej.org/headlines/fake-pesticides-are-growing-danger`. Accessed July 1, 2013.

Hu, K., Huang, Y., Li, H., Li, B., Chen, D., and White, R. E. (2005). Spatial variability of shallow groundwater level, electrical conductivity and nitrate concentration, and risk assessment of nitrate contamination in North China Plain. *Environment International*, 31(6):896–903.

Huang, J. and Rozelle, S. (1995). Environmental stress and grain yields in China. *American Journal of Agricultural Economics*, 77(4):853–864.

Jiang, Y. and Jiang, Q. (2013). North China Plain groundwater: More than 70 percent unfit for human touch. Institute of Hydrogeology & Environmental Geology, China Academy of Geological Sciences. Available at `http://chinawaterrisk.org/notices/north-china-plain-groundwater-70-unfit-for-human-touch/`. Accessed July 1, 2013.

Kaliba, A. R., Verkuijl, H., and Mwangi, W. (2000). Factors affecting adoption of improved maize seeds and use of inorganic fertilizer for maize production in the intermediate and lowland zones of Tanzania. *Journal of Agricultural and Applied Economics*, 32(1):35–47.

Kendy, E., Zhang, Y., Liu, C., Wang, J., and Steenhuis, T. (2004). Groundwater recharge from irrigated cropland in the North China Plain: Case study of Luancheng county, Hebei province, 1949–2000. *Hydrological Processes*, 18(12):2289–2302.

Lamb, R. L. (2003). Fertilizer use, risk, and off-farm labor markets in the semi-arid tropics of India. *American Journal of Agricultural Economics*, 85(2):359–371.

Lin, J. Y. (1987). The household responsibility system reform in China: A peasant's institutional choice. *American Journal of Agricultural Economics*, 69(2):410–415.

Lin, J. Y. (1992). Rural reforms and agricultural growth in China. *The American Economic Review*, 82(1):34–51.

Liu, C., Yu, J., and Kendy, E. (2001). Groundwater exploitation and its impact on the environment in the North China Plain. *Water International*, 26(2):265–272.

Liu, X., Zhang, Y., Han, W., Tang, A., Shen, J., Cui, Z., Vitousek, P., Erisman, J. W., Goulding, K., Christie, P., Fangmeier, A., and Zhang, F. (2013). Enhanced nitrogen deposition over China. *Nature*, 494(7438):459–462.

Liverpool-Tasie, S., Olaniyan, B., Salau, S., and Sackey, J. (2010). A review of fertilizer policy issues in Nigeria. Working paper no. 0019, Nigeria Strategy Support Program, International Food Policy Research Institute (IFPRI).

Ministry of Agriculture, P. R. C. (2010). Research Center for Rural Economy Household and Village Surveys 2004 - 2008.

Mwakalebela, L. (2012). Government declares war on fake fertilizer dealers. Tanzania Daily News. Available at `http://dailynews.co.tz/index.php/parliament-news/7122-government-declares-war-on-fake-fertilizer-dealers`. Accessed July 1, 2013.

Piotrowski, S. (2009). *Land Property Rights and Natural Resource Use: An Analysis of Household Behavior in Rural China*. PhD thesis, University Hohenheim.

Ravallion, M. and Chen, S. (2007). China's (uneven) progress against poverty. *Journal of Development Economics*, 82(1):1–42.

Robison, L. J. and Barry, P. J. (1987). *The Competitive Firm's Response to Risk*. Macmillan Publishing Company, New York.

Rozelle, S. (1994). Rural industrialization and increasing inequality: Emerging patterns in China's reforming economy. *Journal of Comparative Economics*, 19(3):362–391.

Shen, J. L., Tang, A. H., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2009). High concentrations and dry deposition of reactive nitrogen species at two sites in the North China Plain. *Environmental Pollution*, 157(11):3106–3113.

Sun, Q., Kroebel, R., Mueller, T., Roemheld, V., Cui, Z., Zhang, F., and Chen, X. (2011). Optimization of yield and water-use of different cropping systems for sustainable groundwater use in North China Plain. *Agricultural Water Management*, 98(5):808–814.

Tambwe, A. (2013). Grappling with challenges of fake seeds. Tanzania Standard Newspapers. Available at `http://www.dailynews.co.tz/index.php/features/popular-features/18923-grappling-with-challenges-of-fake-seeds`. Accessed July 1, 2013.

Tian, W. and Wan, G. H. (2000). Technical efficiency and its determinants in China's grain production. *Journal of Productivity Analysis*, 13(2):159–174.

Viet Nam News (2010). Officials warn of low-quality fertilizer. AccessMyLibrary. Available at `http://www.accessmylibrary.com/article-1G1-229054286/vietnam-officials-warn-low.html`. Accessed July 1, 2013.

Wang, G. (2011). China cracks down on counterfeit seeds, pesticides. Xinhua News Agency. Available at `http://news.xinhuanet.com/english2010/china/2011-05/19/c_13883191.htm`. Accessed July 1, 2013.

Wang, Q., Halbrendt, C., and Johnson, S. R. (1996). Grain production and environmental management in China's fertilizer economy. *Journal of Environmental Management*, 47(3):283–296.

Wik, M., Pingali, P., and Broca, S. (2008). Global agricultural performance: Past trends and future prospects. Background paper for the World Development Report 2008, The World Bank.

Young, A. (2000). The razor's edge: Distortions and incremental reform in the People's Republic of China. *The Quarterly Journal of Economics*, 115(4):1091–1135.

Zahur, A. (2010). Spurious fertilizers: A threat to agriculture. The Daily Star. Available at `http://www.thedailystar.net/newDesign/news-details.php?nid=125044`. Accessed July 1, 2013.

Zeller, M., Sharma, M., Henry, C., and Lapenu, C. (2006). An operational method for assessing the poverty outreach performance of development policies and projects: Results of case studies in Africa, Asia, and Latin America. *World Development*, 34(3):446–464.

Zellner, A., Kmenta, J., and Dreze, J. (1966). Specification and estimation of Cobb-Douglas production function models. *Econometrica*, 34(4):784–795.

Zhang, B. and Carter, C. A. (1997). Reforms, the weather, and productivity growth in China's grain sector. *American Journal of Agricultural Economics*, 79(4):1266–1277.

Zhang, Y., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2008a). Nitrogen inputs and isotopes in precipitation in the North China Plain. *Atmospheric Environment*, 42(7):1436–1448.

Zhang, Y., Zheng, L., Liu, X., Jickells, T., Cape, J. N., Goulding, K., Fangmeier, A., and Zhang, F. (2008b). Evidence for organic N deposition and its anthropogenic sources in China. *Atmospheric Environment*, 42(5):1035–1041.

Zhen, L. and Routray, J. K. (2002). Groundwater resource use practices and implications for sustainable agricultural development in the North China Plain: A case study in Ningjin county of Shandong province, PR China. *International Journal of Water Resources Development*, 18(4):581–593.

Zhen, L., Routray, J. K., Zoebisch, M. A., Chen, G., Xie, G., and Cheng, S. (2005). Three dimensions of sustainability of farming practices in the North China Plain: A case study from Ningjin county of Shandong province, PR China. *Agriculture, Ecosystems & Environment*, 105(3):507–522.

Zhen, L., Zoebisch, M. A., Chen, G., and Feng, Z. (2006). Sustainability of farmers' soil fertility management practices: A case study in the North China Plain. *Journal of Environmental Management*, 79(4):409–419.

Chapter 2

Doubts on input quality: The effect of inaccurate fertilizer content on the estimation of production functions

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Abstract

In recent newspaper articles, there have been reports of low quality agricultural inputs, because of a discrepancy between the labeled content and the real content of the inputs. The problem exists in many countries, such as Bangladesh, Cambodia, China, Nigeria, Tanzania and Vietnam, and leads to doubts on input quality. We analyze in our article the effect of low quality fertilizer, which contains less nitrogen than is advertised on the packaging. We show that this could lead to bias in the estimation of production functions. Using panel data from the Hebei province of China and Monte Carlo simulation, we examine the magnitude of the bias across different levels of fertilizer quality under various scenarios of

uncertainty. We find that ignoring the uncertainty leads to an overestimation of fertilizer's effectiveness. Depending on the scenarios of uncertainty, the bias could even switch the sign of fertilizer's partial elasticity.

2.1 Introduction

Rising food prices push farmers to increase agricultural output, and given the existing land constraints, much of this is achieved by applying more farm inputs (Wik et al., 2008; Fuglie, 2010). A question that follows is whether this increase in input use is actually beneficial. An example is the overuse of chemical fertilizer that leads to problems such as a rise in the deposition of atmospheric nitrogen that degrades both the land and water ecosystems (He et al., 2007; Zhang et al., 2008), and nitrate leaching into groundwater (Chen et al., 2005; Wan et al., 2009) that pollutes the main water sources for many different uses including drinking water, which might cause gastric cancer (Fraser et al., 1980; Hu et al., 2005).

The primary focuses of socioeconomic studies of fertilizer use are on application level and determining factors (Denbaly and Vroomen, 1993; Babcock and Hennessy, 1996; Lamb, 2003), the marginal productivity of fertilizer (Wang et al., 1996b; Chen et al., 2003), its efficiency (Reinhard et al., 1999; Fernandez et al., 2002), and its effects on changing production risks (SriRamaratnam et al., 1987; Kumbhakar, 1993; Battese et al., 1997). Babcock (1992) examines how the uncertainty of weather and soil fertility affects optimal fertilizer use. To the best of our knowledge, there is no previous study on how quality uncertainty of purchased agricultural inputs, such as fertilizer, seed, and pesticide, affects the estimation of farm production.

There have been recent reports of low quality or fake fertilizer in countries such as Bangladesh (Zahur, 2010), Cambodia (Hamaguchi, 2011), China (Wang, 2011), Nigeria (Liverpool-Tasie et al., 2010), Tanzania (Mwakalebela, 2012) and Vietnam (Viet Nam News, 2010). In China alone, the value of fake agricultural input reached 23.5 million U.S. dollars in just the first six months of 2011 (Wang, 2011). We incorporate fertilizer content into the estimation of production functions and technical efficiency in our article and show that the estimates will be biased if we ignore the quality effect, for example when the real fertilizer content is less than the labeled content on the package. We then derive a measurement for the bias and use panel data to illustrate its magnitude. We focus our attention on fertilizer, but the method of analysis can be used for other inputs as well, if the input has a lower than labeled quality, such as seed (Tambwe, 2013) and pesticide (Fishel, 2009; Henshaw, 2011). The inaccuracy in this case is of a one-sided nature, which is different from the two-sided variety that usually exists in the analysis of random measurement errors.

We present in our article a few different scenarios of uncertainty for fertilizer quality because the distribution of uncertainty depends on the socio-economic structure as well as the number of manufacturers in the market. The constant scenario applies more to a static economy with only one or a few manufacturers, who collude and decide to reduce a certain amount of content from their products. We include this case mainly for illustrative purposes, as we find that the non-constant scenarios to be more realistic with many manufacturers in the market. The second scenario of random uncertainty applies to the situation in which the manufacturers reduce their product content randomly, in order to lower the chances of being detected and deemed a low quality brand by the buyers. In this case, it depends on luck which type of fertilizer the farmers get. It is also plausible that awareness of the problem and expectation about the content may differ based on the location of the households. In addition, there might be factors that are household-specific, such as networking for accessing the information and education for processing the information obtained, which determine the type of fertilizer the farmers receive. So, we include a third scenario, household-specific uncertainty, in our analysis.

2.2 Model

We start with a stochastic production function with only two inputs. The basic model is modified from Zellner et al. (1966): $Y = AF^{\lambda_1}X^{\lambda_2}e^{\epsilon}$, with Y as output, A as total factor productivity, F as fertilizer, X as another input, λ_1 and λ_2 as elasticities, and ϵ as the production error term. Based on the model of Aigner et al. (1977), the error term consists of two components: $\epsilon = u + v$, where v is the stochastic component with a normal $N(0, \sigma_v^2)$ distribution and u is the efficiency component, which is made up of the non-positive portion of a normal $N(0, \sigma_u^2)$ distribution. The two error components are assumed to be independent of each other.

Similar to how the error term, e^{ϵ}, enters the production function, we include an additional term, e^z, to capture the real fertilizer content: $Y = A(e^z F)^{\lambda_1} X^{\lambda_2} e^{u+v}$. We restrict the e^z term to be between zero and one, as we are trying to account for the fertilizer manufacturer deliberately reducing the content of their products to save costs. It means that the effective fertilizer quantity the farmers use is less than the actual amount labeled on the product package. The term z has to be non-positive, as e^z is bound between zero and one. The value of z is more negative the more the manufacturer reduces its fertilizer content, and it approaches $-\infty$ when the fertilizer has no nutrient at all. If the manufacturer provides the same content as labeled on the product package, z would be zero and the e^z term would become one. The production function would then be the same as the original function without any reduction in fertilizer quality.

Since this is a stochastic production function, farmers choose the input level that maximizes their expected profits assuming risk neutrality:

$$E(\pi) = p_y E(Y) - w_f E(e^z F) - w_x X. \tag{2.1}$$

The farmers do not know the actual content of the fertilizer when they buy the product. They can only base their decision on what the expected content is. So, the expected value of z, and not its actual value, is used in the expected profit function of Equation (2.1). The first order conditions are

$$\frac{\partial E(\pi)}{\partial E(e^z F)} = 0 \text{ and } \frac{\partial E(\pi)}{\partial X} = 0. \tag{2.2}$$

Solving for the first order conditions in Equation (2.2), we get the optimal input decisions:

$$\begin{aligned} \ln Y - \ln F = \ln\left(\frac{w_f}{p_y \lambda_1}\right) - E(u+v) \\ + u + v + (1-\lambda_1)E(z) + \lambda_1 z + \gamma_1, \end{aligned} \tag{2.3}$$

$$\ln Y - \ln X = \ln\left(\frac{w_x}{p_y \lambda_2}\right) - E(u+v) + u + v + \gamma_2, \tag{2.4}$$

where γ is the stochastic error term of input use, and the other variables are the same as previously defined. The model can also be generalized to include more inputs.

Using Equations (2.3) and (2.4), we can solve for the optimal input use and output produced:

$$\ln Y = (1 - \lambda_1 - \lambda_2)^{-1}[\ln A - \lambda_1(k_1 + \gamma_1) + \lambda_1(1 - \lambda_1)(z - E(z)) - \lambda_2(k_2 + \gamma_2) + (1 - \lambda_1 - \lambda_2)(u + v) + (\lambda_1 + \lambda_2)E(u)], \quad (2.5)$$

$$\ln F = (1 - \lambda_1 - \lambda_2)^{-1}[\ln A + (\lambda_2 - 1)(k_1 + \gamma_1) - \lambda_2(k_2 + \gamma_2) + (\lambda_2 - 1)(1 - \lambda_1)E(z) + \lambda_1\lambda_2 z + E(u)], \quad (2.6)$$

$$\ln X = (1 - \lambda_1 - \lambda_2)^{-1}[\ln A - \lambda_1(k_1 + \gamma_1) + (\lambda_1 - 1)(k_2 + \gamma_2) + \lambda_1(1 - \lambda_1)(z - E(z)) + E(u)], \quad (2.7)$$

where k_1 is $\ln\left(\frac{w_f}{p_y\lambda_1}\right)$ and k_2 is $\ln\left(\frac{w_x}{p_y\lambda_2}\right)$. Other than the additional efficiency term, u, and the fertilizer quality term, z, Equations (2.6) and (2.7) are the same as the optimal input decisions derived by Zellner et al. (1966). They find that the function of optimal input use does not contain the stochastic error term of the production function, v. It shows that input use is exogenous and is not correlated with the error term. The reasoning behind this is that farmers make the input decision before the output is known. Due to the stochastic nature of the production function, the farmers decide on how much input to use based on the expected output, not the real output. The input decision, on the other hand, affects the real output, not the expected output. So, the input decision is contemporaneously exogenous in the estimation of a stochastic production function.

2.3 Empirical studies

Stochastic frontier analysis (SFA) has been a widely used method to examine the technical efficiency of farmers in various parts of the world. Fan (1991) is one of the first to use the stochastic approach to estimate the efficiency of agriculture in China. His analysis is based on the provincial level panel data that cover 29 provinces and municipalities between 1965 and 1985. The data are mainly taken from the various editions of the country's statistical yearbooks published by the State Statistical Bureau (SSB). The author examines the technical efficiency at the provincial level and also the regional level. There are seven regions in total based on his own grouping. He includes the interaction terms between each input variable and the year to examine the changing trend in the importance of the inputs. Fan (1991) finds that labor and land have a decreasing influence on output over time, while chemical fertilizer has an increasing influence. He also separates the production growth into three components and examines which component has the strongest influence on growth. The three components are change in input use, change in technology, and change in institution. Their contributions to production growth between 1965 and 1985 are 57.7 percent, 15.7 percent, and 26.6 percent, respectively. Studies on increasing agricultural input use, especially chemical fertilizer, and its impact can be found in Huang and Rozelle (1995), Wang et al. (1996b), and Zhen et al. (2006). More details on the change in agricultural institutions in China are available in Lin (1987), Lin (1992), and Young (2000).

Building on the more generic analysis offered by the provincial level data, Wang et al. (1996a) examine both the technical and allocative efficiency at the household level using the data from the National Rural Household Survey by SSB. The authors randomly select the data for 1,786 households from the year 1991 survey and estimate a stochastic profit function with two outputs: crop and livestock. They find that the average production efficiency is 62 percent, with individual values between 6 percent and 93 percent.

Another paper that utilizes household level data is Chen et al. (2003). The authors randomly select 591 households from the RCRE dataset from year 1995 to 1999 in nine provinces. They estimate the technical efficiency and its determinants in grain production using the same method as Battese and Coelli (1995). The results indicate that the production elasticities for labor and fertilizer are quite small or negative, implying that there might be an overuse of labor and fertilizer. In a later study with the same sample, Chen et al. (2009) separate the households into four groups based on their location, and run a separate regression for each group. The main finding is that provinces in the North and Northeast are relatively efficient, but those in the East and

Southwest are not.

All the aforementioned papers on China look at the efficiency of the agricultural sector or grain production as a whole. Their focus is on the aggregate level of all grains, not on individual crops. Tian and Wan (2000) analyze the efficiency and its determinants for four separate crops: Indica rice, Japonica rice, wheat, and maize. They take their production data from the Farm Production Costs and Returns Survey between year 1983 and 1996, which are available at the household level. Their results show that fertilizer has a high impact on wheat and Japonica rice production, but the impact is low on maize, and there is fertilizer overuse in Indica rice production as shown by its negative elasticity.

2.3.1 Data

We will focus our analysis on household farms because they are more likely to be affected by low quality fertilizer, as they have neither the buying power of big corporate farms nor the testing equipment in order to verify the fertilizer content. We use a household panel dataset from the Hebei province collected by the Research Center for Rural Economy (RCRE) of China. The RCRE uses the stratified random sampling method for the survey. Counties in the province are separated into three groups based on their income level: high, middle, and low. Villages are then selected from each group of counties to ensure that all three groups are well represented in the survey. Finally, 40 to 120 households are randomly selected from each village. Selected households are asked to keep a diary recording their incomes and expenses. Designated villagers then collect the diaries once a month from the households (Benjamin et al., 2005). Table 2.1 shows a list of variables we use in our regression, and their respective descriptions.

The RCRE survey started in 1986, and its questionnaire has undergone significant changes over the years. Some of the household information is highly inconsistent across the years, for example in household size and household head characteristics. Some possible causes could be that there is a mismatch of household IDs over the years or that some IDs of dropped-out households are being reused. We decide to err on the side of caution and drop these inconsistent entries from our analysis. A downside to doing this is that the

Table 2.1: Descriptions of variables

Variable	Description	Detail
$lnoutput\_m$	Output	ln {Total output for maize (kg)}
$lnfer\_m$	Fertilizer	ln {Fertilizer use for maize (kg)}
$lnland\_m$	Land	ln {Area of planted land for maize (mu)}
$lnseed\_m$	Seed	ln {Quantity of seed for maize (kg)}
$lnlabor\_m$	Labor	ln {Total labor for maize (day)}
$lnfer2\_m$	Fertilizer × Fertilizer	$\frac{1}{2} \times lnfer\_m \times lnfer\_m$
$lnland2\_m$	Land × Land	$\frac{1}{2} \times lnland\_m \times lnland\_m$
$lnseed2\_m$	Seed × Seed	$\frac{1}{2} \times lnseed\_m \times lnseed\_m$
$lnlabor2\_m$	Labor × Labor	$\frac{1}{2} \times lnlabor\_m \times lnlabor\_m$
$lnferland\_m$	Fertilizer × Land	$lnfer\_m \times lnland\_m$
$lnferseed\_m$	Fertilizer × Seed	$lnfer\_m \times lnseed\_m$
$lnferlabor\_m$	Fertilizer × Labor	$lnfer\_m \times lnlabor\_m$
$lnlandseed\_m$	Land × Seed	$lnland\_m \times lnseed\_m$
$lnlandlabor\_m$	Land × Labor	$lnland\_m \times lnlabor\_m$
$lnseedlabor\_m$	Seed × Labor	$lnseed\_m \times lnlabor\_m$

households with new household heads during the research period also drop out of the analysis together with the other inconsistent entries. The filter criteria that we use on the household heads are that the gender remains the same and the yearly difference of age, as well as highest education, is between zero and two. Highest education in the dataset is measured by the number of years of school education. A range of two years is used to allow for the possibility that the survey is conducted in different months across the years, and that there might be differences in whether households calculate their ages by birthday or by calendar year. The same applies for highest education, as there might be differences in whether households measure education by academic year or by calendar year.

The most recent dataset that we receive, which comes from the same version of the questionnaire, is for the period 2004 to 2008. This is the group of data that we use in our analysis. Due to attrition, the panel is unbalanced, with a total of 4,218 observations from 894 households in five years. Although the set contains data for a few different crops, we choose to focus on maize, as it is the main crop in that area, and it has the most complete data among the crops covered by the survey. All the output and input variables are for the production of maize. As urea is the most common fertilizer in the study region, we estimate the fertilizer used for maize by first calculating the price of urea for each household using the variables of household urea expenses and total urea purchased. We then divide the total fertilizer expenses for maize by the urea price to obtain an estimate of the fertilizer quantity for maize.

In addition to Hebei province, we also receive from RCRE the data for Yunnan province. We run the analysis on this second province and include the results for comparison purposes. The data from Yunnan consist of fewer observations and we only have the data for every other year. So, our analysis on the second province is based on 1,157 observations from 397 households in three time periods: 2004, 2006, and 2008. The variables included are the same as those of Hebei province.

2.3.2 Study region

A main difference between the provinces of Hebei and Yunnan is their income levels. According to the China Agriculture Yearbook, the annual net income per capita in 2003 is 2,853 yuan for Hebei and 1,697 yuan for Yunnan. This ranks Hebei at seventh and Yunnan at 24^{th} out of the 27 provinces and autonomous regions in Mainland China (Ministry of Agriculture, 2004). At the end of our study period in 2008, the annual net income per capita is 4,293 yuan for Hebei, which remains at the seventh spot on the list. Yunnan drops one spot to 25^{th} with an annual net income per capita of 2,634 yuan (Ministry of Agriculture, 2009). Other than having a lower income per capita, the income disparity between agricultural villages and cities is much higher in Yunnan as well with a ratio of 4.5 in 2003, while Hebei has a ratio of 2.49 (State Statistical Bureau, 2003).[1] With these numbers, Yunnan has the second highest inequality in the country, while Hebei has the fourth lowest. The country average for that year is 3.11.

Maize is the main grain crop grown in both provinces, closely followed by wheat in Hebei and rice in Yunnan. The total planted area for maize in Hebei is about 2.6 million hectare, making it the second largest maize growing province in China. The corresponding area for Yunnan is about 1.1 million hectare, which is the ninth largest in the country. On the intensity of chemical fertilizer usage, the average at the country level is 0.281 ton per hectare, with Hebei having a higher usage intensity at 0.312 ton per hectare. The figure for

[1] The information of this subsection is taken from State Statistical Bureau (2003), unless otherwise stated. The focus is on the end of years 2003 and 2008 because they represent the start and the end of our study period.

Yunnan is comparatively much lower at 0.215 ton per hectare.

In a 2008 study by Boeber et al. (2009), the authors collect 14 samples of fertilizer from five villages in the southern part of Hebei Province. They find that 12 of the samples contain nitrogen levels that are different from what is labeled on the package, with four of those samples having less than 80 percent of the advertised nitrogen level.[2] The sample size of the study is too small to reach a conclusion on the severity of the problem, but it supports the claims of a few other news reports on this issue in China (Han, 2009) with the value of fake input at 23.5 million U.S. dollars in the first six months of 2011 (Wang, 2011). In a separate household survey that we conducted in 2012 with fertilizer data from 86 households in the Hebei province, we found that on average, the fertilizer samples contain only 71 percent of the nitrogen share labeled on the package.

2.3.3 Econometric model

A common method used in a production function estimation is the maximum likelihood (ML) approach, in which the efficiency term is part of the total error term, so we need the exogeneity of input use assumption and a distribution assumption for the efficiency term. These two assumptions are not needed if we have panel data and assume that the efficiency term is constant over time (Bravo-Ureta and Pinheiro, 1993). The constant efficiency assumption allows us to use the fixed effects (FE) approach, in which the fixed effects dummy for each household acts as the efficiency term of the individual household (Schmidt and Sickles, 1984). This takes the efficiency term, u, out of the total error term and the efficiency level is captured instead by the individual intercept of each household. In this case, the use of FE would prevent the endogeneity problem between input use and error term that leads to biased estimates.

Technical efficiency can be estimated as part of a production function (Bravo-Ureta and Evenson, 1994; Keil et al., 2008), or a distance function (Bruemmer et al., 2002), which can be used for the analysis of multiple outputs. As we focus on only one output, we will use the production function

[2] In our article, we use nitrogen content to represent fertilizer quality, as the main fertilizer used in the study region is urea.

approach with a translog functional form:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j \ln(X_{jit}) + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln(X_{jit}) \ln(X_{kit}) + u_i + v_{it}. \tag{2.8}$$

Y_{it} and X_{it} are the output and input use, respectively, of household i in year t. Following Reinhard et al. (1999), who estimate the production function with labor, capital, variable input, and nitrogen surplus, we include the variables of labor, land, seed, and fertilizer in our production function estimation. Although we focus on these four inputs, the analysis can be easily extended to include more inputs. The term u_i is the fixed effects dummy and captures the technical efficiency of each household. v_{it} is the stochastic error term of the production function. In an ML estimation, the $+u_i$ term becomes $-u_{it}$, where u_{it} is non-negative and reflects the inefficiency of each household.

Having inaccurate input data is comparable to the measurement error problem that produces biased estimates if the measurement error is correlated with any of the input variables, as the fertilizer quality term, z, is present in both the fertilizer variable and the error term. The bias is an attenuation bias in a univariate setting but the direction is less clear in a multivariate case (Levi, 1973). Similar to the use of validation data in analyzing measurement error bias (Bound et al., 2001), we include a fertilizer quality term, z, into the translog production function to get the unbiased estimates. We analyze the results with three different types of z characteristics: constant, random, and household-specific. In the case of constant z, the unbiased translog function is

$$\begin{aligned} lnoutput\_m_{it} &= \alpha_0 + \alpha_1(lnfer\_m_{it} + z) + \alpha_2 lnland\_m_{it} + \alpha_3 lnseed\_m_{it} \\ &+ \alpha_4 lnfwork\_total_{it} + \frac{1}{2}\alpha_{11}(lnfer\_m_{it} + z)(lnfer\_m_{it} + z) \\ &+ \frac{1}{2}\alpha_{22} lnland2\_m_{it} + \frac{1}{2}\alpha_{33} lnseed2\_m_{it} + \frac{1}{2}\beta_{44} lnfwork2\_total_{it} \\ &+ \alpha_{12}(lnfer\_m_{it} + z) lnland\_m_{it} + \alpha_{13}(lnfer\_m_{it} + z) lnseed\_m_{it} \\ &+ \alpha_{14}(lnfer\_m_{it} + z) lnfwork\_total_{it} + \alpha_{23} lnlandseed\_m_{it} \\ &+ \alpha_{24} lnlandfwork\_total_{it} + \alpha_{34} lnseedfwork\_total_{it} + u_i + v_{it}. \end{aligned} \tag{2.9}$$

Rearranging the terms, we rewrite Equation (2.9) to show the bias in regression output if we ignore the z term:

$$\begin{aligned}lnoutput\_m_{it} &= \alpha_0 + (\alpha_1 + \alpha_{11}z)lnfer\_m_{it} + (\alpha_2 + \alpha_{12}z)lnland\_m_{it} \\ &+ (\alpha_3 + \alpha_{13}z)lnseed\_m_{it} + (\alpha_4 + \alpha_{14}z)lnfwork\_total_{it} \\ &+ \frac{1}{2}\alpha_{11}lnfer2\_m_{it} + \frac{1}{2}\alpha_{22}lnland2\_m_{it} + \frac{1}{2}\alpha_{33}lnseed2\_m_{it} \\ &+ \frac{1}{2}\alpha_{44}lnfwork2\_total_{it} + \alpha_{12}lnferland\_m_{it} + \alpha_{13}lnferseed\_m_{it} \\ &+ \alpha_{14}lnferfwork\_total_{it} + \alpha_{23}lnlandseed\_m_{it} \\ &+ \alpha_{24}lnlandfwork\_total_{it} + \alpha_{34}lnseedfwork\_total_{it} \\ &+ \alpha_1 z + \frac{1}{2}\alpha_{11}z^2 + u_i + v_{it}. \qquad (2.10)\end{aligned}$$

In our regression, we first obtain the coefficients in Equation (2.8), $\boldsymbol{\beta}$, from a production function estimation. By referring to Equation (2.10), we then calculate the real coefficients, $\boldsymbol{\alpha}$:

$$\begin{aligned}\alpha_k = \beta_k - \beta_{1k}z, \text{and } \alpha_{jk} = \beta_{jk}, \\ \forall j = \{2,3,4\}, k = \{1,2,3,4\}, \text{ and } j \leq k. \qquad (2.11)\end{aligned}$$

In terms of technical efficiency, we can see that the bias is $\beta_1 z - \frac{1}{2}\beta_{11}z^2$ from Equations (2.10) and (2.11).

For the analysis on non-constant z, the solution in Equation (2.11) no longer holds, as the coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are constant across households, whereas the z term is not. So, for the scenarios where z is not constant, we use the Monte Carlo method to simulate the uncertainty in fertilizer quality. Past studies that use the Monte Carlo method to analyze uncertainty in agriculture include Babcock (1992) who simulates the uncertain conditions of weather and soil to examine their effects on optimal nitrogen applications, and Hansen et al. (1999) who simulate uncertainty in input data to analyze nitrate leaching. In our study, we use the Monte Carlo method with 1,000 repetitions to generate the different levels of fertilizer uncertainty. The simulated uncertainty levels are drawn by a random number generator of STATA from a normal distribution. As the real fertilizer content is lower than labeled on the package, we restrict the uncertainty term, z, to non-positive values only. So, after we obtain the simulation from the random number generator, we use the negative of its absolute value, creating a folded normal distribution for the uncertainty level.

In order to examine how the results respond to changes in the uncertainty levels, we make the 1,000 Monte Carlo repetitions at every level of mean in the set {-4.75, -4.50, ..., -0.25, 0}[3] with the standard deviation fixed at one. We then repeat the same procedure but by varying the standard deviation through the set {0.05, 0.10, ..., 0.95, 1} and holding the mean at zero. In other words, there are 1,000 draws of random uncertainty levels at each set of mean and standard deviation. Each draw generates a new fertilizer quality term for every observation, and a new estimation of partial elasticities and technical efficiency is performed after each draw. After the 1,000$^{\text{th}}$ draw, we have 1,000 estimates and we record the mean, the first quartile, and the third quartile of the estimates. We then change the mean or the standard deviation of the uncertainty distribution and repeat the same procedure of making 1,000 draws again. At the end, we plot in two graphs to show how the average and the interquartile range of the estimates vary with the mean and the standard deviation, respectively, of the uncertainty distribution.

The results are separated into sections based on the different characteristics of quality uncertainty, such as constant and non-constant uncertainty. The latter case is further separated by how the quality term is assigned to each observation: random or household-specific. In the case of random fertilizer quality, we simulate an uncertainty level, z_{it}, for each household in each year. We replace these z_{it} values with the household mean, z_i, for the scenario of household-specific fertilizer quality. In the latter case, the quality values vary between households, but are constant over time within each household.

2.4 Results

The main effect of adding fertilizer uncertainty is that the partial elasticity of fertilizer changes from insignificant to negative in our study region. It is possible that there are two effects causing the changes in partial elasticity. The first occurs when there is a discrepancy between real and labeled fertilizer content. This creates doubts in farmers' minds and makes the use of fertil-

[3]The mean is for the normal distribution from which we draw the fertilizer quality terms. This range of z corresponds roughly to $0.01 \leq e^z \leq 1$.

izer less effective, which explains the switch in sign of partial elasticity from insignificant to negative. The second effect happens when we increase the difference between real and labeled fertilizer content. This latter effect from the increasing scarcity of real fertilizer content leads to a rise in partial elasticity. So, the first effect from farmers' doubts has a relatively big, discrete, and negative impact on partial elasticity, while the second effect from content scarcity has a smaller, more gradual, and positive impact on partial elasticity. This could explain why there is a big negative shift in partial elasticity when we introduce uncertainty, but the elasticity increases gradually when the content discrepancy becomes greater.

If we examine each of the 1,000 Monte Carlo repetitions individually and focusing on the more realistic distribution means between -0.25 and 0, which correspond roughly to between 0.8 and 1 for the fertilizer quality multiplier, e^z, we can calculate the percentage of repetitions with a negative fertilizer partial elasticity, the results of which are shown in Table 2.2. We see that in the case

Table 2.2: Percentage of Monte Carlo repetitions with a negative fertilizer partial elasticity

Uncertainty[a]	Significance level[b]				$\frac{\partial \ln Y}{\partial \ln X} < 0$
	0.01	0.05	0.10	Total	
Random					
0.8	21.1%	18.0%	9.1%	48.2%	88.3%
1.0	23.5%	17.2%	9.6%	50.3%	88.2%
Household-specific					
0.8	98.9%	1.1%	0.0%	100.0%	100.0%
1.0	99.5%	0.5%	0.0%	100.0%	100.0%
No uncertainty	partial elasticity = 0.023; p-value = 0.272				

Notes: [a] Approximately 0.8 and 1.0 in the mean of e^z distribution.
[b] From two-sided t-test.

of random uncertainty, about 50 percent of repetitions have a negative and statistically significant partial elasticity for fertilizer, and almost 90 percent of total repetitions produce a negative estimate. The outcome is stronger in the case of household-specific uncertainty, with almost all repetitions showing a negative partial elasticity for fertilizer at the one percent level of statistical significance. This is quite a major change, considering that without uncertainty, the partial elasticity of fertilizer is statistically insignificant.

We look now more specifically at the three separate scenarios of uncertainty, with each of them having a different fertilizer quality characteristic: constant, random, and household-specific. For the first scenario, in addition to the main results, we also include the output of how we select the model and method of estimation, and compare the results with another province, Yunnan. For the subsequent two scenarios, we will just discuss the main issue of our study. We analyze the effects of varying fertilizer quality on the estimation of partial elasticities and technical efficiency, and only in Hebei.

2.4.1 No uncertainty and constant uncertainty

We estimate first a translog (TL) production function, assuming no fertilizer quality uncertainty, for the Hebei and Yunnan agricultural households using both fixed effects (FE) and maximum likelihood (ML) methods. We also check the joint significance of the interaction terms in the TL production function to see whether we can simplify the functional form to Cobb-Douglas (CD) or if we should keep the TL model. The first two numeric columns of Table 2.3 show the results of production function estimation in Hebei. The signs of most coefficients are consistent across both FE and ML methods, even though there are some differences in the statistical significance. We also run some specification tests on the estimated production function and we include the results in Table 2.4. Test (i) rejects the null hypothesis that the interaction terms have no effect, which means that using the TL functional form is an appropriate choice. Test (ii) rejects the null hypothesis that the households are fully efficient, as the efficiency component of the production function is statistically significant at one percent.

The procedure is repeated for the Yunnan province. We can see that for TL in Table 2.3, the coefficients are statistically insignificant.[4] When we analyze the joint significance of all the interaction terms, we find that it is not significant either, suggesting that the interaction terms are not necessary in the estimation of the production function. So, we estimate a CD production

[4]Unless otherwise mentioned, we measure statistical significance at the five percent level for the remainder of this article.

Table 2.3: Production function estimates

Variable	FE^h	ML^h	TL^y	CD^y
Fertilizer	-1.143^{***}	-0.258	0.413	0.051
	(0.190)	(0.170)	(0.274)	(0.046)
Land	1.564^{***}	0.496^{*}	0.046	0.689^{***}
	(0.293)	(0.258)	(0.753)	(0.081)
Seed	-0.542^{***}	-0.190	0.343	0.146^{***}
	(0.169)	(0.154)	(0.385)	(0.042)
Labor	0.590^{***}	0.611^{***}	-0.467	0.014
	(0.172)	(0.145)	(0.606)	(0.038)
Fertilizer × Fertilizer	0.172^{***}	0.019	-0.032	
	(0.039)	(0.033)	(0.058)	
Land × Land	-0.051	-0.132^{*}	-0.115	
	(0.093)	(0.076)	(0.208)	
Seed × Seed	0.012	0.004	0.000	
	(0.028)	(0.026)	(0.095)	
Labor × Labor	-0.094^{***}	-0.087^{***}	0.124	
	(0.032)	(0.028)	(0.096)	
Fertilizer × Land	-0.085^{*}	0.077^{*}	0.031	
	(0.051)	(0.044)	(0.083)	
Fertilizer × Seed	0.138^{***}	0.088^{***}	-0.064	
	(0.033)	(0.030)	(0.049)	
Fertilizer × Labor	-0.035	-0.033	-0.013	
	(0.027)	(0.023)	(0.066)	
Land × Seed	-0.114^{**}	-0.050	0.023	
	(0.048)	(0.040)	(0.120)	
Land × Labor	0.044	0.069^{**}	0.126	
	(0.040)	(0.034)	(0.133)	
Seed × Labor	-0.015	-0.042^{*}	0.003	
	(0.027)	(0.024)	(0.122)	

Notes: Standard errors are in parentheses. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.
^{h} Hebei province.
^{y} Yunnan province.

function and show the results in Table 2.3. In this case, the coefficients for both land and seed are positive and significant. Test (iii) in Table 2.4 shows that the input coefficients in the CD production function are jointly significant. As there are many interaction terms involved, direct interpretation of the results from the coefficients table does not provide much insight. Therefore, we calculate the marginal effect of each input at the mean input levels and show

Table 2.4: Specification tests of the estimated production functions

H_0		Test statistics		
		FE[h]	TL[y]	CD[y]
(i)	$\beta_{jk} = 0$	9.25***	1.41	
(ii)	$u_i = 0$	2.34***	1.32*	1.34**
(iii)	$\beta_j = 0$			50.80***

Notes: For all $j, k = \{1, 2, 3, 4\}$ and $j \leq k$. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.
[h] Hebei province.
[y] Yunnan province.

the results in Table 2.5,

$$\frac{\partial Y}{\partial X_k} = \left[\alpha_k + \sum_{j=1}^{4} \alpha_{jk} \overline{\ln X_j}\right] \left[\frac{\overline{Y}}{\overline{X_k}}\right], \quad \forall k = \{1, 2, 3, 4\}, \tag{2.12}$$

with X_1 being the true amount of fertilizer. The analysis is more straightforward in the case of CD, as there is no interaction term involved. Therefore we can simplify the estimation equation of the production function, and Equation (2.9) now becomes

$$\begin{aligned} lnoutput\_m_{it} = \alpha_0 + \alpha_1(lnfer\_m_{it} + z) + \alpha_2 lnland\_m_{it} \\ + \alpha_3 lnseed\_m_{it} + \alpha_4 lnfwork\_total_{it} + u_i + v_{it}. \end{aligned} \tag{2.13}$$

We can then expand the equation to show that there is no bias in the estimation of coefficients, as the fertilizer quality term now affects only the intercept of the production function, and not its slope:

$$\begin{aligned} lnoutput\_m_{it} = \alpha_0 + \alpha_1 lnfer\_m_{it} + \alpha_2 lnland\_m_{it} + \alpha_3 lnseed\_m_{it} \\ + \alpha_4 lnfwork\_total_{it} + \alpha_1 z + u_i + v_{it}. \end{aligned} \tag{2.14}$$

This means that the marginal effect of each input at the mean input levels is just a product of the input coefficient and the mean of output-input ratio:

$$\frac{\partial Y}{\partial X_k} = \alpha_k \left[\frac{\overline{Y}}{\overline{X_k}}\right], \quad \forall k = \{1, 2, 3, 4\}. \tag{2.15}$$

As there is no bias in the estimation of the coefficients, we can substitute β_k for α_k in Equation (2.15) when calculating the marginal effect.

The coefficient for fertilizer is insignificant in both provinces, suggesting that there is an overuse of the input. For the remaining marginal effects, land and labor are significantly positive in Hebei at the one percent level, while seed is insignificant. For Yunnan, the marginal effects of land and seed are

Table 2.5: Marginal effects at mean input levels

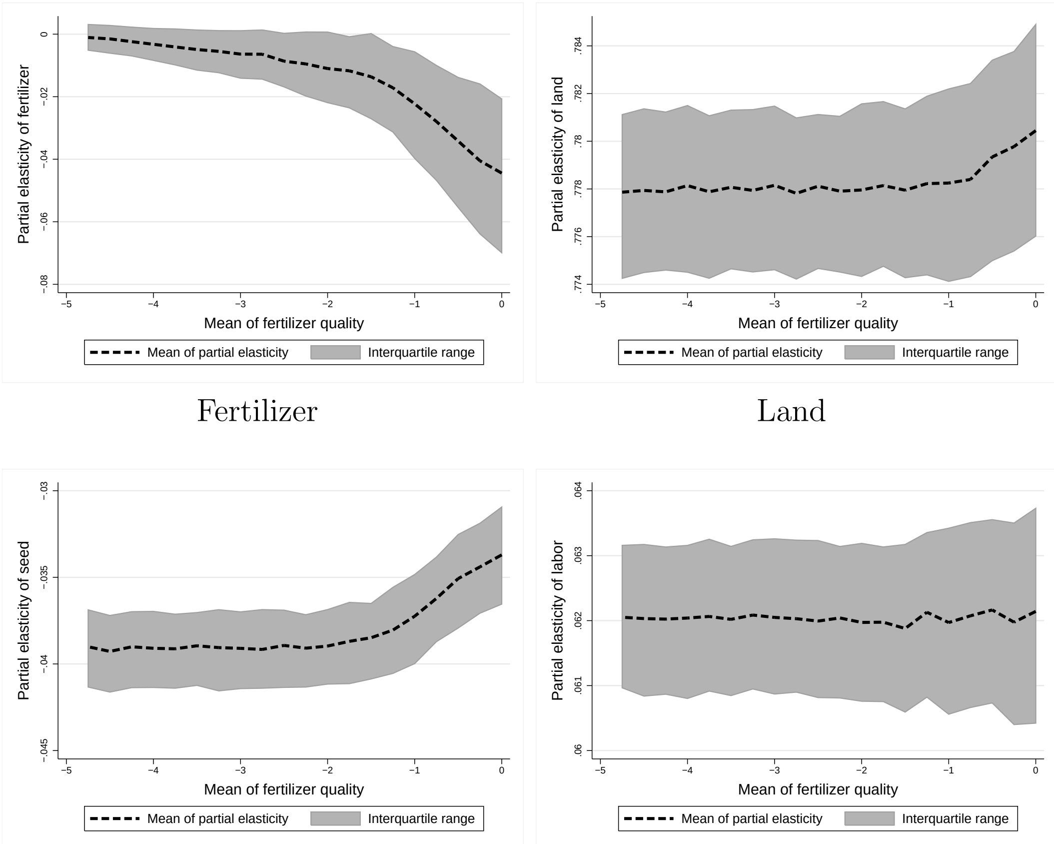
Input	FE^h	TL^y	CD^y
Fertilizer	0.034	0.082	0.083
	(0.031)	(0.093)	(0.075)
Land	5.266***	6.494***	7.152***
	(0.239)	(1.079)	(0.836)
Seed	−0.023	0.233**	0.272***
	(0.037)	(0.110)	(0.077)
Labor	0.110***	0.031	0.024
	(0.040)	(0.106)	(0.065)

Notes: Standard errors are in parentheses. Double asterisk (**) and triple asterisk (***) denote significance at 5% and 1%, respectively.
^{h} Hebei province.
^{y} Yunnan province.

positive and significant. Yunnan is a relatively isolated province with no big city nearby, whereas Hebei is next to big cities such as Beijing and Tianjin. So, the labor in Hebei has more off-farm alternatives than the labor in Yunnan. This might explain why the labor effect is insignificant in the latter province, as there is an oversupply of labor in agriculture. This view is supported by the heavy reliance of Yunnan agricultural households on own farm income, which makes up 74.18 percent of their total household income in 2003, the sixth highest in the country. The figure is only 56.09 percent for Hebei, which ranks 23rd out of the 27 provinces and autonomous regions in Mainland China (State Statistical Bureau, 2003). Partial elasticities of inputs are not affected by the lower fertilizer quality because the quality term is assumed to be constant, and it just cancels out when we look at percentage change, which is the case in calculating partial elasticities.

2.4.2 Random uncertainty

We proceed now to scenarios in which the uncertainty is not constant and the Monte Carlo method is used. After estimating the production function that includes random fertilizer quality terms, we calculate the partial elasticity of each input at the mean input levels. We then plot in Figures 2.1 and 2.2 its changes across a range of means and standard deviations, respectively, of the distribution from which we draw the fertilizer quality values. In general,

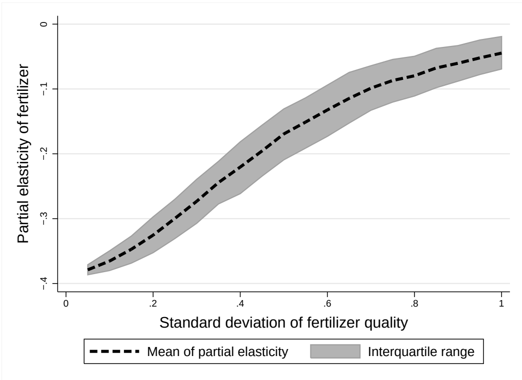


Fertilizer Land

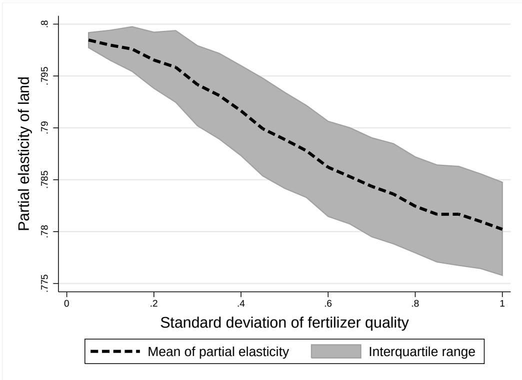
Seed Labor

Figure 2.1: Partial elasticity across a range of fertilizer quality means under the random uncertainty scenario

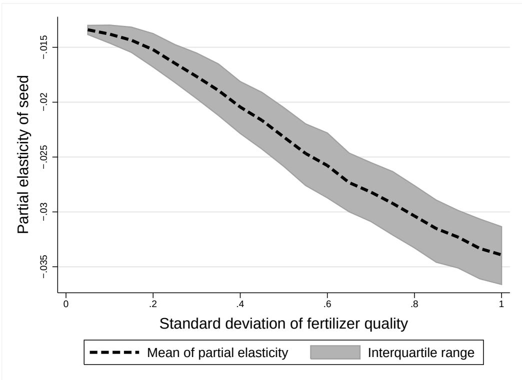
by comparing the values from Table 2.6 and Figures 2.1 and 2.2, we see that there would be an overestimation of most partial elasticities if we ignored the uncertainty in fertilizer quality. As is also shown in Table 2.6, focusing on the range between 0.8 and 1 for the fertilizer quality multiplier, the bias in the partial elasticity of seed is quite big at between 61 percent and 62 percent, but less so for both land and labor, with the magnitude of the bias being lower than 10 percent. The main problem is in the fertilizer estimate, as its



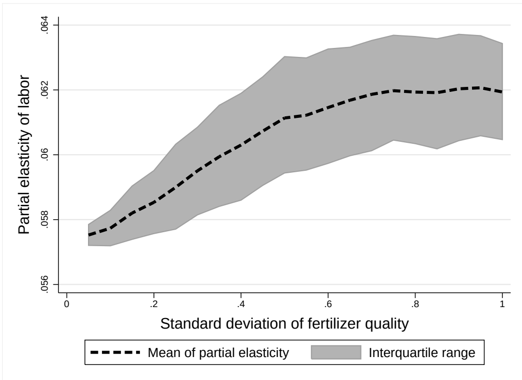
Fertilizer



Land



Seed



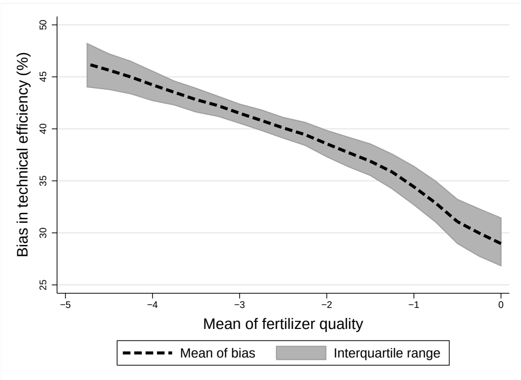
Labor

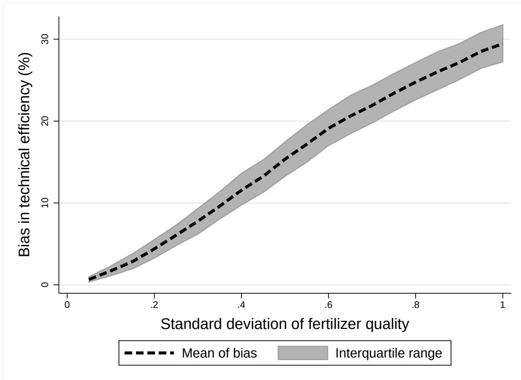
Figure 2.2: Partial elasticity across a range of fertilizer quality standard deviations under the random uncertainty scenario

partial elasticity actually switches from being insignificant, when there is no uncertainty, to negative, when there is uncertainty. This means that if we ignored the uncertainty in fertilizer quality, we might reach the misleading conclusion that fertilizer has an insignificant impact on output, when the real effect is negative. A policy implication from this outcome is that instead of continuing to subsidize the production and use of fertilizer, the government should channel the fund to help set up a third party testing service for fertilizer in the market or a sector-wide monitoring body. It can also pass a legislation that gives a quality label to the products that meet the standards.

As the mean of the distribution becomes more negative, i.e. when the real fertilizer quality becomes lower, there is an increase in the partial elasticity of fertilizer. This is an expected outcome because as the real fertilizer amount decreases, the input becomes scarcer and has a greater impact. The trend is opposite in the case of seed and land, but labor stays relatively constant. In the case where we vary the standard deviation of the fertilizer quality distribution, the partial elasticity of fertilizer increases with the deviation. This is because there are more observations of lower fertilizer quality when the standard deviation is big.[5] So, similar to the explanation given in varying the mean, the input is scarcer and has a greater effect on output.

Uncertainty in fertilizer quality also affects the estimation of technical efficiency. Figure 2.3 shows the magnitude of bias for an average household[6] if we estimate technical efficiency with the assumption that the fertilizer content is as labeled on the package. Making the no uncertainty assumption leads





Mean Standard deviation

Figure 2.3: Bias in technical efficiency estimate of an average household across a range of fertilizer quality means and standard deviations under the random uncertainty scenario

to an overestimation of technical efficiency. The upward bias becomes more severe with an increasing standard deviation and a more negative mean. This shows that a higher variation in the quality lowers technical efficiency, and a bigger discrepancy between the real and labeled fertilizer content also has the same negative effect. If we concentrate on the range between 0.8 and 1 in e^z,[7] we see that ignoring the real content of fertilizer results in overestimating the technical efficiency of an average household by about 30 percent.

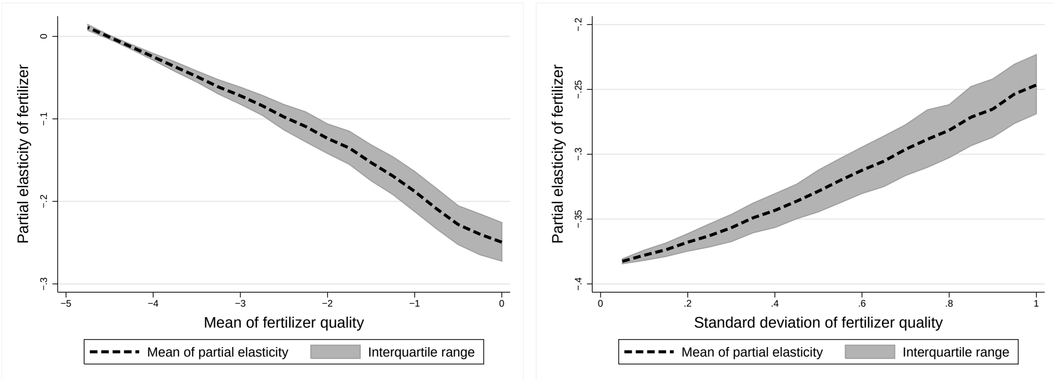
[5]This is because the quality term has a folded normal distribution with only negative values.

[6]In this case, average household refers to a household with mean technical efficiency.

[7]This corresponds to the region between -0.25 and 0 in the 'Mean' graph of Figure 2.3.

2.4.3 Household-specific uncertainty

In this part, we impose the assumption that fertilizer quality is household-specific. So, the fertilizer quality term is allowed to vary across households, but not time. We plot in Figure 2.4 the changes of partial elasticity over a range of means and standard deviations, respectively, of the distribution from which we draw the fertilizer quality values. Similar to the scenario of random



Mean Standard deviation

Figure 2.4: Partial elasticity of fertilizer across a range of fertilizer quality means and standard deviations under the household-specific uncertainty scenario

fertilizer quality, the bias is quite big for fertilizer, with its partial elasticity switching from being insignificant to negative after we include the discrepancy in real fertilizer content.

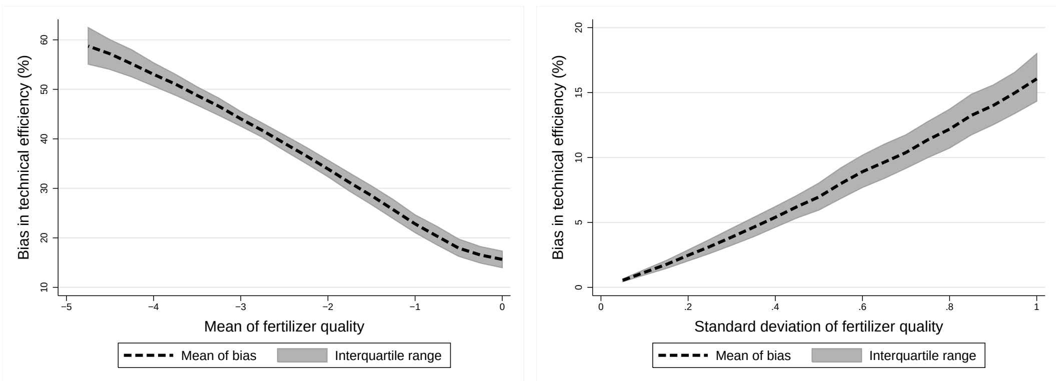
Table 2.6 shows the difference in partial elasticity estimates between random uncertainty and household-specific uncertainty. Concentrating on the distribution means at 0.8 and 1 for the fertilizer quality multiplier, we find that the difference in fertilizer estimates between the no uncertainty scenario and the with uncertainty scenarios, i.e. the bias, is the greatest with household-specific uncertainty. This is not surprising considering that random uncertainty has a higher variation than household-specific uncertainty, and we can see from Figures 2.2 and 2.4 that the estimation bias for fertilizer decreases with standard deviation. Note that the figures show the partial elasticity of fertilizer increasing with standard deviation, but as it has negative values, and the elasticity for the no uncertainty scenario is insignificant, the bias is actually decreasing.

Table 2.6: Partial elasticity with and without uncertainty

Uncertainty[a]	Input			
	Fertilizer	Land	Seed	Labor
Random				
0.8	−0.041	0.780	−0.034	0.062
1.0	−0.044	0.780	−0.034	0.062
Household-specific				
0.8	−0.240	0.780	−0.018	0.059
1.0	−0.249	0.780	−0.018	0.058
No uncertainty	0.023	0.799	−0.013	0.057

Note: [a] Approximately 0.8 and 1.0 in the mean of e^z distribution.

Household-specific uncertainty in the fertilizer quality also affects the estimation of technical efficiency. Figure 2.5 shows the magnitude of bias for an average household if we estimate technical efficiency with the assumption that there is no uncertainty in fertilizer content. As the bias becomes more



Mean Standard deviation

Figure 2.5: Bias in technical efficiency estimate of an average household across a range of fertilizer quality means and standard deviations under the household-specific uncertainty scenario

severe with an increasing standard deviation, it is to be expected that the bias is higher in the random uncertainty scenario than in the household-specific scenario. This is confirmed by comparing the 'Mean' graphs in Figures 2.3 and 2.5. For the approximate range between 0.8 and 1 in e^z, the no uncertainty assumption results in overestimating the technical efficiency of an average household by about 16 percent.

We rerun the analysis of the more plausible household-specific scenario for robustness testing using two other distribution assumptions for the fertilizer quality terms: exponential and gamma.[8] In both cases, we analyze the changes in partial elasticities and technical efficiency as we vary the mean and standard deviation of the distribution, and we find that the main results remain consistent. The partial elasticity of fertilizer is negative at the realistic range of fertilizer quality multiplier, average $e^z \geq 0.02$, and technical efficiency is lower with the inclusion of uncertainty. The reduction in technical efficiency becomes greater when the difference between real and labeled fertilizer content increases. One thing to note is that even though we mention a 'realistic' range of fertilizer quality in our article, that is just to illustrate the magnitude of bias at that range. The main finding of our study, that uncertainty in fertilizer quality leads to an overestimation on the impact of fertilizer, does not depend on where the 'realistic' range is.

2.5 Conclusions

Questionable fertilizer quality is a problem in countries of different regions, such as Bangladesh, Cambodia, China, Nigeria, Tanzania and Vietnam, where the real fertilizer content might not be the same as the labeled content. Our article shows that ignoring this lower content could lead to bias in the estimates of production functions. We also show how to estimate the magnitude of the bias. Using panel data of household surveys from the Hebei province of China, we calculate the bias across a range of fertilizer content under three separate scenarios. Each scenario assumes a different characteristic for the uncertainty in fertilizer content: constant, random, and household-specific. For the more plausible scenarios of non-constant uncertainty, we analyze the estimation bias using the Monte Carlo method. The fertilizer quality terms are allowed to vary over households and time for the random scenario, but are assumed to be constant over time within a household for the household-specific scenario. In our article, we randomly assign the quality values to households,

[8] We take the negative of the generated values, as the real fertilizer content is lower than labeled.

but an extension to the analysis could be carried out so that the assignment of fertilizer quality is based on other factors, such as wealth, education, or geographical location.

The main finding in the non-constant uncertainty scenarios is that the partial elasticity of fertilizer switches from insignificant to negative with the inclusion of uncertainty. This means that a negative fertilizer partial elasticity is mistaken as insignificant due to the bias. The problem is especially pronounced in the household-specific scenario, in which almost all of the 1,000 Monte Carlo repetitions produce a negative partial elasticity of fertilizer at the one percent significance level. The technical efficiency estimate is biased too, if the real fertilizer content is not the same as that labeled on the package. The assumption of no uncertainty overestimates technical efficiency by 30 percent and 16 percent, respectively, for the random and household-specific fertilizer quality scenarios.

This article focuses on fertilizer with lower than reported content, but the same method can also be applied to other inputs, when the true content of inputs is not the same as labeled. Some examples include the mixture of fertile and infertile seeds, and pesticides that have been combined with less effective chemicals. In all these cases, the uncertainty is one-sided and negative, which is different from the two-sided uncertainty that usually exists in other measurement error situations.

Low quality fertilizer seems to be a problem in the study region as well as in other countries. Future studies and surveys could be carried out to examine how it affects household production decisions, and testing of fertilizer content could also be incorporated into market and household surveys to better understand the severity of the problem and its impact. In addition, due to a lack of data for our empirical analysis, we do not include risk behavior in our study. According to a study by Chavas and Holt (1996) on maize and soybean production in the U.S., most farmers are risk averse and show a decreasing absolute risk aversion with wealth, which is a finding supported by Bar-Shira et al. (1997). So, future research can also look at how farmers' attitudes towards risk affect the results.

Poorly regulated fertilizer not only leads to bias in estimation and reduction in technical efficiency, it also has food security implications, as risk is found to have a negative effect on food supply (Just, 1974; Lin, 1977). Therefore, it is important to improve government supervision and regulation on fertilizer. It would help to have independent testing facilities carry out regular examinations of fertilizer content in the market. Extension services can also play a role in testing the fertilizer, in addition to raising the awareness of farm households on this issue and recommending better quality fertilizer to them.

The negative partial elasticity for fertilizer shows that there might be a need to review the fertilizer policy in China, and other countries affected by poor quality fertilizer. Offering tax cuts and subsidies to manufacturers helps to lower the fertilizer price, but it also encourages the use of more fertilizer and leads to a waste of subsidies on an input that has been overused. This is not only a waste of valuable resources but also causes environmental (He et al., 2007; Zhang et al., 2008; Liu et al., 2013) and health problems, e.g. through pollution of ground water (Chen et al., 2005; Zhen et al., 2005; Jiang and Jiang, 2013). In addition, the policy also encourages more small-scale fertilizer manufacturers to enter the market and this makes quality control of the products even more difficult. According to a study by Cheng et al. (2010), there are about 1,000 ammonia fertilizer manufacturers in China with 800 of them producing less than the sector-wide average production of 20,000 tons per year. So, the focus of policy should switch from lowering the fertilizer price to having stricter quality control and increasing the quality of fertilizer by, for example, passing a legislation that gives quality labels to satisfactory products and helping to set up a sector-wide monitoring body.

2.6 References

Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1):21–37.

Babcock, B. A. (1992). The effects of uncertainty on optimal nitrogen applications. *Review of Agricultural Economics*, 14(2):271–280.

Babcock, B. A. and Hennessy, D. A. (1996). Input demand under yield and revenue insurance. *American Journal of Agricultural Economics*, 78(2):416–427.

Bar-Shira, Z., Just, R. E., and Zilberman, D. (1997). Estimation of farmers' risk attitude: An econometric approach. *Agricultural Economics*, 17(2-3):211–222.

Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2):325–332.

Battese, G. E., Rambaldi, A. N., and Wan, G. H. (1997). A stochastic frontier production function with flexible risk properties. *Journal of Productivity Analysis*, 8:269–280.

Benjamin, D., Brandt, L., and Giles, J. (2005). The evolution of income inequality in rural China. *Economic Development and Cultural Change*, 53(4):769–824.

Boeber, C., Kuehl, Y., and Rumbaur, C. (2009). Land degradation in the North China Plain (NCP): Recent evidence, farmers concerns and policy implications. In *International Association of Agricultural Economists conference*, Beijing, China.

Bound, J., Brown, C., and Mathiowetz, N. (2001). Measurement error in survey data. In Heckman, J. J. and Leamer, E., editors, *Handbook of Econometrics*, chapter 59, pages 3705–3843. Elsevier, The Netherlands.

Bravo-Ureta, B. E. and Evenson, R. E. (1994). Efficiency in agricultural production: The case of peasant farmers in eastern Paraguay. *Agricultural Economics*, 10(1):27–37.

Bravo-Ureta, B. E. and Pinheiro, A. E. (1993). Efficiency analysis of developing country agriculture: A review of the frontier function literature. *Agricultural and Resource Economics Review*, 22(1):88–101.

Bruemmer, B., Glauben, T., and Thijssen, G. (2002). Decomposition of productivity growth using distance functions: The case of dairy farms in three European countries. *American Journal of Agricultural Economics*, 84(3):628–644.

Chavas, J.-P. and Holt, M. T. (1996). Economic behavior under uncertainty: A joint analysis of risk preferences and technology. *The Review of Economics and Statistics*, 78(2):329–335.

Chen, A. Z., Huffman, W. E., and Rozelle, S. (2003). Technical efficiency of Chinese grain production: A stochastic production frontier approach. In *American Agricultural Economics Association annual meeting*, Montreal, Canada.

Chen, J., Tang, C., Sakura, Y., Yu, J., and Fukushima, Y. (2005). Nitrate pollution from agriculture in different hydrogeological zones of the regional groundwater flow system in the North China Plain. *Hydrogeology Journal*, 13(3):481–492.

Chen, Z., Huffman, W. E., and Rozelle, S. (2009). Farm technology and technical efficiency: Evidence from four regions in China. *China Economic Review*, 20(2):153–161.

Cheng, C., Shi, Y., and Wen, T. (2010). The real cost of nitrogen fertilizer. Technical report, School of Agriculture and Rural Development, Renmin University of China.

Denbaly, M. and Vroomen, H. (1993). Dynamic fertilizer nutrient demands for corn: A cointegrated and error-correcting system. *American Journal of Agricultural Economics*, 75(1):203–209.

Fan, S. (1991). Effects of technological change and institutional reform on production growth in Chinese agriculture. *American Journal of Agricultural Economics*, 73(2):266–275.

Fernandez, C., Koop, G., and Steel, M. F. J. (2002). Multiple-output production with undesirable outputs: An application to nitrogen surplus in agriculture. *Journal of the American Statistical Association*, 97(458):432–442.

Fishel, F. M. (2009). The global increase in counterfeit pesticides. Institute of Food and Agricultural Sciences, University of Florida. Available at `http://edis.ifas.ufl.edu/pdffiles/PI/PI21000.pdf`. Accessed July 1, 2013.

Fraser, P., Chilvers, C., Beral, V., and Hill, M. J. (1980). Nitrate and human cancer: A review of the evidence. *International Journal of Epidemiology*, 9(1):3–12.

Fuglie, K. O. (2010). Total factor productivity in the global agricultural economy: Evidence from FAO data. In Alston, J. M., Babcock, B. A., and Pardey, P. G., editors, *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, chapter 4, pages 63–95. The Midwest Agribusiness Trade Research and Information Center, Iowa.

Hamaguchi, T. (2011). Awareness raising activities on proper selection and use of chemical fertilizers have been started. Japan International Cooperation Agency. Available at `http://www.jica.go.jp/project/english/cambodia/006/news/general/110617.html`. Accessed July 1, 2013.

Han, P. (2009). China cracks down on shoddy fertilizers, seeds. Chinese Government's Official Web Portal. Available at `http://english.gov.cn/2009-01/06/content_1196983.htm`. Accessed July 1, 2013.

Hansen, S., Thorsen, M., Pebesma, E. J., Kleeschulte, S., and Svendsen, H. (1999). Uncertainty in simulated nitrate leaching due to uncertainty in input data. A case study. *Soil Use and Management*, 15(3):167–175.

He, C.-E., Liu, X., Fangmeier, A., and Zhang, F. (2007). Quantifying the total airborne nitrogen input into agroecosystems in the North China Plain. *Agriculture, Ecosystems & Environment*, 121(4):395–400.

Henshaw, C. (2011). Fake pesticides are a growing danger. Wall Street Jounal. Available at `http://www.sej.org/headlines/fake-pesticides-are-growing-danger`. Accessed July 1, 2013.

Hu, K., Huang, Y., Li, H., Li, B., Chen, D., and White, R. E. (2005). Spatial variability of shallow groundwater level, electrical conductivity and nitrate concentration, and risk assessment of nitrate contamination in North China Plain. *Environment International*, 31(6):896–903.

Huang, J. and Rozelle, S. (1995). Environmental stress and grain yields in China. *American Journal of Agricultural Economics*, 77(4):853–864.

Jiang, Y. and Jiang, Q. (2013). North China Plain groundwater: More than 70 percent unfit for human touch. Institute of Hydrogeology & Environmental Geology, China Academy of Geological Sciences. Available at `http://chinawaterrisk.org/notices/north-china-plain-groundwater-70-unfit-for-human-touch/`. Accessed July 1, 2013.

Just, R. E. (1974). An investigation of the importance of risk in farmers' decisions. *American Journal of Agricultural Economics*, 56(1):14–25.

Keil, A., Zeller, M., Wida, A., Sanim, B., and Birner, R. (2008). What determines farmers' resilience towards ENSO-related drought? An empirical assessment in Central Sulawesi, Indonesia. *Climatic Change*, 86(3):291–307.

Kumbhakar, S. C. (1993). Production risk, technical efficiency, and panel data. *Economics Letters*, 41(1):11–16.

Lamb, R. L. (2003). Fertilizer use, risk, and off-farm labor markets in the semi-arid tropics of India. *American Journal of Agricultural Economics*, 85(2):359–371.

Levi, M. D. (1973). Errors in the variables bias in the presence of correctly measured variables. *Econometrica*, 41(5):985–986.

Lin, J. Y. (1987). The household responsibility system reform in China: A peasant's institutional choice. *American Journal of Agricultural Economics*, 69(2):410–415.

Lin, J. Y. (1992). Rural reforms and agricultural growth in China. *The American Economic Review*, 82(1):34–51.

Lin, W. (1977). Measuring aggregate supply response under instability. *American Journal of Agricultural Economics*, 59(5):903–907.

Liu, X., Zhang, Y., Han, W., Tang, A., Shen, J., Cui, Z., Vitousek, P., Erisman, J. W., Goulding, K., Christie, P., Fangmeier, A., and Zhang, F. (2013). Enhanced nitrogen deposition over China. *Nature*, 494(7438):459–462.

Liverpool-Tasie, S., Olaniyan, B., Salau, S., and Sackey, J. (2010). A review of fertilizer policy issues in Nigeria. Working paper no. 0019, Nigeria Strategy Support Program, International Food Policy Research Institute (IFPRI).

Ministry of Agriculture, P. R. C. (2004). *China Agriculture Yearbook 2004*. China Agriculture Press, Beijing.

Ministry of Agriculture, P. R. C. (2009). *China Agriculture Yearbook 2008*. China Agriculture Press, Beijing.

Mwakalebela, L. (2012). Government declares war on fake fertilizer dealers. Tanzania Daily News. Available at `http://dailynews.co.tz/index.php/parliament-news/7122-government-declares-war-on-fake-fertilizer-dealers`. Accessed July 1, 2013.

Reinhard, S., Lovell, C. A. K., and Thijssen, G. (1999). Econometric estimation of technical and environmental efficiency: An application to Dutch dairy farms. *American Journal of Agricultural Economics*, 81(1):44–60.

Schmidt, P. and Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business & Economic Statistics*, 2(4):367–374.

SriRamaratnam, S., Bessler, D. A., Rister, M. E., Matocha, J. E., and Novak, J. (1987). Fertilization under uncertainty: An analysis based on producer yield expectations. *American Journal of Agricultural Economics*, 69(2):349–357.

State Statistical Bureau, P. R. C. (2003). *China Rural Statistical Yearbook 2003*. China Statistics Press, Beijing.

Tambwe, A. (2013). Grappling with challenges of fake seeds. Tanzania Standard Newspapers. Available at `http://www.dailynews.co.tz/index.php/features/popular-features/18923-grappling-with-challenges-of-fake-seeds`. Accessed July 1, 2013.

Tian, W. and Wan, G. H. (2000). Technical efficiency and its determinants in China's grain production. *Journal of Productivity Analysis*, 13(2):159–174.

Viet Nam News (2010). Officials warn of low-quality fertilizer. AccessMyLibrary. Available at `http://www.accessmylibrary.com/article-1G1-229054286/vietnam-officials-warn-low.html`. Accessed July 1, 2013.

Wan, Y., Ju, X., Ingwersen, J., Schwarz, U., Stange, C. F., Zhang, F., and Streck, T. (2009). Gross nitrogen transformations and related nitrous oxide emissions in an intensively used calcareous soil. *Soil Science Society of America Journal*, 73(1):102–112.

Wang, G. (2011). China cracks down on counterfeit seeds, pesticides. Xinhua News Agency. Available at `http://news.xinhuanet.com/english2010/china/2011-05/19/c_13883191.htm`. Accessed July 1, 2013.

Wang, J., Cramer, G. L., and Wailes, E. J. (1996a). Production efficiency of Chinese agriculture: Evidence from rural household survey data. *Agricultural Economics*, 15(1):17–28.

Wang, Q., Halbrendt, C., and Johnson, S. R. (1996b). Grain production and environmental management in China's fertilizer economy. *Journal of Environmental Management*, 47(3):283–296.

Wik, M., Pingali, P., and Broca, S. (2008). Global agricultural performance: Past trends and future prospects. Background paper for the World Development Report 2008, The World Bank.

Young, A. (2000). The razor's edge: Distortions and incremental reform in the People's Republic of China. *The Quarterly Journal of Economics*, 115(4):1091–1135.

Zahur, A. (2010). Spurious fertilizers: A threat to agriculture. The Daily Star. Available at `http://www.thedailystar.net/newDesign/news-details.php?nid=125044`. Accessed July 1, 2013.

Zellner, A., Kmenta, J., and Dreze, J. (1966). Specification and estimation of Cobb-Douglas production function models. *Econometrica*, 34(4):784–795.

Zhang, Y., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2008). Nitrogen inputs and isotopes in precipitation in the North China Plain. *Atmospheric Environment*, 42(7):1436–1448.

Zhen, L., Routray, J. K., Zoebisch, M. A., Chen, G., Xie, G., and Cheng, S. (2005). Three dimensions of sustainability of farming practices in the North China Plain: A case study from Ningjin county of Shandong province, PR China. *Agriculture, Ecosystems & Environment*, 105(3):507–522.

Zhen, L., Zoebisch, M. A., Chen, G., and Feng, Z. (2006). Sustainability of farmers' soil fertility management practices: A case study in the North China Plain. *Journal of Environmental Management*, 79(4):409–419.

Chapter 3

Wealth effect in the presence of uncertainty on input quality: The case of fertilizer

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Abstract

Previous studies of wealth effect on fertilizer use have produced mixed results on the direction of the impact. Our article looks at this issue from a different perspective by considering the presence of doubts, such as on the effect of fertilizer use or on the true content of fertilizer. The theoretical model shows that there could be different responses between the high wealth and low wealth groups. The richer farmers can afford to use more of the input. However, as the low wealth farmers are less able to cope with a shortfall in output, they might apply more fertilizer to compensate for the potential lack of quality. We analyze the wealth effect using household production panel data from two provinces of China, one rich and one poor. The results show that the direction of the wealth effect is indeed different between the two provinces. Furthermore

the effect changes within the same province when we move from one end of the wealth scale to the other.

3.1 Introduction

Fertilizer application has been on a growing trend in the past few decades (Wik et al., 2008). Its overuse not only leads to resource wastage, but also causes environmental degradation and health problems (Fraser et al., 1980; Hu et al., 2005; He et al., 2007; Zhang et al., 2008; Shen et al., 2009; Liu et al., 2013). However, the rise in usage is not uniform throughout the world as there are also countries where the input is underused. Fertilizer use in early 2000s was almost 200kg per hectare in East Asia and Pacific but was below 25kg per hectare in Sub-Saharan Africa (Wik et al., 2008).

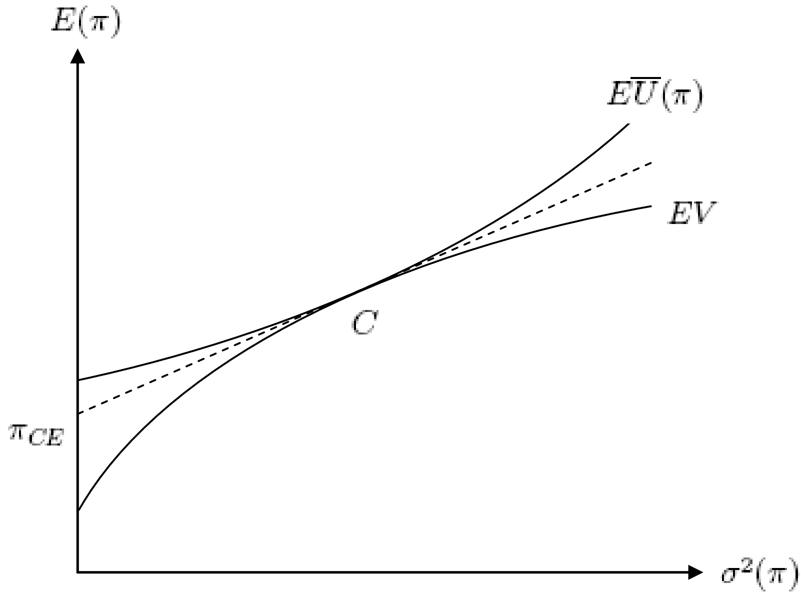
A focus of the literature has been on trying to identify the factors determining the level of fertilizer use in order to understand why there is different intensity in application rate among farmers (Babcock and Hennessy, 1996; Alem et al., 2010; Duflo et al., 2011). One of the factors considered is the wealth level of farmers. However, the conclusions reached from empirical studies in this area of research are mixed. Abdoulaye and Sanders (2005) and Lamb (2003) find that wealth has a positive effect on fertilizer use, but in the latter the effect disappears when fixed effect is added. On the other hand, Kaliba et al. (2000) find that the wealth impact on fertilizer application is negative while Ariga et al. (2008) show that the effect is insignificant. We look at the issue from a different perspective by including the presence of doubts on input quality. This differs from previous studies on uncertainty and fertilizer use as they focus on uncertainty in output, weather and soil quality (Babcock, 1992; Isik and Khanna, 2003; Rajsic et al., 2009; Paulson and Babcock, 2010), while we focus on uncertainty in the purchased input itself. Our article shows that it is possible to reconcile the conflicting findings on wealth impact when there is input uncertainty. For example, farmers might have doubts on the effectiveness of fertilizer in societies where fertilizer use is not widespread, or there might be doubts on the true content of fertilizer, especially in places affected by uncertainty in quality. The problem of low quality or fake fertilizer seems to be quite prevalent with occurrences in countries of different regions such as Bangladesh (Zahur, 2010), Cambodia (Hamaguchi, 2011), China (Wang, 2011), Nigeria (Liverpool-Tasie et al., 2010), Tanzania (Mwakalebela, 2012) and Vietnam (Viet Nam News, 2010).

We incorporate uncertainty into our model and derive the optimal level of fertilizer that a farmer would choose in this situation. We then analyze how the farmer's wealth affects the optimal outcome by looking at the comparative statics, before and after adding two constraints that capture respectively the ability of a farmer to purchase the inputs and to cover for own household consumption using current wealth. The purpose of this is to look at how the decision of a low wealth household differs from that of a high wealth household as the latter is more able to cope with a big drop in output, in case of fake or low quality fertilizer. In our empirical study, we construct a wealth index and examine the impact of wealth on fertilizer application using the household panel data of two provinces in China: Hebei and Yunnan. The former is one of the richest provinces in China while the latter is one of the poorest.

3.2 Model

We first construct a simple two input model with no uncertainty where π is profit, F is fertilizer and X is the other input: $\pi = ph(F, X) - qF - rX$, with $h(\cdot)$ being the production function and p, q and r being the prices of output, fertilizer and the other input respectively. The first order condition with respect to fertilizer is $ph_F - q = 0$.

We then add an uncertainty term, ϵ, into the model to capture the uncertainty in fertilizer content. The production function is now $h(\epsilon F, X)$ with ϵF being the real content of the fertilizer, where $0 \leq \epsilon \leq 1$. If $\epsilon = 0$, the fertilizer is fake, but if $\epsilon = 1$, the fertilizer content is as labeled on the package. The expected value of profit is $E(\pi) = pE[h(\epsilon F, X)] - qF - rX$ with a variance of $\sigma^2(\pi) = p^2\sigma^2(h)$. We follow Robison and Barry (1987) and incorporate risk behavior into our analysis using the expected value - variance (EVV) method, which maximizes the certainty equivalent (CE) expression. The main advantage of this approach is its relative ease in deriving the optimal outcome and performing equilibrium analysis (Robison and Barry, 1987, pp. 73–75). This fits our main focus of analyzing how wealth level affects the equilibrium amount of fertilizer use. Figure 3.1 illustrates how the certainty equivalent of profit is derived. Robison and Barry represent the slope of the optimal solution



Source: Robison and Barry (1987, p. 74)

Figure 3.1: Expected value - variance (EVV) approach to uncertainty analysis. $E\overline{U}(\pi)$ is the isoexpected utility function representing the combinations of expected value and variance that produce the same level of expected utility. The EV curve captures the set of choices that are efficient, i.e. those with the minimum variance among all the possible choices. The optimal solution is at the point the two functions touch, which is point C in the figure. A dotted line that passes through point C and has the same slope as the tangency of the two curves crosses the y-axis at point π_{CE}. The point has a zero variance and is thus the certainty equivalent of profit.

with the term $\frac{\lambda}{2}$ to facilitate the process of equilibrium analysis. λ is positive for a risk averse individual and increases with the level of risk aversion. The optimization problem can then be represented by the objective function of $\max \pi_{CE} = E(\pi) - \frac{\lambda}{2}\sigma^2(\pi)$, which means maximizing the certainty equivalent of profit subject to the equality in slope of the two functions, $E\overline{U}$ and EV. Following the EVV approach, the objective function of our analysis becomes $\max \pi_{CE} = pE[h(\epsilon F, X)] - qF - rX - \frac{\lambda}{2}p^2\sigma^2(h)$.

There are two conditions that reflect the constraints faced by the households. First is the affordability of inputs:

$$qF + rX \leq W_0, \tag{3.1}$$

where W_0 is the initial wealth. This constraint is likely to be binding only for households with a very low wealth level. In addition to the affordability issue, farmers also need to produce at least a certain amount of output, either for own consumption or for sale in order to buy some other products. The absolute minimum amount that they need to produce will depend on their current level of wealth. If they are affluent, they can use their existing wealth to cover for any shortfall in output. Therefore we add a constraint to capture this situation:

$$\pi + W_0 \geq \overline{W}, \tag{3.2}$$

where $\overline{W}$ is the total wealth needed to pay for consumption. Note that $\overline{W}$ in this case is not strictly the amount needed for survival. It can be a level of wealth that is higher; a level that the farmer feels is needed for the basic consumption of the family, such as education or more nutritious food for the children. In our article we treat $\overline{W}$ as fixed, but it can also be made into a variable that depends on the characteristics of the farmers. However, that is beyond the scope of our study and so we leave it as a possible future extension to the topic.

If the initial wealth of a farmer's household is high enough, i.e. W_0 is much greater than input costs and $\overline{W}$, the constraints become non-binding because the existing wealth is enough to cover for inputs and the potential shortfall in profit caused by inferior fertilizer quality. The first order condition with respect to fertilizer is then

$$pE(\epsilon h_F) - q - \frac{\lambda}{2} p^2 \frac{\partial \sigma^2}{\partial F} = 0. \tag{3.3}$$

The arguments of the production function are suppressed to simplify the notation. Applying implicit function theorem on Equation (3.3), we examine how farmers' risk behavior affects fertilizer use:

$$\frac{\partial F}{\partial \lambda} = \frac{-p^2 \frac{\partial \sigma^2}{\partial F}}{-2pE(\epsilon^2 h_{FF}) + \lambda p^2 \frac{\partial \sigma^4}{\partial^2 F}}. \tag{3.4}$$

Before determining the sign of the derivative, we need to form an assumption on whether fertilizer is a risk increasing or decreasing input. Papers on this topic in the literature generally suggest that fertilizer use leads to greater risk (Just and Pope, 1978; Love and Buccola, 1991; Roosen and Hennessy, 2003).

In addition, the uncertainty in fertilizer content also increases the risk of using it. With that assumption, $\frac{\partial \sigma^2}{\partial F}$ is positive and the numerator in Equation (3.4) is negative. As h_{FF} is less than zero due to diminishing marginal returns, the denominator becomes positive if the risk of fertilizer use changes at a constant or increasing rate. This means that a risk averse farmer uses less fertilizer because it is a risk increasing input. However, if the rate of change decreases with higher fertilizer use, the effect of risk behavior becomes ambiguous.

In order to analyze the wealth effect on fertilizer use, we sum up both its direct and indirect components:

$$\frac{dF}{dW_0} = \frac{\partial F}{\partial W_0} + \frac{\partial F}{\partial \lambda} \times \frac{\partial \lambda}{\partial W_0}. \tag{3.5}$$

Constraints in Equations (3.1) and (3.2) are non-binding for farmers with high wealth, so the direct wealth effect is negligible and most of the total wealth effect comes from the indirect component, which is obtained from multiplying the risk effect in Equation (3.4) with a term that measures how risk behavior changes with wealth. The sign of $\frac{\partial \lambda}{\partial W_0}$ depends on the risk pattern of the farmers with it being respectively positive, zero or negative, for farmers with increasing, constant or decreasing absolute risk aversion with wealth (Robison and Barry, 1987, p. 80).

The situation above refers to the group of farmers that are wealthier. For those who are unable to use their existing wealth to cover shortfalls in output, the binding condition they face is

$$pE(h) - qF - rX - \frac{\lambda}{2} p^2 \sigma^2 + W_0 = \overline{W}, \tag{3.6}$$

after substituting into Equation (3.2) the certainty equivalent of profit. From Equation (3.6), we solve for the effect of risk behavior on fertilizer use:

$$\frac{\partial F}{\partial \lambda} = \frac{p^2 \sigma^2}{2pE(\epsilon h_F) - 2q - \lambda p^2 \frac{\partial \sigma^2}{\partial F}}. \tag{3.7}$$

The numerator in Equation (3.7) is positive so the direction of the effect depends on the relative magnitude of the three terms in the denominator. The first reflects the marginal revenue product of the input, the second is the input price, and the third captures the risk changing property of the input. If the first term is larger than the other two terms, greater risk aversion would lead to higher fertilizer use even if the input is risk increasing. This is opposite to the outcome from the previous scenario of non-binding constraint as in that case a risk averse farmer uses less fertilizer when it is a risk increasing input. It makes sense intuitively because in the presence of doubts, a risk averse low wealth farmer will apply more fertilizer to make sure that at least a certain amount of content is present in the ground. This is to reduce the likelihood that the crop output will dip below the absolute minimum needed. However, this rise in usage only happens if the marginal revenue product of the input is high enough to overcome the downward effect that a risk increasing input has on a risk averse farmer.

Finally, the constraint in Equation (3.1) is binding for the group of poorest farmers and the condition they face is $qF + rX = W_0$. The total wealth effect for them is thus dominated by the direct component, which is $\frac{\partial F}{\partial W_0} = \frac{1}{q}$. The effect is positive because the wealthier of these farmers can afford to buy more fertilizer.

3.3 Data

The data we use for our empirical analysis are taken from a panel dataset of household surveys provided by the Research Center for Rural Economy (RCRE) of China. We decide to focus on household farms as they are more likely to be affected by the fertilizer quality problem due to their lack of buying power and instruments for fertilizer testing. RCRE started data collection in 1986, but the survey questionnaire has gone through several changes over the years. The most recent data from the same version of questionnaire that we obtained is for the Hebei province of China for a period of five years from 2004 to 2008. Hebei is located in the North China Plain and is a relatively high income province, ranking seventh among the 27 provinces and autonomous regions in Mainland China with an annual net income per capita of 2853 Yuan in 2003 and 4293 Yuan in 2008 (Ministry of Agriculture, 2004, 2009). For comparison purposes, we also ran the same analysis on a low income province, Yunnan, which was ranked 24^{th} and 25^{th} in terms of net income per capita with 1697 Yuan and 2634 Yuan in 2003 and 2008 respectively (Ministry of Agriculture, 2004, 2009). The Yunnan dataset is more limited as it covers less households and only for four years: 2002, 2004, 2006, and 2008. Therefore the focus of our empirical analysis will be on Hebei province. The total observations for our regressions are about 1,500 for Hebei and 400 for Yunnan.

The RCRE survey uses the stratified random sampling method. Counties in the province are first separated according to their income levels into high, middle and low categories. Villages are sampled from each category to ensure that villages across a range of income levels are represented in the dataset. Between 40 and 120 households are then randomly chosen from each sampled village to be interviewed in the survey (Benjamin et al., 2005).

Table 3.1 introduces the variables we use in our regression analysis. The estimation equation is $ferpm_{it} = \alpha + \boldsymbol{\beta}\mathbf{A}_{it} + \boldsymbol{\gamma}\mathbf{B}_{it} + \epsilon_{it}$, where the left hand side variable is the fertilizer use intensity and the right hand side variables are made up mainly from two groups: labor and farm characteristics ($\mathbf{A}_{it}$), and household wealth ($\mathbf{B}_{it}$). Group $\mathbf{A}_{it}$ consists of data about the household

Table 3.1: Descriptions of variables

Variable	Mean[a]
Total fertilizer use intensity (kg per mu[b])	70.39
Age of household head	50.70
Self-assessed health status of household head (5 categories; 1 = excellent)	1.61
Percentage of off-farm work for household head	62.69
Percentage of agricultural land area used for fruit plantation	9.48
Percentage of agricultural land area used for cash crop	20.62
Log {previous year agricultural output (Yuan)}	8.38
Fertilizer price per kg (Yuan)	1.96
Log {annual household income (Yuan)}	9.85

Notes: [a] Mean values are calculated from the 1,536 Hebei observations with data in all included variables of the regression.
[b] 15 mu = 1 hectare.

head, such as age, farm time and health. The health information is obtained directly from the farmers. In the survey they are asked to choose one of the five categories that best describes their health, ranging from excellent health to losing the ability to work. The hypothesis is that farmers who are younger, healthier and with higher farm time will be able to spend more effort in maintaining their farms and might apply more fertilizer. In order to capture the difference in fertilizer intensity between grain farms and fruit plantations, we include the percentage of farm land used for different crops and previous year output. Also added are the year variable to account for any changing trend over time, and fertilizer price which is calculated from dividing the reported fertilizer expenditure by the total amount purchased.

Data in group $\mathbf{B}_{it}$ include the annual household income and a wealth index. We create for each household an index that represents its overall wealth level using the method by Henry et al. (2003). The use of an index is a more appropriate indicator because wealth is multi-dimensional and we might miss some important factors if we focus on only one variable, such as household income or total assets. The authors recommend the inclusion of variables from four main dimensions of wealth to ensure that there is breadth in the index: human capital, food security, living condition and other assets. Before constructing the index, we collect a list of potential variables that could reflect the wealth of a household. All four categories of wealth dimensions mentioned above are well represented so the final wealth index is not lopsided and biased towards a certain aspect of wealth. Principal component analysis (PCA) is then used to isolate the wealth component in all these variables. As we have a panel dataset, we follow Cavatassi et al. (2004) and pool all the observations for the analysis. Only variables with a loading factor higher than a pre-determined lower bound in the wealth component are chosen to be included in the final list of variables. A weight is then assigned to each of these variables based on how well they explain the wealth component. The variable with a greater explanatory power receives a higher weight. They are then combined with the data of each household to construct a wealth index for the specific household. So although we have only one set of weights, the household wealth index can vary across time because the individual household data might vary across the five-year period.

3.4 Results

The potential variables that can be used in constructing a wealth index are shown in Table 3.2. We follow the procedures recommended by Henry et al. (2003) in filtering the indicators. The first step is to check for the direction and significance of correlation between all the variables on the list and a benchmark wealth or poverty indicator. Henry et al. suggest the use of per capita expenditure on clothing and footwear as the benchmark and filtering out variables with more than five percent missing values. All the indicators

Table 3.2: List of all potential wealth indicators

Category	Indicator
	Clothing and footwear expenditure (*benchmark*)
Human capital	Household size; average age; education level: zero, primary, high school; professional title; agricultural training; other vocational training; health condition; disability
Food security	Food expenditure; consumption of each of the following items: grain, bean, vegetable, fruit, oil and fat, meat, seafood, milk, egg, sugar, cigarette, alcohol
Living condition	Surface area of own house; value of own house; private toilet; indoor toilet; electricity; drinking water source; heating system; household fuel type
Other assets	Farm land area; livestock value; agricultural machinery; other fixed production assets; transportation assets; landline phone; mobile phone; motorbike; car; refrigerator; washing machine; television; color television

in our final wealth index list have expected sign in pair-wise correlation with the benchmark and the correlations are all significant at the one percent level. After the initial list of potential variables have been narrowed down using the benchmark indicator, we run PCA on the remaining variables and keep only the ones with a component loading higher than a pre-determined baseline, 0.30 in absolute value based on the recommendation by Henry et al..

3.4.1 Hebei province

Following this filtration in the Hebei province, there are 17 variables remaining. However, eight are from the same category, the category of other assets. To ensure that the final index is not dominated by one aspect of wealth, we drop some of the variables with a lower loading factor, especially those whose asset groups are already represented on the list. In this case, ownerships of bicycle, cell phone and television are dropped while ownerships of motorbike, telephone and color television are kept, which leaves a total of 14 final indicators. We list these variables in Table 3.3 together with their respective loading factors. In terms of distribution among the different dimensions of wealth, the final list of variables is quite evenly spread out among three of the four main categories: human capital, living condition and other assets, with five, three and five

Table 3.3: Final list of indicators in the Hebei wealth index

Variable	Mean	Loading
Per capita expenditure for clothing and footwear (thousand Yuan)	0.16	0.3865
Household size	3.65	0.6754
Average age of household	42.53	−0.7022
Percentage of household members with primary education or higher	47.22	0.5761
Percentage of household members with good health (self-assessed)	78.39	0.4192
Percentage of household members who cannot work	3.83	−0.3750
Electric or gas heating system (1 = yes)	0.20	0.3800
Area of own house (thousand m^2)	0.11	0.5817
Value of own house (thousand Yuan)	20.18	0.5813
Ownership of motorbike (1 = yes)	0.38	0.6209
Ownership of color television (1 = yes)	0.76	0.5719
Ownership of washing machine (1 = yes)	0.64	0.6534
Ownership of refrigerator (1 = yes)	0.26	0.4812
Ownership of telephone (1 = yes)	0.59	0.7076

variables respectively. The only non-represented group is food security as all its variables have low component loadings for wealth with the highest being 0.23 for per capita food expenditure followed by 0.09 for per capita vegetable consumption. As their loadings are lower than the cut-off point of 0.30, these variables are excluded from the final list of wealth indicators. According to studies by Zeller et al. (2006) in four different countries, the food security dimension of wealth tends to play a more important role in poorer countries where severe food shortage is widespread. This is probably less of a problem in Hebei province as it is one of the high income provinces in China.

We examine the validity of our final list of wealth indicators by checking whether it fulfills the following two criteria: its eigenvalue should be higher than one and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy has to be more than 0.60. Low KMO scores indicate that the variables have too little in common and the model is not appropriate. A score of 0.60 is considered mediocre, 0.70 is middling, 0.80 is good, and 0.90 is excellent (Kaiser, 1974). The eigenvalue for our index is 4.43 and it has a KMO measure of 0.83.

Using the index we created, we examine how wealth affects fertilizer use intensity, the results of which can be found in Table 3.4. We run all these regressions with fixed effects and random effects. We then perform a Hausman (1978) test to compare the estimates from the two models. The differences are statistically significant at the one percent level for all the regressions so we use the results from the consistent fixed effects estimation. Among the

Table 3.4: Determinants of fertilizer use by wealth in Hebei

Variable	W1	W2	W3
Age of household head	13.873	14.477	13.189
	(11.446)	(11.558)	(11.584)
Health status of household head	−0.698	−0.729	−1.095
	(3.414)	(3.517)	(3.525)
Percentage of off-farm work for household head	3.338	1.175	1.152
	(9.270)	(9.589)	(9.612)
Percentage of land used for fruit plantation	77.492***	83.892***	84.050***
	(12.001)	(12.734)	(12.732)
Percentage of land used for cash crop	−2.924	−2.525	−3.130
	(9.762)	(9.925)	(9.939)
Previous output	13.921***	13.837***	14.073***
	(2.404)	(2.456)	(2.463)
Fertilizer price	−26.299***	−27.042***	−27.069***
	(2.345)	(2.387)	(2.386)
Year of the data	−5.884	−6.172	−4.910
	(11.458)	(11.573)	(11.598)
Household income	18.094***	21.323***	21.328***
	(3.589)	(3.922)	(3.922)
Household wealth index		−7.387	−21.230**
		(4.872)	(10.338)
Dummy for higher than median wealth index			−0.966
			(6.310)
Household wealth index × Dummy above			19.112
			(12.105)
Number of observations	1,576	1,536	1,536

Note: Standard errors are in parentheses. Double asterisk (**) and triple asterisk (***) denote significance at 5% and 1% respectively.

control variables, fertilizer use intensity decreases with price but increases with previous year output and percentage of land for fruit plantation. Column W1 lists the regression output from the basic model with annual family income as wealth indicator. It has a statistically significant and positive impact on fertilizer use. We add the wealth index in the second regression and find that its coefficient is not significant. This would be misleading, however, had it been the final conclusion. Column W3 shows the results of a subsequent regression which includes two categories for the wealth index: below median and above median. As there are interaction terms involved, we calculate the marginal effects for each wealth category and include them in Table 3.5. The wealth index is statistically significant in the low category, indicating that wealth does affect the intensity of fertilizer use as postulated earlier in the theoretical model of our article.

The wealth effect can be direct or indirect and the magnitude of its impact varies according to the different wealth categories. The direct effect determines how much fertilizer a farmer can afford to buy. This probably has a big impact in the poorer region only and not so much in Hebei. In addition, the fertilizer price is quite cheap in the study region due to direct subsidies and tax cuts on fertilizer production as well as indirect subsidies on fertilizer purchase (Cheng et al., 2010). Therefore the indirect wealth effect shown in Equation (3.5) plays a relatively more important role in these households. From Table 3.5, we see that the low wealth group displays negative fertilizer intensity with wealth while the high wealth category has an insignificant wealth effect. There are two

Table 3.5: Marginal wealth effect for each wealth category in Hebei

Regression	Variable	Wealth category	
		Low	High
W3			
	Household wealth index	-21.230^{**}	-2.118
		(10.338)	(6.552)

Note: Standard errors are in parentheses. Double asterisk (**) denotes significance at 5%.

pathways in which uncertainty in fertilizer content affects its usage. First is that a low wealth household is less able to use its existing means to cover output shortfalls. If there are doubts as to the true content of fertilizer, these farmers apply more fertilizer to ensure that they can meet their consumption targets even if it means overusing the fertilizer. The second pathway is that the poorer farmers could be more risk averse, as shown by Hamal and Anderson (1982), Chavas and Holt (1996), Bar-Shira et al. (1997) and Yesuf and Bluffstone (2009). If this is the case in our study region as well, the wealthier, i.e. less risk averse, farmers will apply more fertilizer as the uncertainty in fertilizer content leads to an increase in the risk level when compared with the situation where the fertilizer content is as labeled on the package. These two pathways work in opposite directions with the first one imposing a greater constraint and thus having a greater impact on the less wealthy farmers. This causes the wealth effect to go from negative in the lower wealth group to insignificant in the higher wealth group.

From the three regressions above we see how a different wealth measurement can lead to a misleading conclusion on wealth effect. If we capture wealth by only family income, we will conclude that fertilizer use increases with wealth. If we add the wealth index as a whole, we will find that wealth has no statistically significant impact on fertilizer intensity. They both offer a contradicting outcome and are also different from the conclusion we reach which is that the direction of wealth impact depends on the wealth levels of the farmers.

3.4.2 Yunnan province

We construct a wealth index for the Yunnan households using the same method as that of Hebei and show the final list of variables in Table 3.6. There are more factors with high loadings in the case of Yunnan. As the recommended number of final indicators for constructing a wealth index is between 10 and 20 (Henry et al., 2003), we raise the loadings cut-off from 0.3 to 0.4 in order to keep the number of variables within the suggested range. In addition, there is also an over-representation from the category of other assets, so we pick the most significant factor only within the same asset group: ownerships of bicycle, color television and telephone are kept, in place of ownerships of motorbike, car, television and cell phone. The eigenvalue of this wealth index is 7.31 and its KMO measure is 0.90, thus fulfilling both the adequacy criteria. In contrast to the richer Hebei province, food security variables play a more important role in the wealth index of Yunnan. This is similar to the findings of Zeller et al. (2006) in other countries, in which poorer regions have more food indicators in the wealth index. In addition, despite Hebei having higher income and human capital, the cost of living seems to be greater in Yunnan with higher means for both food expenditure and housing value.

In the regression on fertilizer intensity, the statistically significant control variables include household head's health, percentage of land used for cash crop and annual family income, all of which have a positive effect on the use level while fertilizer price has a negative coefficient. However, the positive impact from family income disappears when we add the wealth index with both variables being insignificant. Table 3.7 shows the marginal wealth effect

Table 3.6: Final list of indicators in the Yunnan wealth index

Variable	Mean	Loading
Per capita expenditure for clothing and footwear (thousand Yuan)	0.14	0.6245
Percentage of household members with formal education	75.18	0.5127
Percentage of household members with primary education or higher	30.18	0.6530
Percentage of household members with professional title	4.99	0.4640
Percentage of household members with vocational education	5.52	0.4002
Per capita food expenditure (thousand Yuan)	1.20	0.6565
Per capita fruit consumption (kg)	15.64	0.5768
Per capita meat and fat consumption (kg)	38.18	0.4421
Indoor toilet (1 = yes)	0.13	0.7183
Electric or gas heating system (1 = yes)	0.08	0.5665
Gas as household fuel (1 = yes)	0.15	0.7371
Area of own house (thousand m^2)	0.13	0.7153
Value of own house (thousand Yuan)	30.57	0.7098
Ownership of bicycle (1 = yes)	0.44	0.6989
Ownership of color television (1 = yes)	0.69	0.5678
Ownership of washing machine (1 = yes)	0.39	0.7706
Ownership of refrigerator (1 = yes)	0.24	0.7661
Ownership of telephone (1 = yes)	0.37	0.7103

that we have calculated from the coefficients of the interaction terms. Similar to the case of Hebei, the wealth index as a whole is insignificant, but it becomes partially significant when it is split into two categories. The lower

Table 3.7: Marginal wealth effect for each wealth category in Yunnan

Regression	Variable	Wealth category	
		Low	High
W3			
	Household wealth index	91.818**	−2.000
		(37.873)	(30.155)

Note: Standard errors are in parentheses. Double asterisk (**) denotes significance at 5%.

half shows a significant and positive wealth effect opposite from the results of Hebei province. This could be because Yunnan is one of the poorest provinces in China while Hebei is on the other end of the spectrum. This means that the issue of affordability is of a greater concern in Yunnan, especially among low wealth farmers. Therefore the direct wealth effect in Equation (3.5) becomes more prominent, i.e. wealthier farmers use more fertilizer because they can afford to purchase more. For high wealth households, the direct effect diminishes in its influence and the two pathways of indirect wealth effect have a stronger impact. As mentioned in the case of Hebei, these two pathways act in different directions with the negative one having a greater effect at the lower end of the wealth scale.

In order to get a clearer view on this switch in impact across the wealth scale, we change the groupings for high and low wealth from equally distributed to one-third in one group and two-third in another. We then calculate their respective marginal wealth effects and show them in Table 3.8. The wealth

Table 3.8: Marginal wealth effect in Yunnan with different grouping size

Farmer grouping		Wealth category	
Low	High	Low	High
One-third	Two-third	128.900***	18.352
		(48.842)	(24.525)
Half	Half	91.818**	−2.000
		(37.873)	(30.155)
Two-third	One-third	50.848*	32.987
		(25.946)	(52.630)

Note: Standard errors are in parentheses. Asterisk (*), double asterisk (**) and triple asterisk (***) denote significance at 10%, 5% and 1% respectively.

effect for low wealth farmers reduces both in magnitude and statistical significance when the group expands while the effect is insignificant for the high wealth group throughout the change. This could be due to the positive direct wealth effect getting weaker and the indirect effect having a greater impact as we move up the wealth scale.

These empirical findings support the theoretical model, which shows that the direction of wealth effect depends on farmers' wealth levels. The effect can be split roughly into three categories based on the impact on farmers of different wealth groups: the direct effect of affordability, the indirect effect of risk aversion to output dipping below a certain level, and the indirect effect from the change in risk preference on an uncertain input such as fertilizer. The first category mostly affects the lowest wealth group, especially when the fertilizer price is relatively low. The second category has a stronger influence on the lower wealth farmers who cannot cover the shortfall in output using their existing wealth. The third category affects farmers of all wealth levels. However, its effect is the most obvious in the highest wealth group because the impact from the two other categories has either disappeared or become very small towards the high end of the wealth scale. In terms of relative importance, we have a situation where the influence of the first category is the most pronounced in the low wealth group, the second category in the middle wealth group and the third category in the high wealth group.

Among the three categories mentioned above, the first effect leads to an increase in fertilizer use with wealth while the second effect is the opposite. The direction of the third effect depends on the risk behavior of the farmers. If they exhibit decreasing (increasing) absolute risk aversion, fertilizer intensity would increase (decrease) with wealth. The farmers in the study region seem to show decreasing risk aversion with wealth because when we extend the analysis in Table 3.8, and put three-quarter farmers in the low group and one-quarter in the high group, we find that the low group's coefficient for wealth index becomes insignificant. However, the farmers in the high group, which is the group most likely to display the third effect without the noises from the other two effects, have a positive coefficient for wealth index that is statistically significant at the five percent level.

3.5 Conclusions

The literature has a wide range of papers looking at factors affecting the intensity of fertilizer use. One of these factors analyzed is the wealth of farmers, but the conclusions reached on this area of analysis are mixed. Some papers show that the effect is positive; some find that it is negative and there are also studies with the outcome that the wealth effect is insignificant. Our article analyzes this issue from a new angle, doubts on the input, and shows both theoretically and empirically that the direction of wealth effect changes across the different levels of farmers' wealth. In general, the article also highlights the importance of taking input uncertainty into consideration, especially for future research in countries that are affected by substandard input. It might help shed light on actions that seem irrational or puzzling at first.

We incorporate doubts on input quality into the theoretical model and use comparative statics to analyze how a change in wealth affects the intensity of fertilizer use. Wealth effect can be split into the direct and indirect components. The direct effect is positive because wealthier farmers can afford to buy more fertilizer. The sign of the indirect effect is less certain and depends on the relative importance of a few factors, such as farmers' ability to pay for household consumption using their current wealth in case the output is very low due to fake or low quality fertilizer. This affects mainly the farmers of lower wealth. In this situation, a lower wealth might increase fertilizer use as these farmers want to ensure that enough fertilizer is added to make up for its potentially lower content. We also test the wealth effect on fertilizer intensity empirically using data from two provinces in China: Hebei, which is one of the richest, and Yunnan, which is one of the poorest. We can separate the direct and indirect wealth effects from the theoretical section into three categories based on the strength of their impact on various wealth groups. These effects are the direct effect of affordability, the indirect effect of aversion to output dropping below a certain level and the indirect effect of aversion to a risky input. We can observe the changes of effect in the case of Yunnan as its coefficient of wealth index goes from significantly positive in the low wealth group to being insignificant in the middle group and then back to being significantly positive in the high wealth group. The transition is, however, less clear in the case of Hebei as only two categories of the effect are observed. Its wealth index coefficient goes from being significantly negative to being insignificant. This could be because Hebei farmers are wealthier than their Yunnan counterparts so we only see the second and third wealth effects mentioned above and not the first effect of affordability. Therefore, it is possible to find that wealth has a positive, negative or insignificant impact on fertilizer use depending on the level of farmers' wealth of the study region. This effect could even change in direction within the same region itself as we move from low wealth farmers to high wealth farmers.

It is important to examine what affects fertilizer intensity, especially since it is an input that has been overused in some countries and underused in other. Our theoretical model shows that in the presence of uncertainty on fertilizer, farmers of the low wealth group might increase their fertilizer use if they are risk averse. It is opposite for the wealthier farmers as it is the less risk averse among them that raise their fertilizer application. There have been previous studies, but in different regions, which show that farmers are risk averse and their risk aversion decreases with wealth. This is of special concern in countries with intensive fertilizer application because high risk aversion for poor farmers and low risk aversion for rich farmers are the risk patterns that would lead to increase in fertilizer use in the presence of doubts on fertilizer content. Therefore it is important to have measures to counter the issue of uncertainty in fertilizer content. Some possibilities include setting up a sector-wide monitoring body or a third-party testing service that examines the fertilizer in the market. The government can also help facilitate the process by passing a legislation that gives special labels to products that meet a certain standard. This would help to reduce the doubts of farmers on the fertilizer that they purchase.

3.6 References

Abdoulaye, T. and Sanders, J. H. (2005). Stages and determinants of fertilizer use in semiarid African agriculture: The Niger experience. *Agricultural Economics*, 32(2):167–179.

Alem, Y., Bezabih, M., Kassie, M., and Zikhali, P. (2010). Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, 41(2):165–175.

Ariga, J., Jayne, T. S., Kibaara, B., and Nyoro, J. K. (2008). Trends and patterns in fertilizer use by smallholder farmers in Kenya, 1997-2007. Food security collaborative working paper no. 55169, Department of Agricultural, Food, and Resource Economics, Michigan State University.

Babcock, B. A. (1992). The effects of uncertainty on optimal nitrogen applications. *Review of Agricultural Economics*, 14(2):271–280.

Babcock, B. A. and Hennessy, D. A. (1996). Input demand under yield and revenue insurance. *American Journal of Agricultural Economics*, 78(2):416–427.

Bar-Shira, Z., Just, R. E., and Zilberman, D. (1997). Estimation of farmers' risk attitude: An econometric approach. *Agricultural Economics*, 17(2-3):211–222.

Benjamin, D., Brandt, L., and Giles, J. (2005). The evolution of income inequality in rural China. *Economic Development and Cultural Change*, 53(4):769–824.

Cavatassi, R., Davis, B., and Lipper, L. (2004). Estimating poverty over time and space: Construction of a time-variant poverty index for Costa Rica. Working Paper No. 04-21, Agricultural and Development Economics Division, Food and Agriculture Organization of the United Nations (FAO).

Chavas, J.-P. and Holt, M. T. (1996). Economic behavior under uncertainty: A joint analysis of risk preferences and technology. *The Review of Economics and Statistics*, 78(2):329–335.

Cheng, C., Shi, Y., and Wen, T. (2010). The real cost of nitrogen fertilizer. Technical report, School of Agriculture and Rural Development, Renmin University of China.

Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review*, 101(6):2350–90.

Fraser, P., Chilvers, C., Beral, V., and Hill, M. J. (1980). Nitrate and human cancer: A review of the evidence. *International Journal of Epidemiology*, 9(1):3–12.

Hamaguchi, T. (2011). Awareness raising activities on proper selection and use of chemical fertilizers have been started. Japan International Cooperation Agency. Available at `http://www.jica.go.jp/project/english/cambodia/006/news/general/110617.html`. Accessed July 1, 2013.

Hamal, K. B. and Anderson, J. R. (1982). A note on decreasing absolute risk aversion among farmers in Nepal. *Australian Journal of Agricultural and Resource Economics*, 26(3):220–225.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, 46(6):1251–1271.

He, C.-E., Liu, X., Fangmeier, A., and Zhang, F. (2007). Quantifying the total airborne nitrogen input into agroecosystems in the North China Plain. *Agriculture, Ecosystems & Environment*, 121(4):395–400.

Henry, C., Sharma, M., Lapenu, C., and Zeller, M. (2003). *Microfinance Poverty Assessment Tool*. Technical Tools Series No. 5. The World Bank and Consultative Group to Assist the Poor, Washington, DC.

Hu, K., Huang, Y., Li, H., Li, B., Chen, D., and White, R. E. (2005). Spatial variability of shallow groundwater level, electrical conductivity and nitrate concentration, and risk assessment of nitrate contamination in North China Plain. *Environment International*, 31(6):896–903.

Isik, M. and Khanna, M. (2003). Stochastic technology, risk preferences, and adoption of site-specific technologies. *American Journal of Agricultural Economics*, 85(2):305–317.

Just, R. E. and Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, 7(1):67–86.

Kaiser, H. (1974). An index of factorial simplicity. *Psychometrika*, 39(1):31–36.

Kaliba, A. R., Verkuijl, H., and Mwangi, W. (2000). Factors affecting adoption of improved maize seeds and use of inorganic fertilizer for maize production in the intermediate and lowland zones of Tanzania. *Journal of Agricultural and Applied Economics*, 32(1):35–47.

Lamb, R. L. (2003). Fertilizer use, risk, and off-farm labor markets in the semi-arid tropics of India. *American Journal of Agricultural Economics*, 85(2):359–371.

Liu, X., Zhang, Y., Han, W., Tang, A., Shen, J., Cui, Z., Vitousek, P., Erisman, J. W., Goulding, K., Christie, P., Fangmeier, A., and Zhang, F. (2013). Enhanced nitrogen deposition over China. *Nature*, 494(7438):459–462.

Liverpool-Tasie, S., Olaniyan, B., Salau, S., and Sackey, J. (2010). A review of fertilizer policy issues in Nigeria. Working paper no. 0019, Nigeria Strategy Support Program, International Food Policy Research Institute (IFPRI).

Love, A. H. and Buccola, S. T. (1991). Joint risk preference-technology estimation with a primal system. *American Journal of Agricultural Economics*, 73(3):765–774.

Ministry of Agriculture, P. R. C. (2004). *China Agriculture Yearbook 2004*. China Agriculture Press, Beijing.

Ministry of Agriculture, P. R. C. (2009). *China Agriculture Yearbook 2008*. China Agriculture Press, Beijing.

Mwakalebela, L. (2012). Government declares war on fake fertilizer dealers. Tanzania Daily News. Available at http://dailynews.co.tz/index.php/parliament-news/7122-government-declares-war-on-fake-fertilizer-dealers. Accessed July 1, 2013.

Paulson, N. D. and Babcock, B. A. (2010). Readdressing the fertilizer problem. *Journal of Agricultural and Resource Economics*, 35(3):368–384.

Rajsic, P., Weersink, A., and Gandorfer, M. (2009). Risk and nitrogen application levels. *Canadian Journal of Agricultural Economics*, 57(2):223–239.

Robison, L. J. and Barry, P. J. (1987). *The Competitive Firm's Response to Risk*. Macmillan Publishing Company, New York.

Roosen, J. and Hennessy, D. A. (2003). Tests for the role of risk aversion on input use. *American Journal of Agricultural Economics*, 85(1):30–43.

Shen, J. L., Tang, A. H., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2009). High concentrations and dry deposition of reactive nitrogen species at two sites in the North China Plain. *Environmental Pollution*, 157(11):3106–3113.

Viet Nam News (2010). Officials warn of low-quality fertilizer. AccessMyLibrary. Available at http://www.accessmylibrary.com/article-1G1-229054286/vietnam-officials-warn-low.html. Accessed July 1, 2013.

Wang, G. (2011). China cracks down on counterfeit seeds, pesticides. Xinhua News Agency. Available at http://news.xinhuanet.com/english2010/china/2011-05/19/c_13883191.htm. Accessed July 1, 2013.

Wik, M., Pingali, P., and Broca, S. (2008). Global agricultural performance: Past trends and future prospects. Background paper for the World Development Report 2008, The World Bank.

Yesuf, M. and Bluffstone, R. A. (2009). Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from Ethiopia. *American Journal of Agricultural Economics*, 91(4):1022–1037.

Zahur, A. (2010). Spurious fertilizers: A threat to agriculture. The Daily Star. Available at `http://www.thedailystar.net/newDesign/news-details.php?nid=125044`. Accessed July 1, 2013.

Zeller, M., Sharma, M., Henry, C., and Lapenu, C. (2006). An operational method for assessing the poverty outreach performance of development policies and projects: Results of case studies in Africa, Asia, and Latin America. *World Development*, 34(3):446–464.

Zhang, Y., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2008). Nitrogen inputs and isotopes in precipitation in the North China Plain. *Atmospheric Environment*, 42(7):1436–1448.

Chapter 4

Perception and truth: The real quality of fertilizer

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Abstract

Poor quality fertilizer is a growing problem in many countries. This is of special concern to small household farms as they have neither the buying power nor the testing instruments to verify the authenticity of the input. We analyze the effect of fertilizer quality on use intensity. Our study distinguishes between perceived quality by farmers and true quality. We ask farmers during a household survey about the self-assessed quality of their fertilizer, and collect fertilizer samples from them to have the contents tested in a laboratory. Results show that perceived quality reduces fertilizer use intensity, but the impact from true quality is not statistically significant. There is also no significant correlation between true and perceived quality. We find widespread and severe quality problems with fertilizer, and these could lead to an overuse of fertilizer with high economic and environmental costs. The article concludes with implications for research and policy.

4.1 Introduction

Since the 1960s the value of world agricultural output has increased at an average of 2.3 percent per year, staying ahead of the annual population growth rate of 1.7 percent (Wik et al., 2008). A major factor is in the increase of input use, which accounts for about 60 percent of the output growth, with total factor productivity being responsible for the other 40 percent (Fuglie and Nin-Pratt, 2013). In addition to improved genetic material, irrigation and mechanization, the level of fertilizer usage has gone up from less than 25kg per hectare in early 1960s in all regions of the world, to almost 200kg per hectare in early 2000s in East Asia and Pacific, and more than 100kg per hectare in South Asia (Fuglie, 2010; Wik et al., 2008). Even though the rise in fertilizer use has helped promote output growth (Fan and Pardey, 1997), it has also led to negative outcomes such as the degradation of land and water ecosystems (He et al., 2007; Zhang et al., 2008) as well as the pollution of drinking water, which might cause gastric cancer (Fraser et al., 1980; Hu et al., 2005).

The increase in fertilizer consumption is not uniform throughout the world as its usage in Sub-Saharan Africa remained below 25kg per hectare in early 2000s (Wik et al., 2008). In addition to the overuse or underuse of the resource, the true content of agricultural input is another growing issue in many countries. The problem of low quality or fake fertilizer seems to be quite widespread in countries of various regions such as Bangladesh (Zahur, 2010), Cambodia (Hamaguchi, 2011), China (Wang, 2011), Nigeria (Liverpool-Tasie et al., 2010), Tanzania (Mwakalebela, 2012) and Vietnam (Viet Nam News, 2010). This is of special concern to small household farms as they have neither the buying power nor the testing instruments to verify the authenticity of the input.

We study in our article the link between fertilizer quality and its level of usage. We use two different types of quality measurement for fertilizer. They are the perceived quality according to farmers' opinion and the true quality based on laboratory testing. For our research, we conduct a household survey to collect the data on household characteristics and farm production. The survey also includes questions to the farmers on what they think about the quality of the fertilizer that they use. In addition, we take some samples of fertilizer from them and have those samples tested in a lab. We then analyze how these two different measures affect the level of fertilizer use and examine whether the two effects are similar.

4.2 Model

We base the model on Zellner et al. (1966), but we add an extra term e^z to capture the varying fertilizer quality, similar to the way Zellner et al. include the production error term into their function: $Y = A(e^z F)^{\alpha_1} X^{\alpha_2} e^{\epsilon}$, with Y as output, A as total factor productivity, F as fertilizer, X as another input, α_1 and α_2 as elasticities, and e^{ϵ} as production error term. In this case, F is the labeled content of fertilizer, while $e^z F$ is the true content. As the fertilizer manufacturer reduces the ingredients to save costs, the true content is lower than the labeled content, and the term e^z is therefore bound between zero and one. This means that the value of z can range from negative infinity to zero. The lowest end of the range is reached when the fertilizer is fake, while the highest end represents the case in which the true content is the same as that labeled on the fertilizer package.

When the farmers decide on the amount of inputs to apply, they do not know for certain the level of output they will be able to harvest. The input decision is thus based on what would maximize their expected profit assuming risk neutrality. In addition, they do not know the true content of fertilizer either, so it is the expected content of fertilizer that influences the decision making: $E(\pi) = p_y E(Y) - w_f E(e^z F) - w_x X$. The other terms in the optimization equation are p_y, w_f and w_x, which represent the output and input prices, respectively. Solving for the first order conditions with respect to the two inputs, F and X, we find the optimal decisions of the farmers:

$$\ln Y - \ln F = k_1 + \alpha_1 z + (1 - \alpha_1)E(z) + \epsilon + \gamma_1, \tag{4.1}$$

$$\ln Y - \ln X = k_2 + \alpha_1 z - \alpha_1 E(z) + \epsilon + \gamma_2, \tag{4.2}$$

with k_1 being $\ln\left(\frac{w_f}{p_y \alpha_1}\right)$, k_2 being $\ln\left(\frac{w_x}{p_y \alpha_2}\right)$, and γ_i being the stochastic error term of the use of input i. The model is a basic construct for two inputs, but it can be extended to include more inputs as well.

Combining Equations (4.1) and (4.2) with the production function, we can solve for the optimal decision for fertilizer use:

$$\ln F = (1 - \alpha_1 - \alpha_2)^{-1}[\ln A - (1 - \alpha_2)(k_1 + \gamma_1) - \alpha_2(k_2 + \gamma_2) \\ - \alpha_1(1 - \alpha_1)(1 - \alpha_1 - \alpha_2)E(z) - \epsilon]. \tag{4.3}$$

We examine from Equation (4.3) the effect of a change in expected fertilizer quality on the level of fertilizer use:

$$\frac{\partial F}{\partial E(z)} = -\alpha_1(1 - \alpha_1)F. \tag{4.4}$$

If fertilizer use is non-zero, then the direction of the effect in Equation (4.4) depends on the production elasticity of fertilizer, α_1. The effect is positive at places where the elasticity is greater than one. However, this is an unlikely scenario, as it means the impact of the input is so great that doubling the quantity of fertilizer alone, while holding the other inputs constant, would more than double the output. In this case, a higher expected fertilizer quality would increase the fertilizer application rate. A more realistic scenario is that the fertilizer elasticity is less than one, especially in regions where the input use is very high, for example at our research site in China. This makes the term in Equation (4.4) negative, and an increase in $E(z)$ (i.e. its value becomes less negative) would therefore lead to a lower level of F. So, a higher expected fertilizer quality decreases the amount of fertilizer being applied.

If we repeat the same analysis on Equation (4.3), but with true fertilizer quality instead of expected quality, we get

$$\frac{\partial F}{\partial z} = -\alpha_1(1 - \alpha_1)F\frac{\partial E(z)}{\partial z}. \tag{4.5}$$

The main point here is that true quality affects the level of fertilizer use through expected quality. Equation (4.5) shows that the direction of the effect depends on the link between true and expected quality. If the link is positive (negative), true and expected quality would have the same (opposite) direction of effect on fertilizer use. It is also possible that true quality has no effect on fertilizer application rate at all. This happens when there is no connection between true and expected fertilizer quality.

4.3 Data

The main aim of our study is to examine the link between fertilizer quality and fertilizer use. We also want to differentiate between the quality as perceived by the farmers and the true quality. Thus, there are two main parts to the data that we collect. The first is from a household survey, while the second is from the laboratory testing of fertilizer samples. When it comes to perception, the spread of information plays a very important role. With this in mind, we choose to run our household survey and collect fertilizer samples from a township in our project area of North China Plain that includes both villages with structured extension services and those without.

4.3.1 Household survey

We conducted a household survey in the Disituan Township of China during the second half of 2012. The township is located in the southern part of Hebei province and has a population of about 40,000 in 40 villages (Quzhou County Government, 2011). China Agriculture University (CAU) has a research station within the township. Their main activity has been running field experiments at the station, but in the past five years they have started to set up some centers in this and other townships to conduct training sessions for local villagers as well as spreading information on good farming practices, including the appropriate amount of fertilizer to apply. We choose the five villages for our survey based on whether they have an extension service center and their distance from the CAU research station. The first is Wangzhuang, which is the only village in the Disituan Township with an extension service center. There is a CAU student who lives at the center full-time. In addition to official training sessions, the villagers can also visit him at the center when they have questions. The other four villages chosen consist of two villages that are located nearest to the CAU research station (Liuzhuang and Disituan[1]), and two villages that are located in the two corners of the township furthest away from the research station (Diliutuan and Nanlongtang). All these four villages have no extension service center within the village.

Before our main survey, we carry out a pretest in some villages from other nearby townships. We find out that close to half of the household heads spend

[1]This is a village within the Disituan Township with the same name.

most of their time living in big cities and not in their respective villages. They do so because there are more job opportunities in those cities and the pay is also better. The rest of their families remain in the villages, but the households heads come back only for a short period of time, usually during the sowing and harvest seasons. We try to interview some of these households, but they are not willing to share the contact information of their household heads in the cities and most of them are quite reluctant to answer the other questions in the survey as well. In addition, it is also not possible to interview the household heads during the sowing and harvest seasons when they return to the villages because they are only back for a short time and are very busy during that period. As a result of this experience in the pretest, we decide to redefine the sampling frame of our survey to include only the households whose household heads live in the villages and not in some other cities. Through some informal interview sessions with the villagers, it seems like the main difference between the two groups of households is that those household heads that work in other cities usually belong to households with higher expenditures and therefore income. Some household heads say that the reason they do not go off-village to work is because they need to take care of their parents at home.

We randomly select 20 households from each of the five villages to be interviewed for our survey. About five percent of the original households could not be reached even after two revisits. So, we resample other households from the same villages to ensure that we have 20 households for each village, making it a total of 100 observations. The household survey includes questions on various household characteristics as well as crop production. In order that the production and fertilizer use data collected from different households can be compared with one another, we have to focus on one crop. We choose maize for this purpose because it is the main grain crop in the region. In terms of fertilizer, we record the data for all the fertilizer that the farmers use during the 2012 summer maize growing season. These include the brand, the content, the price and the amount applied for each of the fertilizer used in maize production. The content information consists of the share of nitrogen (N), phosphorus (P), and potassium (K) in the fertilizer as labeled on the package. We always request to see the package of the fertilizer to confirm the information, as most farmers do not know or cannot remember the exact share of the three elements in their NPK fertilizer. We also ask the farmers to give a score (between zero and ten inclusive) to their fertilizer based on how good they think the fertilizer is, with zero for fake fertilizer and ten for fertilizer with excellent quality. During the survey pretest, we try to phrase the question more specifically, by asking the farmers how many percent of the labeled nitrogen content they think is actually contained in the fertilizer. The farmers just reply that they do not know the answer. So, we decide to focus on their general perception of the quality instead. When the farmers use more than one fertilizer for maize production, we ask them to give the score based on the most-used fertilizer. This score constitutes the perceived fertilizer quality in our analysis.

4.3.2 Fertilizer testing

During our survey, we also collect fertilizer samples from the households that we interview and have them tested at a third-party private laboratory,[2] in order to construct a measure for true fertilizer quality.[3] Similar to perceived fertilizer quality, the score for true quality is also based on the most-used fertilizer of a household for maize production. However, if the households have extra of other fertilizer, we also collect them just in case there are other households that use those fertilizer as their main fertilizer for maize production but do not have any leftover for us to sample. We do not collect any fertilizer from a household if both the brand and content are the same with what we already have. We manage to assign a score for true fertilizer quality to 47 households based on the test results of their own fertilizer. The remaining households are given a score based on fertilizer samples collected from other households. In these cases, we first try to allocate to the households the quality measure from fertilizer with the same brand and content. When that fails, we take the score from other fertilizer of the same brand. At the end, 86 percent of the total households have a measure for true fertilizer quality. The remaining households do not have fertilizer left for us to collect and the brands they use

[2]The analysis methods used by the laboratory are: determination of total nitrogen content by dry combustion according to the method DIN ISO 13878; determination of total phosphorus content by Inductively Coupled Plasma Emission Spectrometry according to the method DIN 38406 part 22; and determination of available phosphorus content by calcium acetate lactate extraction according to the method VDLUFA A6.2.1.1.

[3]How we come up with a score for true fertilizer quality will be explained in more details in the next paragraphs.

are different from those of the other samples we have.

The two main aspects that distinguish one fertilizer from another are the amount of nutrients they contain and the availability of these nutrients to the plants (Vitosh, 1996). We use these criteria to construct two separate measures of true fertilizer quality. The first is whether the actual content of the fertilizer matches the amount of nutrients labeled on the package. In this case, we choose to focus on nitrogen because it is the main fertilizer element used in the region and appears in at least one fertilizer of every household. We construct a score from the ratio of labeled content that is actually in the fertilizer. For example, if it is labeled on the package that the fertilizer contains 20 percent nitrogen, and the results from laboratory testing show that it has only 16 percent of the element, then the fertilizer receives a score of 0.8. A score of zero means that none of the labeled content is found in the fertilizer, and the score approaches one when the true content is close to that labeled on the package. Figure 4.1 shows the distribution of this fertilizer quality measure among the interviewed households. The mean of the distribution is about 0.71, i.e. on average only

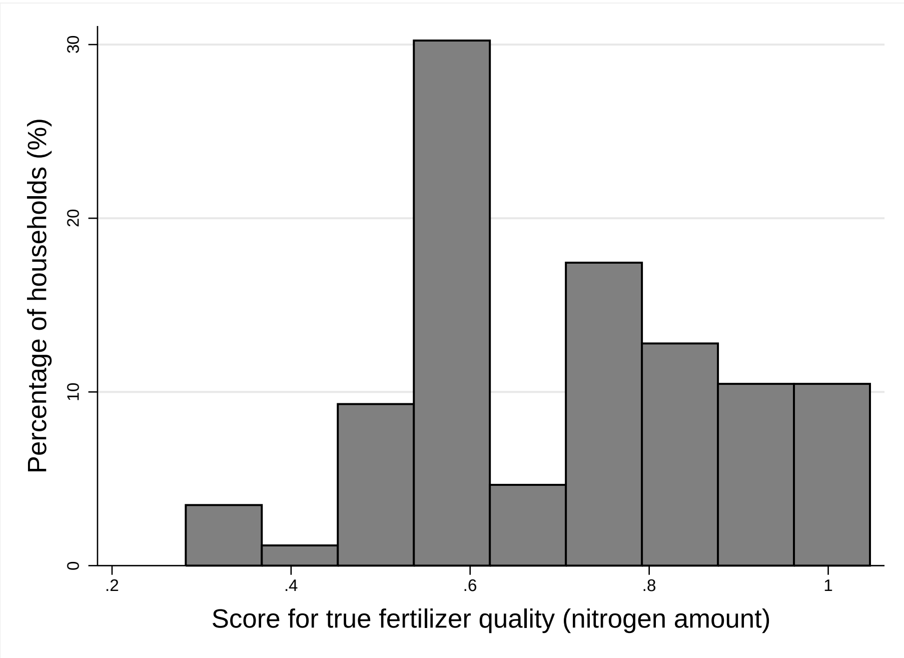

Figure 4.1: Distribution of the true fertilizer quality score based on the ratio of labeled nitrogen that is actually in the fertilizer

71 percent of the labeled nitrogen content is contained in the fertilizer. As we can see from the graph, most of the households have fertilizer with true

nitrogen content that is lower than the labeled level. This finding is similar to that of Boeber et al. (2009), who tested 14 fertilizer samples collected from the southern part of Hebei province in 2008. They find that 12 of the samples have less nitrogen than that labeled on the package, with the mean of the true content at around 80 percent. It also supports the news on the severity of this issue in the region (Han, 2009), where 23.5 million U.S. dollars worth of fake input was confiscated in China in the first six months of 2011 (Wang, 2011).

The second measure of fertilizer quality reflects how much of the contained element is actually available to the crops. Due to the many different sources of fertilizer and the varied solubility of them, it is possible that a fertilizer has as much content as labeled on the package but not all are readily available to be absorbed by the plants. For this analysis, we have to focus on an element other than nitrogen because nitrogen is a nutrient with high availability (Vitosh, 1996) and has thus no problem in this regard. Instead, we look at the second most common element in the fertilizers of that region, phosphorus. According to Kratz et al. (2010), the availability of phosphorus can be roughly separated into three groups: immediately available; available during the first vegetation period; and total amount that is or might become available in the long-term. Note that the first group is a subset of the second group, which in turn is a part of the third group. We define our second measure of true fertilizer quality as the ratio of group two to group three from the abovementioned phosphorus availability. In other words, it is the ratio of nutrient that is available during the first vegetation period to the total nutrient that is available or may become available in the future. The range of possible values is between zero and one. A score of zero indicates that none of the phosphorus in the fertilizer is available to the plants during the vegetation season that the fertilizer is applied, while a value of one means that all of the phosphorus is available during that first season. In our research region, the fertilizer quality measure of phosphorus availability ranges from zero to 0.8. The mean of the distribution is about 0.47, i.e. the availability is about 47 percent. To put this into perspective, the raw material of most commercial phosphorus fertilizers is rock phosphate, which has a low availability of 10 to 25 percent (Rehm et al., 1997). It is treated with acid to increase its availability, the level of which is determined by the type and amount of acid used (Sander and Penas, 2000). Based on an analysis by Ohio State University, the availability of typical phosphorus fertilizers is very high, ranging from about 95 percent for concentrated superphosphates to 100 percent for ammonium polyphosphate (Mullen et al., 2005, p. 22).

4.4 Empirical analysis

We use the data that we have collected to examine empirically the effects of perceived fertilizer quality and true quality on the intensity of fertilizer use. Table 4.1 provides a summary of the variables that we include in our regressions. There are two different measures of fertilizer intensity that we have from our study. The first is the total fertilizer applied per unit of land for summer maize production. Admittedly, this is not a precise measurement because there is a great variety in types and nutrient contents among the fertilizer being used. Aggregating all of them together solely by weight would overlook the finer details. However, this could be an appropriate measurement in our research region because only five out of the 100 households interviewed know the exact nutrient share of nitrogen (N), phosphorus (P) and potassium (K) in their NPK composite fertilizer, while all of them can remember clearly their fertilizer use intensity by total weight.

Table 4.1: Descriptions of variables

Description	Mean[a]
Use intensity of all fertilizer for summer maize (kg per mu[b])	66.45
Nitrogen use intensity for summer maize (kg per mu)	14.36
Age of household head	46.57
Percentage of total income from agriculture	61.08
Education level of household head (5 categories)	3.00[c]
Dummy indicating previous interaction with extension or research station	0.29
Distance from house to the furthest farm plot (km)	1.48
Percentage of plot size that one would use for a new fertilizer that has good results in another village	37.80
Price per kg of the main fertilizer for summer maize (yuan)	3.01
Annual household income (thousand yuan)	23.29
Labor for summer maize (day)	16.39
Area of planted land for summer maize (mu)	6.66
Self-assessed fertilizer quality by farmers (0 to 10; 10=best)	8.60
True fertilizer quality based on lab test of nitrogen content (0 to 1; 1=best)	0.71

Notes: [a] Mean values are calculated from all 100 observations in our survey.
[b] 15 mu = 1 hectare.
[c] The mode category, which corresponds to nine years of formal education.

As we also have a more precise measurement of fertilizer intensity in the form of total nitrogen applied per unit of land, we rerun the same analysis with this new dependent variable, in order to see whether there are any differences in results. We calculate this information on nitrogen intensity from the data collected during our household survey, by multiplying the weight of every fertilizer used for summer maize with the nitrogen share of each fertilizer respectively. When we compare the use intensity of each household individually relative to their yield level, we find that only about 20 percent of them fall within the range recommended by Zhang et al. (2009) for summer maize production in this region of China.

The remaining variables in our regressions can be grouped roughly into two categories. They are the fertilizer quality measures and the control variables, which are potential factors that could affect fertilizer use intensity. Among the control variables, we expect farmers with less land and stronger dependency on agricultural income to use more fertilizer, as they are less able to cope with crop failure. The ability to remain in the farm longer would probably increase the use level as well because the farmers can then spend more time in fertilization and do it more frequently. Therefore, younger household head, shorter distance from house to plot, and more family labor should lead to an increase in fertilizer application. Awareness on issues related to fertilizer overuse, such as wastage and environmental degradation, and receptiveness to changes could also affect fertilizer use intensity. So, we expect farmers with a higher education and those who are more willing to try out new input to be more receptive to the idea of reducing fertilizer use. Finally, lower fertilizer price and higher household income should increase fertilizer use due to the input becoming more affordable.

We have three different fertilizer quality measures in total. They are the perceived quality by farmers, and two true quality variables based on laboratory testing of fertilizer for its nitrogen content and phosphorus availability. Table 4.2 shows the pairwise correlation between them. It is no surprise that the two variables for true fertilizer quality are highly correlated. A test sample that has a higher quality score in one measure fares better in the other as well. This means that a fertilizer with true nitrogen content that is close to that labeled on the package also tends to contain phosphorus that is highly available to the crops. A more surprising result is that there is no signifi-

Table 4.2: Pairwise correlation between the three different types of measurements for fertilizer quality

	Perceived quality by farmers	True quality (nitrogen)
True quality (nitrogen)		
Pearson correlation	−0.1674	
Spearman's rank	−0.0155	
True quality (phosphorus)		
Pearson correlation	−0.0487	0.4610***
Spearman's rank	0.0205	0.4434***

Notes: Triple asterisk (***) denotes significance at 1%. The other coefficients are not significant at 10%.

cant correlation between the fertilizer quality as perceived by farmers and the true quality measures based on laboratory testing, be it in nitrogen content or phosphorus availability. In other words, the farmers themselves have no clue about the true quality of fertilizer, and all of them are being cheated in the same way. We include both the perceived and true indicators in our regressions to study their impact on fertilizer intensity. As mentioned earlier, extension service probably plays an important role too in farmers' input use decision. We examine such effect by adding a dummy variable that indicates whether a household is located in a village with extension service or CAU research station nearby.

4.5 Results

The first part of our analysis is on determining the factors that affect total fertilizer use intensity. For the dependent variable, we consider at the moment only the amount of fertilizer and not its nutrient content. We construct the variable by aggregating all the different fertilizer used in summer maize production by weight, and dividing this sum by the total cultivated area for summer maize. The variable ranges from 480 to 5,100 kg per hectare with a mean of 1,000 kg per hectare and a mode of 750 kg per hectare. As the error term is not normally distributed, we run the regression with the Huber-White robust standard errors. Table 4.3 shows the results. The two columns represent separate regressions with the same control factors, but each of them has a different fertilizer quality indicator: the perceived quality and the true quality based on nitrogen content. From the control factors, we see that greater

Table 4.3: Regression coefficients on total use intensity of all fertilizer in summer maize production

Variable	Total fertilizer intensity (1)	(2)
Age of household head	−0.148	−0.263
	(0.348)	(0.423)
Percentage of total income from agriculture	0.346*	0.423*
	(0.200)	(0.243)
Education level of household head	0.560	−0.073
	(3.926)	(4.335)
Dummy indicating interaction with extension service	−1.797	−5.856
	(6.263)	(8.183)
Distance from house to the furthest farm plot	−3.632	−4.771
	(5.849)	(6.731)
Percentage of plot size one would use for a new fertilizer	−0.181**	−0.224*
	(0.087)	(0.117)
Unit price of the main fertilizer for summer maize	−12.339***	−14.102
	(3.544)	(8.695)
Annual household income	1.040**	1.125**
	(0.500)	(0.561)
Labor for summer maize	0.937	0.943
	(0.598)	(0.648)
Land area for summer maize	−2.404*	−2.629*
	(1.301)	(1.423)
Self-assessed fertilizer quality by farmers	−4.837**	
	(2.170)	
True fertilizer quality (nitrogen content)		−9.352
		(24.467)
R^2	0.31	0.29
N	100	86

Notes: Robust standard errors are in parentheses. Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1%, respectively.

household income and stronger dependency on agricultural income lead to an increase in fertilizer use intensity. On the other hand, larger land area, higher unit price of fertilizer, and willingness to change input use pattern lower the application rate. The price effect disappears in the second column of the results table due to the multicollinearity problem from a high correlation between the price variable and the true fertilizer quality measure. As there is no significant correlation between the price variable and the self-assessed fertilizer quality measure, the price effect is observable in the first column of the table. We also attempt to use the instrumental variable (IV) approach to address the potential endogeneity of the perceived quality variable. The concern here is that there is a reverse causation effect, as fertilizer use intensity affects output and this, in turn, influences farmers' perception of fertilizer quality. The two instruments that we have are membership in the communist party and number of years of buying from the same fertilizer shop. Party membership offers the farmers wider networking opportunity and possible information on which fertilizer is better. Other than that, the longer a farmer has been buying from the same shop, the higher is the trust level towards that fertilizer seller. Therefore we expect both variables to have a positive effect on farmers' perception of the quality of their fertilizer. These instruments have the expected sign in the first stage regression with statistical significance at five percent and ten percent respectively, and they pass the Sargan-Hansen overidentification test. However, the first stage F stat is weak with a value of about four, so we cannot use the instrumental variable approach in our regression. A mitigating factor is that the coefficient of perceived fertilizer quality is negative while the abovementioned reverse causation effect is positive, as a higher fertilizer intensity increases output, which then improves farmers' perception of fertilizer quality. The presence of this reverse causation effect means that we cannot get a good estimate on the magnitude of the perceived quality coefficient. It does however strengthen the finding that perceived quality has a negative impact on fertilizer intensity because the coefficient remains statistically significant and negative despite the positive feedback effect.

Farmers who think that their fertilizer is good tend to apply less fertilizer, while those who believe that the quality is bad compensate by applying more fertilizer. It is as reflected in Equation (4.4) of the model, which indicates that an increase in expected quality lowers the use level when the production elasticity of fertilizer is less than one. This condition applies to our research region in China, as the country has a high fertilizer usage and the production elasticity of this input is very low or close to zero (Tian and Wan, 2000; Chen et al., 2003). Even though there is a negative effect from perceived quality, the true fertilizer quality measure has no statistically significant effect on fertilizer intensity. We mention earlier that the price variable becomes insignificant after we add the true quality measure into our regression. This is due to the high correlation between these variables. In order to be sure that the insignificance of true fertilizer quality is not due to this multicollinearity problem, we rerun the same regression without the price variable. The coefficient of true fertilizer quality remains insignificant, regardless of whether we have the price variable in our regression or not.

One potential argument against the use of total fertilizer intensity in an analysis is that it is constructed from aggregating the weight of all the different fertilizer. The variable is not precise because it includes fertilizer of various types and nutrient contents. These details are overlooked in a sum of just the weight alone. So, we repeat the same regressions with a more precise measurement of fertilizer intensity as our dependent variable. We focus on just one nutrient, and we choose the most commonly used fertilizer nutrient in that region, which is nitrogen. It is also the only main nutrient that can be found in at least one fertilizer of every household. During our survey, we ask the households about all the different fertilizer that they use in summer maize production. We record the amount applied and the nitrogen share of every fertilizer. We then calculate the total nitrogen use intensity in summer maize production of each household based on this information. The mean nitrogen intensity is 215.4 kg per hectare and the range is between 78 and 855 kg per hectare. Table 4.4 shows the results of using this new dependent variable instead of total fertilizer intensity in our regression. The error term is not normally distributed, so we use the Huber-White robust standard errors. In comparison with the results of Table 4.3, we see that the regression coefficients have become less significant in general. In addition, both fertilizer quality variables are statistically insignificant, including the perceived quality, which is significant in the previous regression on total fertilizer intensity. This means that a lower perceived quality increases the intensity of total fertilizer use in weight, but it has no statistically significant effect on the total nitrogen use intensity. This is probably because many farmers are not aware of the nutrient content in their fertilizer. In our study, even though all households can remember clearly the total weight of fertilizer being applied, only five out of 100 know the exact share of the three main nutrients in their NPK composite fertilizer. This raises a question on the appropriate choice of variable in this type of regression. Scientifically the nutrient content and the type of fertilizer

Table 4.4: Regression coefficients on the use intensity of nitrogen in summer maize production

Variable	Total nitrogen intensity (1)	(2)
Age of household head	−0.023	−0.061
	(0.066)	(0.077)
Percentage of total income from agriculture	0.046	0.062
	(0.037)	(0.043)
Education level of household head	−0.209	−0.247
	(0.877)	(0.963)
Dummy indicating interaction with extension service	0.980	0.460
	(1.684)	(1.991)
Distance from house to the furthest farm plot	0.180	0.317
	(1.343)	(1.411)
Percentage of plot size one would use for a new fertilizer	−0.029	−0.027
	(0.023)	(0.026)
Unit price of the main fertilizer for summer maize	−1.521**	−3.345*
	(0.737)	(1.999)
Annual household income	0.119	0.130
	(0.090)	(0.098)
Labor for summer maize	0.152	0.186
	(0.100)	(0.116)
Land area for summer maize	−0.351	−0.397
	(0.240)	(0.260)
Self-assessed fertilizer quality by farmers	−0.589	
	(0.450)	
True fertilizer quality (nitrogen content)		−2.328
		(5.621)
R^2	0.16	0.19
N	100	86

Notes: Robust standard errors are in parentheses. Asterisk (*) and double asterisk (**) denote significance at 10% and 5%, respectively.

are very important factors that need to be considered in a production analysis. However, when the farmers are not aware of these differences themselves, it could be more appropriate to use a less precise measurement instead if the purpose of the analysis is to explain the actual observed behavior. Needless to say this depends on the situation of each research region, as the choice for a precise measurement is clearly preferred if the farmers are more aware of the fertilizer nutrient that they use.

The results suggest that when farmers think that the fertilizer is of low quality, they compensate by applying more. However, when the true nitrogen content is actually low compared to the labeled level on the package, there is not any significant impact on farmers' action, not in total fertilizer applied and not in total nitrogen used. Equation (4.5) has indicated that true quality only affects fertilizer use through expected quality. If there is no correlation between expected quality and true quality, as is shown in Table 4.2 to be the case among our surveyed households, then there is no effect from true quality on fertilizer application rate. A possible explanation for this phenomenon in our research region is that the farmers cannot tell for certain whether the quality of a fertilizer is good or not. They do not have the equipment to do the tests themselves and it is also difficult to determine the quality of fertilizer just by observing the crop output alone, as there are many other factors that could affect the level of output. The farmers can only act based on what they believe to be the true fertilizer quality. One thing to note is that the interviewed farmers change their fertilizer quite frequently, with the average being once every 2.8 years. We ask them how they choose a particular fertilizer when they switch to a new one. 45 percent answer that it is according to the recommendation by the fertilizer sellers, and another 27 percent say that they just follow the other farmers. This means that the fertilizer choice of close to

Table 4.5: Main factor in determining which fertilizer to use

Factor	Percentage[a]
Recommended by fertilizer sellers	45
Follow the other farmers	27
Own experience[b]	13
Recommended by extension service	10
Fertilizer price	4
Random	1

Notes: [a] Percentages are calculated from all 100 observations in our survey.
[b] Reasons given under this factor include appearance of the fertilizer, such as the color and size of its granules.

three quarter of the surveyed households depend on what others tell them. It is thus likely that word of mouth, and not the true fertilizer quality which cannot be easily observed, plays an important role in shaping farmers' perception of fertilizer quality.

In the next part of the analysis, we examine how extension service affects the outcome that we have seen so far. The villages in our survey can be grouped into three categories: with extension service (group A), without extension service but located near the research station (group B), and without extension service or research station nearby (group C). We create three dummy variables, each representing one of the three village categories, and include them one by one into all the regressions in Tables 4.3 and 4.4. This amounts to a total of 12 regressions. We show the coefficients of the variables of interest in Table 4.6. As before, the only quality indicator with a statistically significant effect on fertilizer intensity is the perceived quality by farmers, and not the true quality. The village type dummies that are statistically significant are the following: group C has a positive impact on total fertilizer intensity, while group B has a negative impact on both total and nitrogen intensity. One reason that group A is not statistically significant despite the presence of extension service could be that the service is a relatively new initiative from the recent five years, whereas the research station, near which group B villages are located, has been there since the 1970s.

Table 4.6: Selected regression coefficients on fertilizer intensity for summer maize after adding village type dummy

Variable	Total fertilizer use intensity					
	(1A)	(1B)	(1C)	(2A)	(2B)	(2C)
Self-assessed fertilizer quality by farmers	−4.896**	−4.367**	−4.494**			
	(2.163)	(2.058)	(1.970)			
True fertilizer quality (nitrogen content)				−9.315	1.585	2.751
				(24.745)	(23.849)	(24.779)
Village dummy (extension = yes)	−3.579			−2.362		
	(9.199)			(9.153)		
Village dummy (extension = no; research station = yes)		−10.354*			−17.023**	
		(5.671)			(7.500)	
Village dummy (extension = no; research station = no)			11.922*			18.391**
			(6.319)			(8.358)

Variable	Nitrogen use intensity					
	(1A)	(1B)	(1C)	(2A)	(2B)	(2C)
Self-assessed fertilizer quality by farmers	−0.549	−0.475	−0.547			
	(0.458)	(0.426)	(0.433)			
True fertilizer quality (nitrogen content)				−2.372	0.335	−0.557
				(5.444)	(5.485)	(5.932)
Village dummy (extension = yes)	2.408			2.826		
	(2.970)			(2.880)		
Village dummy (extension = no; research station = yes)		−2.510			−4.145**	
		(1.536)			(1.767)	
Village dummy (extension = no; research station = no)			1.459			2.692
			(1.514)			(1.758)

Notes: Robust standard errors are in parentheses. Asterisk (*) and double asterisk (**) denote significance at 10% and 5%, respectively.

4.6 Conclusions

In examining the link between fertilizer quality and use intensity, we distinguish between perceived quality and true quality. We study how the results from one differ from the other. Based on the theoretical model, a higher expected quality by farmers leads to a decrease in application rate if the production elasticity of fertilizer is less than one. On the other hand, the true quality of fertilizer affects use intensity only through expected quality. If there is no link between true and expected quality, then true quality has no effect on fertilizer use intensity. We conduct a household survey to collect the data we need for our empirical analysis, which includes asking the households about the self-assessed quality of their fertilizer and taking fertilizer samples from them to be tested in a laboratory. The test consists of two components: the true nitrogen content as compared to the level labeled on the package, and the amount of phosphorus that is potentially available to the crops in one season out of the total phosphorus contained in the fertilizer. Results show that a higher perceived quality by farmers reduces the application intensity of fertilizer. However, there is no significant correlation between the perceived and true quality, and both of the true fertilizer quality measures (nitrogen content and phosphorus availability) have no significant effect on fertilizer use.

Farmers in our research region, who believe that their fertilizer quality is low, compensate by increasing the total weight of their fertilizer use. Based on this finding, one would expect that when the true nitrogen content of a fertilizer is lower than that labeled on the package, the farmers would compensate for this by applying more nitrogen as well. However, such effect is not seen in our study. The only fertilizer quality variable that affects use level is the perceived quality by farmers, and it has an impact solely on the fertilizer intensity by total weight. Such perception, as well as the true quality, has no influence on the intensity of nitrogen use. This could be due to the low awareness of farmers on the nutrient content of their fertilizer and the lack of correlation between true and expected quality. Our research provides an insight into the issue of questionable fertilizer quality, especially how perceived quality differs from true quality, and which of them has a real impact on fertilizer use intensity. It would be interesting to see this further developed to include more households and over a longer period of time. It would also help to have the study repeated in another region affected by fertilizer quality problem but with low fertilizer use, in order to see whether there is any difference in farmers' reaction compared to that in our research region with high fertilizer intensity.

Uncertainty in fertilizer quality is an issue in countries of different regions, such as Bangladesh, Cambodia, China, Nigeria, Tanzania and Vietnam. It includes fertilizer that is fake or with content lower than that labeled on the package. This is a growing problem and is therefore crucial to examine how it affects fertilizer use intensity, especially since fertilizer is an input that has been overused in some countries and underused in other. The inaccurate application level leads to health and environmental degradation in the former and low production in the latter. Our study shows that low fertilizer quality increases application intensity, which is a major problem in our research region because it has already a high fertilizer use rate. It is thus important to come up with policy measures or institutions that can help to counter this problem, such as a sector-wide monitoring body, a third-party testing service of the input, or more extension service manpower and facilities in the region. It works to the advantage of the honest fertilizer manufacturers to contribute financially to the formation of the abovementioned testing service. This helps to prevent their image from being tarnished by the unscrupulous manufacturers, as long as such service remains independent. This could reduce farmers' doubt on the quality of fertilizer that they purchase as well, which is an important factor in reducing fertilizer use intensity as shown in our article.

4.7 References

Boeber, C., Kuehl, Y., and Rumbaur, C. (2009). Land degradation in the North China Plain (NCP): Recent evidence, farmers concerns and policy implications. In *International Association of Agricultural Economists conference*, Beijing, China.

Chen, A. Z., Huffman, W. E., and Rozelle, S. (2003). Technical efficiency of Chinese grain production: A stochastic production frontier approach. In *American Agricultural Economics Association annual meeting*, Montreal, Canada.

Fan, S. and Pardey, P. G. (1997). Research, productivity, and output growth in Chinese agriculture. *Journal of Development Economics*, 53(1):115–137.

Fraser, P., Chilvers, C., Beral, V., and Hill, M. J. (1980). Nitrate and human cancer: A review of the evidence. *International Journal of Epidemiology*, 9(1):3–12.

Fuglie, K. and Nin-Pratt, A. (2013). Agricultural productivity: A changing global harvest. In *2012 Global Food Policy Report*, chapter 2, pages 15–27. International Food Policy Research Institute (IFPRI).

Fuglie, K. O. (2010). Total factor productivity in the global agricultural economy: Evidence from FAO data. In Alston, J. M., Babcock, B. A., and Pardey, P. G., editors, *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, chapter 4, pages 63–95. The Midwest Agribusiness Trade Research and Information Center, Iowa.

Hamaguchi, T. (2011). Awareness raising activities on proper selection and use of chemical fertilizers have been started. Japan International Cooperation Agency. Available at `http://www.jica.go.jp/project/english/cambodia/006/news/general/110617.html`. Accessed July 1, 2013.

Han, P. (2009). China cracks down on shoddy fertilizers, seeds. Chinese Government's Official Web Portal. Available at `http://english.gov.cn/2009-01/06/content_1196983.htm`. Accessed July 1, 2013.

He, C.-E., Liu, X., Fangmeier, A., and Zhang, F. (2007). Quantifying the total airborne nitrogen input into agroecosystems in the North China Plain. *Agriculture, Ecosystems & Environment*, 121(4):395–400.

Hu, K., Huang, Y., Li, H., Li, B., Chen, D., and White, R. E. (2005). Spatial variability of shallow groundwater level, electrical conductivity and nitrate concentration, and risk assessment of nitrate contamination in North China Plain. *Environment International*, 31(6):896–903.

Kratz, S., Haneklaus, S., and Schnug, E. (2010). Chemical solubility and agricultural performance of P-containing recycling fertilizers. *Landbauforschung - vTI Agriculture and Forestry Research*, 60(4):227–240.

Liverpool-Tasie, S., Olaniyan, B., Salau, S., and Sackey, J. (2010). A review of fertilizer policy issues in Nigeria. Working paper no. 0019, Nigeria Strategy Support Program, International Food Policy Research Institute (IFPRI).

Mullen, R., Lentz, E., and Watson, M. (2005). Soil fertility. In *Ohio Agronomy Guide*, volume Bulletin 472, chapter 2, pages 19–30. Ohio State University Extension, 14th edition.

Mwakalebela, L. (2012). Government declares war on fake fertilizer dealers. Tanzania Daily News. Available at `http://dailynews.co.tz/index.php/parliament-news/7122-government-declares-war-on-fake-fertilizer-dealers`. Accessed July 1, 2013.

Quzhou County Government (2011). Quzhou county yearbook 2011. Available at `http://jb.qzx.gov.cn/E_ReadNews.asp?NewsID=6836`. Accessed July 1, 2013.

Rehm, G., Schmitt, M., Lamb, J., Randall, G., and Busman, L. (1997). Phosphorus in the agricultural environment: Understanding phosphorus fertilizers. Extension bulletin FO-6288-B, University of Minnesota Extension.

Sander, D. H. and Penas, E. J. (2000). Phosphorus. In Ferguson, R. B. and Groot, K. M. D., editors, *Nutrient Management for Agronomic Crops in Nebraska*, volume EC 155, chapter 2, pages 17–21. University of Nebraska – Lincoln Extension.

Tian, W. and Wan, G. H. (2000). Technical efficiency and its determinants in China's grain production. *Journal of Productivity Analysis*, 13(2):159–174.

Viet Nam News (2010). Officials warn of low-quality fertilizer. AccessMyLibrary. Available at `http://www.accessmylibrary.com/article-1G1-229054286/vietnam-officials-warn-low.html`. Accessed July 1, 2013.

Vitosh, M. L. (1996). N-P-K fertilizers. Extension bulletin e-896, Michigan State University Extension.

Wang, G. (2011). China cracks down on counterfeit seeds, pesticides. Xinhua News Agency. Available at `http://news.xinhuanet.com/english2010/china/2011-05/19/c_13883191.htm`. Accessed July 1, 2013.

Wik, M., Pingali, P., and Broca, S. (2008). Global agricultural performance: Past trends and future prospects. Background paper for the World Development Report 2008, The World Bank.

Zahur, A. (2010). Spurious fertilizers: A threat to agriculture. The Daily Star. Available at `http://www.thedailystar.net/newDesign/news-details.php?nid=125044`. Accessed July 1, 2013.

Zellner, A., Kmenta, J., and Dreze, J. (1966). Specification and estimation of Cobb-Douglas production function models. *Econometrica*, 34(4):784–795.

Zhang, F. S., Chen, X. P., and Chen, Q. (2009). *Fertilizer Guide for the Main Crop of China*. China Agriculture University Press, Beijing.

Zhang, Y., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2008). Nitrogen inputs and isotopes in precipitation in the North China Plain. *Atmospheric Environment*, 42(7):1436–1448.

Chapter 5

Conclusions and discussion

Fertilizer has been a very crucial factor in the rapid rise of agricultural output in the past 50 years. This is especially true in the earlier part of this growth period. Since then, as the level of usage increases, its marginal effectiveness has diminished. Even though the input is still of great importance in promoting output growth in some parts of the world, its partial elasticity in recent years is shown to be very small or insignificant in our research region of the North China Plain (NCP). Fan and Pardey (1997) find that from the 1960s to mid 1990s, input intensification accounts for 46 percent of the increase in Chinese agricultural output, with about half of it being attributed to chemical fertilizer alone. However, a review of the marginal effect of fertilizer in China indicates that the value is very small since the mid 1990s (Chen et al., 2003). In a more recent case study from the NCP, Zhen et al. (2006) show that nitrogen is not statistically significant in determining crop yield. Despite the decreasing impact of fertilizer, its usage in China has been on a growing trend since the 1960s and is still very high at more than 300kg per hectare (FAO, 2011). This overuse is not only a waste of resources reducing economic efficiency, it also poses great problems for the environment (Chen et al., 2005; He et al., 2007; Zhang et al., 2008; Shen et al., 2009; Liu et al., 2013) as well as human health from the contamination of food and ground water (Zhen et al., 2005; Jiang and Jiang, 2013). In addition to fertilizer overuse, the quality of the input itself is of great concern lately. The value of fake or substandard agricultural input confiscated in China was as high as 29.4 million U.S. dollars in 2008, and 23.5 million U.S. dollars in just the first six months of 2011 (Han, 2009; Wang, 2011). This problem is not an isolated incident in China, as similar news reports have been found in other countries as well, such as Bangladesh, Cambodia, Nigeria, Tanzania, and Vietnam. In view of this widespread issue, the dissertation focuses on the impact caused by questionable fertilizer quality. The different aspects of impact being examined include efficiency, wealth, and fertilizer use intensity.

In the study of efficiency, which is based on the stochastic frontier model of Aigner et al. (1977), we derive an expression for the estimation bias that is caused by ignoring the substandard quality of fertilizer. We examine the magnitude of this bias by using Monte Carlo simulation to generate the different scenarios of uncertainty in fertilizer quality. Results show that the partial elasticity of fertilizer is insignificant before adding the quality term. With the inclusion of the term, we find that all of the 1,000 Monte Carlo repetitions under random scenario and almost half of them under household-specific scenario have negative partial elasticity for fertilizer at the 10 percent significance level, which implies that fertilizer is so overused that a marginal increase in the input would actually lower the output. Results also indicate that ignoring the quality term overestimates technical efficiency by 16 to 30 percent, depending on the scenario of uncertainty. This has strong implications on both research and fertilizer policies, as we see that the bias can even switch the sign of the marginal productivity of fertilizer. Studies ignoring this bias could be misleading, as they overstate the marginal effectiveness of fertilizer and technical efficiency. A weakness of our production function estimation is the low number of inputs we include in it. There are other inputs that are very important, such as soil quality and weather, but we do not have the detailed plot and household data for them. However, the main focus of this study is on the difference between the results before adding the fertilizer quality term and after adding the term. In both of these cases (before and after), we estimate the production functions with the same limited number of inputs. Therefore, the change in marginal productivity of fertilizer and technical efficiency that we observe is due to adding the fertilizer quality term, and not because of other missing inputs.

We produce a theoretical framework in the study of wealth effect on fertilizer use, which shows that the direction of wealth effect is not fixed across farmers of different wealth levels. It reconciles the different findings in the empirical literature on this topic, with some papers indicating that the effect is positive, and others concluding that the effect is negative or insignificant. The framework builds on the concept that there is uncertainty involved in fertilizer use. In our research area of NCP, the uncertainty could be due to doubts on input quality. At other places where the use of chemical fertilizer is not so widespread, the uncertainty could also be caused by unfamiliarity with the input or doubts on its effectiveness in general. The theoretical model of the framework is based on the expected value-variance method by Robison and Barry (1987). The results from comparative statics indicate that there are roughly three main factors determining the direction of wealth effect, with each factor exerting a different degree of influence as we move from the lowest wealth farmers to the highest. The first factor comes from the affordability constraint, which captures whether a farmer is able to buy fertilizer with existing wealth. This effect has a positive sign because wealthier farmers can afford to buy more fertilizer, and the constraint applies mainly to the poorest group of farmers only. The second factor is generated by another constraint. It exists because farmers who are poorer are less able to cope with a big loss of output, which might happen if their fertilizer is substandard or fake. So they apply more fertilizer to compensate for the potential lower quality. In this case, the poorer farmers apply more fertilizer, and the wealth effect is negative. This constraint is binding for more farmers than the first constraint because some farmers who can afford to pay for the fertilizer might have difficulties coping with a big loss of output. The third factor is due to the change in risk preference as the farmers become wealthier. Studies in the literature show that farmers usually exhibit decreasing absolute risk aversion, which means that they become less risk averse as they become wealthier. From this aspect, the less risk averse farmers apply more fertilizer because it is an input with uncertainty. This third factor affects all farmers, and the wealth effect is positive if the assumption of decreasing absolute risk aversion is true. From a combination of these three factors, we can see that the wealth effect is only positive at the highest end of the wealth scale. The effect is ambiguous at the other parts because there are factors acting in opposite direction.

We test the hypotheses from the wealth effect model empirically using the RCRE data for one of the richest provinces in China, Hebei, and one of the poorest provinces, Yunnan. Due to the lack of risk preference data in the RCRE household surveys, we cannot test the effect of risk preference on fertilizer use. However, the dataset allows us to construct a wealth index using principal component analysis (Henry et al., 2003; Zeller et al., 2006) and examine the wealth effect on fertilizer use across different wealth levels. The results support the derivation from the theoretical framework and show that the direction of wealth effect is different between Hebei and Yunnan. The direction shifts even within a province itself as we move from the low wealth farmers to the high wealth farmers.

Analyzing the link between fertilizer quality and use intensity is a timely study especially in the NCP, as it is a region that is facing both problems of fertilizer overuse and substandard input quality. In carrying out this research, we differentiate between the fertilizer quality as perceived by the farmers and the true quality based on lab testing of the input. We build the theoretical framework from the production model of Zellner et al. (1966), and use comparative statics to examine how a marginal change in perceived and true quality affects fertilizer use. The main hypotheses derived are that higher perceived quality reduces fertilizer use, and true quality only affects use intensity through perceived quality. It means that if perceived quality and true quality are positively correlated, then higher true quality will also lead to reduction in fertilizer application. We conduct a household survey to collect the data we need for the empirical analysis. As we need data on both perceived and true quality of fertilizer, we request for a fertilizer sample from the farmers during the survey, in addition to asking them to rate the quality of that fertilizer. We then send the fertilizer samples to the lab to have their nutrient content tested. The empirical results match the hypothesis from the theoretical framework. Perceived quality has a statistically significant and negative effect on fertilizer use intensity. It means if farmers think that their fertilizer is bad, they compensate for the low quality by applying more of the input. Our data also reveal that there is no significant correlation between perceived and true quality, and that true quality has no significant impact on fertilizer intensity in our research region. This outcome is as predicted by the theoretical framework in that true fertilizer quality only affects use intensity through perceived quality.

The main contribution of this dissertation is that despite the growing concern on fertilizer quality, there is previously no systematic analysis on the impact of such problem on efficiency or use intensity. These gaps exist both for the formulation of theoretical models as well as empirical models which test the theoretically derived hypotheses. The methodological contribution of the thesis is not only valid for the issue of quality of fertilizer, but applies also to other production inputs, such as seed or pesticide used in agriculture. The study of uncertain and low fertilizer quality is of special importance in the NCP because the overuse of fertilizer incurs high economic and environmental costs. Beyond what is presented in this dissertation, more can be done on the research of fertilizer quality. The two datasets we use in this dissertation illustrate well the problem we face in our study. On the one hand, we have the panel dataset from RCRE that spans multiple years and covers more than 800 households per year in one province alone. However, it does not contain the more detailed information on fertilizer quality, risk behavior, and soil quality, which are important aspects in the analysis on fertilizer use intensity, especially when the decisions are made under uncertainty. This problem is partially alleviated by the survey we conduct ourselves that forms the second dataset we use. It has more detailed data such as on fertilizer quality and nutrient share of the fertilizer, but it suffers from the small sample size problem. Ideally, for the study that we do, it would be good to have a comprehensive multiyear survey with fertilizer testing and soil analysis at the household level integrated into it. Without such dataset, the scope of analysis becomes more limited. For example, we do not have the risk preference data to examine the effect of risk attitude on fertilizer use empirically. It would be interesting to combine the research on risk behavior with our study of wealth effect, and explore further the theoretical framework that we build. Even though we examine only the wealth aspect of that framework, the model explains also the interaction between wealth and risk effects in decision making on fertilizer use under uncertainty. Finally, the research of this dissertation focuses on the NCP, a region with very intense fertilizer application. However, we have listed that the problem of questionable fertilizer quality is not restricted to our research area only. The same study being repeated in other regions with fertilizer quality issue but low use intensity would also help to shed light on the issue.

The results of our research indicate widespread and severe quality problems with fertilizer in the NCP, and these are shown to lead to an overuse of fertilizer with high economic and environmental costs. Our study also finds that poor fertilizer quality, if not adequately controlled for, leads to an overestimation of both technical efficiency and partial elasticity of fertilizer. This might mislead policymakers into thinking that the input has a greater impact that it actually does. When we take into consideration this estimation bias, the partial elasticity of fertilizer could even be negative. In view of the evidence from our study, the currently implemented policy of subsidizing fertilizer production is a double whammy, as it not only encourages the application of an overused input by driving down the price, it also leads to greater difficulty in monitoring the quality of the product due to the presence of many small and inefficient producers. According to a report by Cheng et al. (2010), the favorable policy in China towards fertilizer producers has led to an unusually high number of small fertilizer manufacturers when compared with the other big producing countries. There are almost 1,000 different producers of nitrogen fertilizer in China, while Russia has 35 and USA has 50. The average production of these Chinese manufacturers is 20,000 tons per year. In Russia and USA, the corresponding averages are 400,000 tons per year and 300,000 tons per year, respectively.

With so many small manufacturers of fertilizer, it is not surprising that the farmers have a hard time differentiating between the good brand and the bad. The sheer number of producers makes the quality control from the government difficult. Without access to testing instruments, the farmers cannot tell the good fertilizer from the bad either, as is shown in our study that there is no significant correlation between the true fertilizer quality and the perceived quality by farmers. These increase the incentives of the producers to cheat as the chances of being detected are low. To counteract this problem, it is recommended that the policy target is switched from trying to reduce the price of the product to ensuring that its quality is not compromised. Awarding quality labels to satisfactory products is a good start, but it is also essential that products in the market, with or without quality labels, are regularly tested by third-party service so that their quality meets the required standards. This is of course more feasible if the number of producers is small. When the number is great with a high turnover rate, the task becomes immensely harder to accomplish. Besides the effort from the government, the industry itself could also take the initiative and set up a sector-wide monitoring body. The honest manufacturers would benefit from such action, as it helps to prevent their image from being tarnished by the less responsible producers. In this case, a greater number of manufacturers might actually be an advantage. The setting up process and coming to an agreement might be more difficult with more members, but the greater number helps to reduce the chances of the producers colluding with each other and cheating. An additional recommendation is to expand the extension services and increase the resources and staff available to them, which helps to enhance the information flow between policymakers and farmers. This facilitates the transfer of new technology or practices to the farmers, and the farmers can also provide feedback if they encounter problems with their fertilizer.

5.1 References

Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1):21–37.

Chen, A. Z., Huffman, W. E., and Rozelle, S. (2003). Technical efficiency of Chinese grain production: A stochastic production frontier approach. In *American Agricultural Economics Association annual meeting*, Montreal, Canada.

Chen, J., Tang, C., Sakura, Y., Yu, J., and Fukushima, Y. (2005). Nitrate pollution from agriculture in different hydrogeological zones of the regional groundwater flow system in the North China Plain. *Hydrogeology Journal*, 13(3):481–492.

Cheng, C., Shi, Y., and Wen, T. (2010). The real cost of nitrogen fertilizer. Technical report, School of Agriculture and Rural Development, Renmin University of China.

Fan, S. and Pardey, P. G. (1997). Research, productivity, and output growth in Chinese agriculture. *Journal of Development Economics*, 53(1):115–137.

FAO (2011). FAOSTAT database. Food and Agriculture Organization of the United Nations. Available at `http://faostat.fao.org/`. Accessed July 1, 2013.

Han, P. (2009). China cracks down on shoddy fertilizers, seeds. Chinese Government's Official Web Portal. Available at `http://english.gov.cn/2009-01/06/content_1196983.htm`. Accessed July 1, 2013.

He, C.-E., Liu, X., Fangmeier, A., and Zhang, F. (2007). Quantifying the total airborne nitrogen input into agroecosystems in the North China Plain. *Agriculture, Ecosystems & Environment*, 121(4):395–400.

Henry, C., Sharma, M., Lapenu, C., and Zeller, M. (2003). *Microfinance Poverty Assessment Tool*. Technical Tools Series No. 5. The World Bank and Consultative Group to Assist the Poor, Washington, DC.

Jiang, Y. and Jiang, Q. (2013). North China Plain groundwater: More than 70 percent unfit for human touch. Institute of Hydrogeology & Environmental Geology, China Academy of Geological Sciences. Available at `http://chinawaterrisk.org/notices/north-china-plain-groundwater-70-unfit-for-human-touch/`. Accessed July 1, 2013.

Liu, X., Zhang, Y., Han, W., Tang, A., Shen, J., Cui, Z., Vitousek, P., Erisman, J. W., Goulding, K., Christie, P., Fangmeier, A., and Zhang, F. (2013). Enhanced nitrogen deposition over China. *Nature*, 494(7438):459–462.

Robison, L. J. and Barry, P. J. (1987). *The Competitive Firm's Response to Risk*. Macmillan Publishing Company, New York.

Shen, J. L., Tang, A. H., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2009). High concentrations and dry deposition of reactive nitrogen species at two sites in the North China Plain. *Environmental Pollution*, 157(11):3106–3113.

Wang, G. (2011). China cracks down on counterfeit seeds, pesticides. Xinhua News Agency. Available at `http://news.xinhuanet.com/english2010/china/2011-05/19/c_13883191.htm`. Accessed July 1, 2013.

Zeller, M., Sharma, M., Henry, C., and Lapenu, C. (2006). An operational method for assessing the poverty outreach performance of development policies and projects: Results of case studies in Africa, Asia, and Latin America. *World Development*, 34(3):446–464.

Zellner, A., Kmenta, J., and Dreze, J. (1966). Specification and estimation of Cobb-Douglas production function models. *Econometrica*, 34(4):784–795.

Zhang, Y., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2008). Nitrogen inputs and isotopes in precipitation in the North China Plain. *Atmospheric Environment*, 42(7):1436–1448.

Zhen, L., Routray, J. K., Zoebisch, M. A., Chen, G., Xie, G., and Cheng, S. (2005). Three dimensions of sustainability of farming practices in the North China Plain: A case study from Ningjin county of Shandong province, PR China. *Agriculture, Ecosystems & Environment*, 105(3):507–522.

Zhen, L., Zoebisch, M. A., Chen, G., and Feng, Z. (2006). Sustainability of farmers' soil fertility management practices: A case study in the North China Plain. *Journal of Environmental Management*, 79(4):409–419.

General Bibliography

Abdoulaye, T. and Sanders, J. H. (2005). Stages and determinants of fertilizer use in semiarid African agriculture: The Niger experience. *Agricultural Economics*, 32(2):167–179.

Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1):21–37.

Alem, Y., Bezabih, M., Kassie, M., and Zikhali, P. (2010). Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, 41(2):165–175.

Ariga, J., Jayne, T. S., Kibaara, B., and Nyoro, J. K. (2008). Trends and patterns in fertilizer use by smallholder farmers in Kenya, 1997-2007. Food security collaborative working paper no. 55169, Department of Agricultural, Food, and Resource Economics, Michigan State University.

Babcock, B. A. (1992). The effects of uncertainty on optimal nitrogen applications. *Review of Agricultural Economics*, 14(2):271–280.

Babcock, B. A. and Hennessy, D. A. (1996). Input demand under yield and revenue insurance. *American Journal of Agricultural Economics*, 78(2):416–427.

Bar-Shira, Z., Just, R. E., and Zilberman, D. (1997). Estimation of farmers' risk attitude: An econometric approach. *Agricultural Economics*, 17(2-3):211–222.

Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2):325–332.

Battese, G. E., Rambaldi, A. N., and Wan, G. H. (1997). A stochastic frontier production function with flexible risk properties. *Journal of Productivity Analysis*, 8:269–280.

Benjamin, D., Brandt, L., and Giles, J. (2005). The evolution of income inequality in rural China. *Economic Development and Cultural Change*, 53(4):769–824.

Boeber, C., Kuehl, Y., and Rumbaur, C. (2009). Land degradation in the North China Plain (NCP): Recent evidence, farmers concerns and policy implications. In *International Association of Agricultural Economists conference*, Beijing, China.

Bound, J., Brown, C., and Mathiowetz, N. (2001). Measurement error in survey data. In Heckman, J. J. and Leamer, E., editors, *Handbook of Econometrics*, chapter 59, pages 3705–3843. Elsevier, The Netherlands.

Bravo-Ureta, B. E. and Evenson, R. E. (1994). Efficiency in agricultural production: The case of peasant farmers in eastern Paraguay. *Agricultural Economics*, 10(1):27–37.

Bravo-Ureta, B. E. and Pinheiro, A. E. (1993). Efficiency analysis of developing country agriculture: A review of the frontier function literature. *Agricultural and Resource Economics Review*, 22(1):88–101.

Bruemmer, B., Glauben, T., and Thijssen, G. (2002). Decomposition of productivity growth using distance functions: The case of dairy farms in three European countries. *American Journal of Agricultural Economics*, 84(3):628–644.

Cavatassi, R., Davis, B., and Lipper, L. (2004). Estimating poverty over time and space: Construction of a time-variant poverty index for Costa Rica. Working Paper No. 04-21, Agricultural and Development Economics Division, Food and Agriculture Organization of the United Nations (FAO).

Chavas, J.-P. and Holt, M. T. (1996). Economic behavior under uncertainty: A joint analysis of risk preferences and technology. *The Review of Economics and Statistics*, 78(2):329–335.

Chen, A. Z., Huffman, W. E., and Rozelle, S. (2003). Technical efficiency of Chinese grain production: A stochastic production frontier approach. In *American Agricultural Economics Association annual meeting*, Montreal, Canada.

Chen, J., Tang, C., Sakura, Y., Yu, J., and Fukushima, Y. (2005). Nitrate pollution from agriculture in different hydrogeological zones of the regional groundwater flow system in the North China Plain. *Hydrogeology Journal*, 13(3):481–492.

Chen, Z., Huffman, W. E., and Rozelle, S. (2009). Farm technology and technical efficiency: Evidence from four regions in China. *China Economic Review*, 20(2):153–161.

Cheng, C., Shi, Y., and Wen, T. (2010). The real cost of nitrogen fertilizer. Technical report, School of Agriculture and Rural Development, Renmin University of China.

Denbaly, M. and Vroomen, H. (1993). Dynamic fertilizer nutrient demands for corn: A cointegrated and error-correcting system. *American Journal of Agricultural Economics*, 75(1):203–209.

Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review*, 101(6):2350–90.

Fan, S. (1991). Effects of technological change and institutional reform on production growth in Chinese agriculture. *American Journal of Agricultural Economics*, 73(2):266–275.

Fan, S. and Pardey, P. G. (1997). Research, productivity, and output growth in Chinese agriculture. *Journal of Development Economics*, 53(1):115–137.

Fan, S., Zhang, X., and Robinson, S. (2003). Structural change and economic growth in China. *Review of Development Economics*, 7(3):360–377.

FAO (2011). FAOSTAT database. Food and Agriculture Organization of the United Nations. Available at `http://faostat.fao.org/`. Accessed July 1, 2013.

Fernandez, C., Koop, G., and Steel, M. F. J. (2002). Multiple-output production with undesirable outputs: An application to nitrogen surplus in agriculture. *Journal of the American Statistical Association*, 97(458):432–442.

Fishel, F. M. (2009). The global increase in counterfeit pesticides. Institute of Food and Agricultural Sciences, University of Florida. Available at `http://edis.ifas.ufl.edu/pdffiles/PI/PI21000.pdf`. Accessed July 1, 2013.

Fraser, P., Chilvers, C., Beral, V., and Hill, M. J. (1980). Nitrate and human cancer: A review of the evidence. *International Journal of Epidemiology*, 9(1):3–12.

Fuglie, K. and Nin-Pratt, A. (2013). Agricultural productivity: A changing global harvest. In *2012 Global Food Policy Report*, chapter 2, pages 15–27. International Food Policy Research Institute (IFPRI).

Fuglie, K. O. (2010). Total factor productivity in the global agricultural economy: Evidence from FAO data. In Alston, J. M., Babcock, B. A., and Pardey, P. G., editors, *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, chapter 4, pages 63–95. The Midwest Agribusiness Trade Research and Information Center, Iowa.

Hamaguchi, T. (2011). Awareness raising activities on proper selection and use of chemical fertilizers have been started. Japan International Cooperation Agency. Available at `http://www.jica.go.jp/project/english/cambodia/006/news/general/110617.html`. Accessed July 1, 2013.

Hamal, K. B. and Anderson, J. R. (1982). A note on decreasing absolute risk aversion among farmers in Nepal. *Australian Journal of Agricultural and Resource Economics*, 26(3):220–225.

Han, P. (2009). China cracks down on shoddy fertilizers, seeds. Chinese Government's Official Web Portal. Available at `http://english.gov.cn/2009-01/06/content_1196983.htm`. Accessed July 1, 2013.

Hansen, S., Thorsen, M., Pebesma, E. J., Kleeschulte, S., and Svendsen, H. (1999). Uncertainty in simulated nitrate leaching due to uncertainty in input data. A case study. *Soil Use and Management*, 15(3):167–175.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, 46(6):1251–1271.

He, C.-E., Liu, X., Fangmeier, A., and Zhang, F. (2007). Quantifying the total airborne nitrogen input into agroecosystems in the North China Plain. *Agriculture, Ecosystems & Environment*, 121(4):395–400.

Henry, C., Sharma, M., Lapenu, C., and Zeller, M. (2003). *Microfinance Poverty Assessment Tool*. Technical Tools Series No. 5. The World Bank and Consultative Group to Assist the Poor, Washington, DC.

Henshaw, C. (2011). Fake pesticides are a growing danger. Wall Street Jounal. Available at `http://www.sej.org/headlines/fake-pesticides-are-growing-danger`. Accessed July 1, 2013.

Hu, K., Huang, Y., Li, H., Li, B., Chen, D., and White, R. E. (2005). Spatial variability of shallow groundwater level, electrical conductivity and nitrate concentration, and risk assessment of nitrate contamination in North China Plain. *Environment International*, 31(6):896–903.

Huang, J. and Rozelle, S. (1995). Environmental stress and grain yields in China. *American Journal of Agricultural Economics*, 77(4):853–864.

Isik, M. and Khanna, M. (2003). Stochastic technology, risk preferences, and adoption of site-specific technologies. *American Journal of Agricultural Economics*, 85(2):305–317.

Jiang, Y. and Jiang, Q. (2013). North China Plain groundwater: More than 70 percent unfit for human touch. Institute of Hydrogeology & Environmental Geology, China Academy of Geological Sciences. Available at `http://chinawaterrisk.org/notices/north-china-plain-groundwater-70-unfit-for-human-touch/`. Accessed July 1, 2013.

Just, R. E. (1974). An investigation of the importance of risk in farmers' decisions. *American Journal of Agricultural Economics*, 56(1):14–25.

Just, R. E. and Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, 7(1):67–86.

Kaiser, H. (1974). An index of factorial simplicity. *Psychometrika*, 39(1):31–36.

Kaliba, A. R., Verkuijl, H., and Mwangi, W. (2000). Factors affecting adoption of improved maize seeds and use of inorganic fertilizer for maize production in the intermediate and lowland zones of Tanzania. *Journal of Agricultural and Applied Economics*, 32(1):35–47.

Keil, A., Zeller, M., Wida, A., Sanim, B., and Birner, R. (2008). What determines farmers' resilience towards ENSO-related drought? An empirical assessment in Central Sulawesi, Indonesia. *Climatic Change*, 86(3):291–307.

Kendy, E., Zhang, Y., Liu, C., Wang, J., and Steenhuis, T. (2004). Groundwater recharge from irrigated cropland in the North China Plain: Case study of Luancheng county, Hebei province, 1949–2000. *Hydrological Processes*, 18(12):2289–2302.

Kratz, S., Haneklaus, S., and Schnug, E. (2010). Chemical solubility and agricultural performance of P-containing recycling fertilizers. *Landbauforschung - vTI Agriculture and Forestry Research*, 60(4):227–240.

Kumbhakar, S. C. (1993). Production risk, technical efficiency, and panel data. *Economics Letters*, 41(1):11–16.

Lamb, R. L. (2003). Fertilizer use, risk, and off-farm labor markets in the semi-arid tropics of India. *American Journal of Agricultural Economics*, 85(2):359–371.

Levi, M. D. (1973). Errors in the variables bias in the presence of correctly measured variables. *Econometrica*, 41(5):985–986.

Lin, J. Y. (1987). The household responsibility system reform in China: A peasant's institutional choice. *American Journal of Agricultural Economics*, 69(2):410–415.

Lin, J. Y. (1992). Rural reforms and agricultural growth in China. *The American Economic Review*, 82(1):34–51.

Lin, W. (1977). Measuring aggregate supply response under instability. *American Journal of Agricultural Economics*, 59(5):903–907.

Liu, C., Yu, J., and Kendy, E. (2001). Groundwater exploitation and its impact on the environment in the North China Plain. *Water International*, 26(2):265–272.

Liu, X., Zhang, Y., Han, W., Tang, A., Shen, J., Cui, Z., Vitousek, P., Erisman, J. W., Goulding, K., Christie, P., Fangmeier, A., and Zhang, F. (2013). Enhanced nitrogen deposition over China. *Nature*, 494(7438):459–462.

Liverpool-Tasie, S., Olaniyan, B., Salau, S., and Sackey, J. (2010). A review of fertilizer policy issues in Nigeria. Working paper no. 0019, Nigeria Strategy Support Program, International Food Policy Research Institute (IFPRI).

Love, A. H. and Buccola, S. T. (1991). Joint risk preference-technology estimation with a primal system. *American Journal of Agricultural Economics*, 73(3):765–774.

Ministry of Agriculture, P. R. C. (2004). *China Agriculture Yearbook 2004*. China Agriculture Press, Beijing.

Ministry of Agriculture, P. R. C. (2009). *China Agriculture Yearbook 2008*. China Agriculture Press, Beijing.

Ministry of Agriculture, P. R. C. (2010). Research Center for Rural Economy Household and Village Surveys 2004 - 2008.

Mullen, R., Lentz, E., and Watson, M. (2005). Soil fertility. In *Ohio Agronomy Guide*, volume Bulletin 472, chapter 2, pages 19–30. Ohio State University Extension, 14th edition.

Mwakalebela, L. (2012). Government declares war on fake fertilizer dealers. Tanzania Daily News. Available at `http://dailynews.co.tz/index.php/parliament-news/7122-government-declares-war-on-fake-fertilizer-dealers`. Accessed July 1, 2013.

Paulson, N. D. and Babcock, B. A. (2010). Readdressing the fertilizer problem. *Journal of Agricultural and Resource Economics*, 35(3):368–384.

Piotrowski, S. (2009). *Land Property Rights and Natural Resource Use: An Analysis of Household Behavior in Rural China*. PhD thesis, University Hohenheim.

Quzhou County Government (2011). Quzhou county yearbook 2011. Available at http://jb.qzx.gov.cn/E_ReadNews.asp?NewsID=6836. Accessed July 1, 2013.

Rajsic, P., Weersink, A., and Gandorfer, M. (2009). Risk and nitrogen application levels. *Canadian Journal of Agricultural Economics*, 57(2):223–239.

Ravallion, M. and Chen, S. (2007). China's (uneven) progress against poverty. *Journal of Development Economics*, 82(1):1–42.

Rehm, G., Schmitt, M., Lamb, J., Randall, G., and Busman, L. (1997). Phosphorus in the agricultural environment: Understanding phosphorus fertilizers. Extension bulletin FO-6288-B, University of Minnesota Extension.

Reinhard, S., Lovell, C. A. K., and Thijssen, G. (1999). Econometric estimation of technical and environmental efficiency: An application to Dutch dairy farms. *American Journal of Agricultural Economics*, 81(1):44–60.

Robison, L. J. and Barry, P. J. (1987). *The Competitive Firm's Response to Risk*. Macmillan Publishing Company, New York.

Roosen, J. and Hennessy, D. A. (2003). Tests for the role of risk aversion on input use. *American Journal of Agricultural Economics*, 85(1):30–43.

Rozelle, S. (1994). Rural industrialization and increasing inequality: Emerging patterns in China's reforming economy. *Journal of Comparative Economics*, 19(3):362–391.

Sander, D. H. and Penas, E. J. (2000). Phosphorus. In Ferguson, R. B. and Groot, K. M. D., editors, *Nutrient Management for Agronomic Crops in Nebraska*, volume EC 155, chapter 2, pages 17–21. University of Nebraska – Lincoln Extension.

Schmidt, P. and Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business & Economic Statistics*, 2(4):367–374.

Shen, J. L., Tang, A. H., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2009). High concentrations and dry deposition of reactive nitrogen species at two sites in the North China Plain. *Environmental Pollution*, 157(11):3106–3113.

SriRamaratnam, S., Bessler, D. A., Rister, M. E., Matocha, J. E., and Novak, J. (1987). Fertilization under uncertainty: An analysis based on producer yield expectations. *American Journal of Agricultural Economics*, 69(2):349–357.

State Statistical Bureau, P. R. C. (2003). *China Rural Statistical Yearbook 2003*. China Statistics Press, Beijing.

Sun, Q., Kroebel, R., Mueller, T., Roemheld, V., Cui, Z., Zhang, F., and Chen, X. (2011). Optimization of yield and water-use of different cropping systems for sustainable groundwater use in North China Plain. *Agricultural Water Management*, 98(5):808–814.

Tambwe, A. (2013). Grappling with challenges of fake seeds. Tanzania Standard Newspapers. Available at `http://www.dailynews.co.tz/index.php/features/popular-features/18923-grappling-with-challenges-of-fake-seeds`. Accessed July 1, 2013.

Tian, W. and Wan, G. H. (2000). Technical efficiency and its determinants in China's grain production. *Journal of Productivity Analysis*, 13(2):159–174.

Viet Nam News (2010). Officials warn of low-quality fertilizer. AccessMyLibrary. Available at `http://www.accessmylibrary.com/article-1G1-229054286/vietnam-officials-warn-low.html`. Accessed July 1, 2013.

Vitosh, M. L. (1996). N-P-K fertilizers. Extension bulletin e-896, Michigan State University Extension.

Wan, Y., Ju, X., Ingwersen, J., Schwarz, U., Stange, C. F., Zhang, F., and Streck, T. (2009). Gross nitrogen transformations and related nitrous oxide emissions in an intensively used calcareous soil. *Soil Science Society of America Journal*, 73(1):102–112.

Wang, G. (2011). China cracks down on counterfeit seeds, pesticides. Xinhua News Agency. Available at `http://news.xinhuanet.com/english2010/china/2011-05/19/c_13883191.htm`. Accessed July 1, 2013.

Wang, J., Cramer, G. L., and Wailes, E. J. (1996a). Production efficiency of Chinese agriculture: Evidence from rural household survey data. *Agricultural Economics*, 15(1):17–28.

Wang, Q., Halbrendt, C., and Johnson, S. R. (1996b). Grain production and environmental management in China's fertilizer economy. *Journal of Environmental Management*, 47(3):283–296.

Wik, M., Pingali, P., and Broca, S. (2008). Global agricultural performance: Past trends and future prospects. Background paper for the World Development Report 2008, The World Bank.

Yesuf, M. and Bluffstone, R. A. (2009). Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from Ethiopia. *American Journal of Agricultural Economics*, 91(4):1022–1037.

Young, A. (2000). The razor's edge: Distortions and incremental reform in the People's Republic of China. *The Quarterly Journal of Economics*, 115(4):1091–1135.

Zahur, A. (2010). Spurious fertilizers: A threat to agriculture. The Daily Star. Available at `http://www.thedailystar.net/newDesign/news-details.php?nid=125044`. Accessed July 1, 2013.

Zeller, M., Sharma, M., Henry, C., and Lapenu, C. (2006). An operational method for assessing the poverty outreach performance of development policies and projects: Results of case studies in Africa, Asia, and Latin America. *World Development*, 34(3):446–464.

Zellner, A., Kmenta, J., and Dreze, J. (1966). Specification and estimation of Cobb-Douglas production function models. *Econometrica*, 34(4):784–795.

Zhang, B. and Carter, C. A. (1997). Reforms, the weather, and productivity growth in China's grain sector. *American Journal of Agricultural Economics*, 79(4):1266–1277.

Zhang, F. S., Chen, X. P., and Chen, Q. (2009). *Fertilizer Guide for the Main Crop of China*. China Agriculture University Press, Beijing.

Zhang, Y., Liu, X. J., Fangmeier, A., Goulding, K. T. W., and Zhang, F. S. (2008a). Nitrogen inputs and isotopes in precipitation in the North China Plain. *Atmospheric Environment*, 42(7):1436–1448.

Zhang, Y., Zheng, L., Liu, X., Jickells, T., Cape, J. N., Goulding, K., Fangmeier, A., and Zhang, F. (2008b). Evidence for organic N deposition and its anthropogenic sources in China. *Atmospheric Environment*, 42(5):1035–1041.

Zhen, L. and Routray, J. K. (2002). Groundwater resource use practices and implications for sustainable agricultural development in the North China Plain: A case study in Ningjin county of Shandong province, PR China. *International Journal of Water Resources Development*, 18(4):581–593.

Zhen, L., Routray, J. K., Zoebisch, M. A., Chen, G., Xie, G., and Cheng, S. (2005). Three dimensions of sustainability of farming practices in the North China Plain: A case study from Ningjin county of Shandong province, PR China. *Agriculture, Ecosystems & Environment*, 105(3):507–522.

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Author's Declaration

I hereby declare that this doctoral thesis is a result of my personal work and that no other than the indicated aids have been used for its completion. All quotations and statements that have been used are indicated. Furthermore, I assure that the work has not been used, neither completely nor in parts, for achieving any other academic degree.

Stuttgart, July 2013

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