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## Research Article

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# Using Financial Risk Criteria to Analyze Rice Production: Farm Sharpe Ratio Evidence on Farmer Risk Aversion and Chemical Input Overuse

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## Abstract

Agricultural production is inherently exposed to multiple sources of uncertainty, including pest outbreaks, crop diseases, and other production shocks. In many developing countries, farmers operate with limited access to formal insurance, credit, and risk-sharing mechanisms, making private risk-management strategies particularly important. Under such conditions, chemical-control inputs may serve not only as productivity-enhancing factors but also as self-insurance mechanisms that help stabilize production outcomes. This study examines whether pesticide and herbicide expenditures function as self-insurance instruments among rice farmers in Northern Thailand. Using farm-level data from Chiang Mai and Chiang Rai provinces, a heteroskedastic production-risk model is employed to estimate production risk and assess the risk-reducing role of chemical-control expenditures. The study also develops a Farm Sharpe Ratio (FSR), a risk-adjusted indicator that evaluates expected production performance relative to estimated production risk.

The results show that pesticide expenditures are consistently associated with lower production risk, while herbicide expenditures exhibit the expected risk-reducing relationship but with weaker statistical support. These findings suggest that chemical-control inputs provide private risk-management benefits and may serve as self-insurance against adverse production shocks. The Farm Sharpe Ratio reveals substantial variation in risk-adjusted performance across farmers, indicating that production outcomes cannot be adequately assessed using yield measures alone. This study contributes by introducing the Farm Sharpe Ratio as a risk-adjusted performance measure for farm-level analysis, linking chemical-input use, production risk, and self-insurance behavior within a unified analytical framework, and providing evidence that intensive chemical-input use may partly reflect rational responses to production uncertainty rather than simple input overuse. The findings offer new insights into the risk-return trade-offs underlying farm management decisions in developing-country agriculture.

**Keywords:** Production risk; Farm Sharpe Ratio; self-insurance; pesticide expenditure; herbicide expenditure; rice farming; Thailand.

## 1. Introduction

Agricultural production decisions are inherently made under uncertainty. Farmers allocate inputs before realizing weather conditions, pest outbreaks, disease incidence, and other stochastic shocks that ultimately determine crop outcomes. Consequently, production inputs may serve not only as productivity-enhancing factors but also as instruments for managing risk. This distinction is

particularly important in the context of chemical-control expenditures, where pesticides and herbicides are commonly evaluated through their effects on productivity, environmental sustainability, and public health.

The existing literature has extensively documented the external costs associated with pesticide use, including environmental degradation, biodiversity loss, and adverse human health outcomes (Praneetvatakul et al., 2013; Pimentel et al., 1992). These studies have provided a strong rationale for policies aimed at reducing chemical dependence on agriculture. Implicit in much of this discussion, however, is the assumption that high levels of chemical use necessarily reflect inefficient or excessive application. Such an interpretation may be incomplete because it overlooks the role of chemical inputs as private risk-management instruments. In production environments characterized by substantial uncertainty, farmers may adopt pesticides and herbicides not solely to increase expected yields but also to reduce the probability of severe production losses. This highlights an important tension in the agricultural economics literature. While the external-cost literature emphasizes the social costs of chemical use, the production-risk literature suggests that input choices may be motivated by farmers' attempts to manage uncertainty (Just & Pope, 1978; Antle, 1983; Kumbhakar, 2002). As a result, observed chemical-use intensity cannot be interpreted straightforwardly as evidence of overuse. A farmer facing substantial production risk may rationally choose higher levels of pesticide or herbicide expenditure because the reduction in yield variability generates private benefits. Ignoring this risk-management dimension risks conflating economically rational self-insurance behavior with inefficient input overuse. In Thailand, concerns regarding excessive pesticide use have stimulated increasing interest in alternative pest management approaches. Evidence from a nationwide survey showed that although biopesticide adoption has expanded, most farmers continue to rely primarily on conventional pesticides for crop protection, suggesting persistent barriers to reducing chemical input dependence (Praneetvatakul et al., 2024).

This issue is particularly relevant in rice production systems in Northern Thailand, where farmers operate under heterogeneous agroecological conditions characterized by variation in rainfall, soil quality, pest pressure, weed infestation, and access to production resources. Under such conditions, production inputs may influence not only the expected level of output but also the variability of output, implying that farmers' input choices reflect both productivity and risk-management considerations (Ray, 2022; Farooq et al., 2023). Recent studies have further emphasized that increasing climate variability, pest outbreaks, and production uncertainty have heightened farmers' reliance on risk-management inputs to stabilize agricultural production outcomes (Girma et al., 2023; Aleksandrova & Bojnec, 2025). In particular, chemical-control expenditures may function as self-insurance mechanisms that reduce exposure to pest- and weed-related production shocks, especially in environments where formal insurance and risk-sharing institutions are limited (Vigani & Kathage, 2019). Consequently, farmers may adopt pesticides and herbicides not only to enhance expected productivity but also to reduce downside production risk and improve production stability. Understanding whether chemical inputs operate primarily as productivity-enhancing factors or as risk-reducing instruments is therefore essential for accurately interpreting farmer behavior and designing policies aimed at reducing chemical dependence without inadvertently increasing production risk.

To address this issue, this paper develops a heteroskedastic production-risk framework in which the mean and variance of rice production are modeled separately. Following the logic of stochastic production theory, labor and fertilizer input determine expected output, whereas pesticide and herbicide expenditures are allowed to influence farmer-specific production risk. This approach recognizes that input may affect the first and second moments of production distribution differently and permits a direct assessment of whether chemical-control expenditures are associated with lower output variability. The paper further proposes a Farm Sharpe Ratio as a risk-adjusted measure of

agricultural performance. Inspired by the Sharpe ratio in financial economics, the indicator evaluates expected production outcomes relative to estimated production risk at the farm level. Rather than focusing exclusively on yield performance, the measure incorporates uncertainty and provides a complementary perspective on production efficiency in risky environments. Because all variables are measured on a per-rai basis, the index avoids scale-related distortions arising from differences in cultivated areas and facilitates comparisons across heterogeneous farms.

This study contributes to the literature in four important ways. First, it integrates agricultural production risk, self-insurance behavior, and chemical-input use within a unified analytical framework. Second, it provides empirical evidence on whether pesticide and herbicide expenditures function as self-insurance mechanisms and risk-reducing inputs rather than solely as productivity-enhancing factors. Third, it extends the concept of risk-adjusted performance from financial economics to agricultural production through the development of a Farm Sharpe Ratio (FSR). Fourth, it provides a framework for distinguishing economically rational responses to production uncertainty from apparent chemical-input overuse. Collectively, these contributions provide a more nuanced framework for evaluating chemical-input use by distinguishing between socially costly overuse and economically rational risk-management responses to production uncertainty.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the theoretical framework linking chemical-input use, production risk, and farmer decision-making under uncertainty. Section 3 describes empirical strategy, econometric methodology, and data. Section 4 presents empirical results, including descriptive statistics, baseline estimates, risk-adjusted performance analysis, and robustness checks. Section 5 discusses the broader implications of the findings for agricultural risk management and chemical-use policies. Section 6 concludes and outlines limitations and avenues for future research.

## **2. Literature Review and Theoretical Framework**

### **2.1 Literature Review**

The use of pesticides and herbicides in agriculture has attracted substantial attention from researchers and policymakers because of its implications for agricultural productivity, environmental sustainability, and food security. While chemical inputs have contributed significantly to crop productivity growth, concerns have increasingly emerged regarding their environmental and social consequences. At the same time, agricultural production remains inherently risky, exposing farmers to uncertainty arising from weather variability, pest outbreaks, diseases, and other biological and economic shocks. Consequently, chemical-input decisions cannot be understood solely through their productivity effects but must also be evaluated within the broader context of agricultural risk management. Despite extensive research in both areas, the relationship between chemical-input use, production risk, and farmer decision-making remains insufficiently understood.

A large body of literature has examined the external costs associated with pesticide and herbicide use. Pimentel et al. (1992) demonstrated that the social costs of pesticides extend far beyond their market prices, encompassing environmental degradation, biodiversity loss, contamination of water resources, and adverse health effects. Similar concerns have been documented in both developed and developing countries, leading to growing calls for policies aimed at reducing dependence on agricultural chemicals. In Thailand, Praneetvatakul et al. (2013) estimated substantial external costs associated with pesticide use and advocated policy interventions promoting safer and more sustainable agricultural practices. More recent studies continue to emphasize the environmental consequences of intensive chemical use and explore mechanisms through which excessive application may be reduced (Xu, 2020; Liu & Wu, 2022). Collectively, this literature suggests that a considerable proportion of chemical use may generate significant social costs while providing only limited additional productivity benefits.

Recent evidence from Thailand indicates that adoption of biopesticides remains complementary rather than substitutive to conventional pesticide use. Praneetvatakul et al. (2024) reported that while 65% of surveyed farmers had adopted biopesticides, most continued to depend heavily on conventional pesticides. Their findings suggest that adoption is positively associated with farmer experience, favorable attitudes toward biopesticides, integrated pest management practices, and contact with extension services. These results highlight that input-use decisions are shaped not only by economic incentives but also by risk perceptions, knowledge, and institutional support.

Although external-cost literature provides important insights into the societal implications of chemical use, it offers a less complete explanation of farmers' input decisions under uncertainty. Much of the discussion implicitly assumes that observed chemical-use intensity reflects either productivity-maximizing behavior or excessive application. However, such interpretations may overlook an important economic function of chemical inputs. Farmers often operate in environments characterized by substantial production uncertainty, where the objective is not only to maximize expected output but also to reduce exposure to adverse shocks. Under these conditions, chemical inputs may generate private benefits through risk reduction even when their marginal contribution to expected output is relatively small. Consequently, observed chemical-use intensity may not necessarily indicate inefficiency but may instead reflect economically rational responses to uncertainty.

This perspective originates from the stochastic production literature. Just and Pope (1978) demonstrated that production inputs may influence both the expected level and the variability of output, thereby challenging conventional production models that focus exclusively on expected production. Subsequent contributions extended this framework and established production risk as a central component of agricultural decision-making (Antle, 1983; Kumbhakar, 2002). These studies suggest that agricultural production should be viewed as a stochastic process in which inputs may affect not only average productivity but also the distribution of production outcomes. Such a perspective is particularly relevant for chemical-control expenditures because pesticides and herbicides are specifically intended to mitigate biological threats that frequently contribute to yield variability.

Recent empirical evidence further supports the argument that agricultural inputs may function as risk-management instruments. Aleksandrova and Bojnec (2025) show that chemical-input adoption can reduce downside yield risk, while Vigani and Kathage (2019) emphasize the importance of risk management in shaping farm productivity outcomes. Comparable findings have been reported in developing-country agriculture, where farmers frequently substitute production-based strategies for formal insurance mechanisms when insurance markets are incomplete or unavailable. Under such conditions, input-based risk management becomes an important component of production stability and farm decision-making (Khanal et al., 2022). These studies suggest that agricultural inputs should be evaluated not only according to their effects on average output but also according to their contribution to reducing farmers' exposure to adverse production shocks.

The importance of risk management is closely linked to farmers' risk preferences. Agricultural households often operate under imperfect credit markets, incomplete insurance coverage, and limited opportunities for formal risk sharing. Consequently, farmers frequently rely on self-insurance strategies to protect themselves against production shocks (Moschini & Hennessy, 2001). More recent evidence indicates that perceptions of production risk significantly influence input allocation decisions and management practices (Girma et al., 2023). Studies focusing on agricultural inputs further suggest that observed variation in chemical use may partly reflect farmers' attempts to stabilize production outcomes rather than simply maximize expected yields (Wu et al., 2021; Xu, 2020).

Despite significant advances in understanding both the environmental consequences and risk-management benefits of agricultural chemicals, these two strands of literature have largely evolved independently. The external-cost literature emphasizes the social costs of chemical use, whereas the

production-risk literature focuses on its private benefits in reducing uncertainty. Consequently, existing research provides limited guidance regarding whether high levels of chemical-input use should be interpreted as evidence of socially undesirable overuse or as economically rational self-insurance behavior. Moreover, while previous studies have examined production risk and input use separately, relatively little attention has been devoted to evaluating farm performance on a risk-adjusted basis that explicitly incorporates both expected production and production uncertainty.

This study addresses these gaps by integrating insights from the external-cost, production-risk, and self-insurance literatures within a unified empirical framework. Specifically, the analysis examines whether pesticide and herbicide expenditures are associated with lower farm-level production risk and develops a Farm Sharpe Ratio as a risk-adjusted measure of agricultural performance. By linking chemical-input use, production risk, and farm-level performance, the study provides a more comprehensive framework for evaluating agricultural decision-making under uncertainty.

## 2.2 Theoretical Framework

Agricultural chemical use presents a fundamental economic trade-off. From a societal perspective, pesticides and herbicides generate environmental and health externalities that increase the social cost of agricultural production (Pimentel et al., 1992; Praneetvatakul et al., 2013). From the perspective of individual farmers, however, these same inputs may serve as input-based self-insurance mechanisms that reduce exposure to pest infestations, weed competition, and other biological shocks. Consequently, observed chemical-input intensity cannot be interpreted solely as evidence of overuse. A farmer may apply pesticides and herbicides not only to increase expected output but also to reduce the probability of severe yield losses. Understanding this distinction is essential because policies designed to reduce chemical dependence may unintentionally increase production risk if alternative risk-management mechanisms are unavailable.

This argument is particularly relevant in agricultural environments characterized by substantial uncertainty. Rice farmers in Northern Thailand operate under heterogeneous agroecological conditions, including variation in rainfall, soil quality, pest pressure, and weed infestation. Such uncertainty implies that production decisions involve not only the pursuit of higher expected yields but also the management of downside risk. Recent evidence suggests that chemical inputs may play an important role in reducing exposure to adverse production outcomes, particularly when formal insurance and risk-sharing institutions are limited (Aleksandrova & Bojnec, 2025; Moschini & Hennessy, 2001). Therefore, the economic value of pesticides and herbicides may extend beyond their contribution to average productivity.

Following Just and Pope (1978), agricultural production is viewed as a stochastic process in which inputs can affect both the expected level and the variability of output. This distinction is important because conventional production models typically focus on expected output alone, implicitly if inputs influence only the mean of the production distribution. Some inputs may primarily function as risk-reducing mechanisms. Pesticides and herbicides provide a clear example. While their direct effect on average yields may vary across production environments, their primary role is often to reduce uncertainty arising from pest outbreaks and weed competition. Consequently, production should be analyzed in terms of both expected output and production risk.

### 2.2.1 Mean Production Function

To evaluate production performance on a comparable basis across farms, the analysis is conducted on a per-rai basis. Let  $Y_i^R$  denote rice yield per rai for farmer  $i$ ,  $L_i^R$  denote labor use per rai, and  $CF_i^R$  denote chemical fertilizer use per rai. The underlying production technology is represented by a Cobb–Douglas specification as equation (1):

$$Y_i^R = A(L_i^R)^{\beta_1}(CF_i^R)^{\beta_2}\exp(v_i), \quad (1)$$

where  $A$  captures technology and managerial conditions and  $v_i$  represents stochastic production shocks.

By taking logarithms of both sides, we obtain the empirical mean production Equation (2):

$$\ln Y_i^R = \beta_0 + \beta_1 \ln(1 + L_i^R) + \beta_2 \ln(1 + CF_i^R) + v_i. \quad (2)$$

The logarithmic specification allows coefficients to be interpreted as elasticities and accommodates the skewed distribution commonly observed in agricultural input data. The transformation  $1 + CF_i^R$  preserves observations with zero fertilizer use, which may represent distinct production systems rather than data anomalies.

### 2.2.2 Production Risk Function

A key implication of stochastic production theory is that production risk itself can be modeled as an economic outcome. Accordingly, the disturbance term is assumed to have farmer-specific variance, as specified in Equation (3).

$$v_i \sim N(0, \sigma_i^2). \quad (3)$$

Production risk is specified as a function of pesticide expenditure per rai ( $PESR_i^R$ ) and herbicide expenditure per rai ( $HERR_i^R$ ). These variables are interpreted as potential risk-management inputs and forms of input-based self-insurance because their primary economic function is to mitigate biological threats to production. The conditional variance is modeled as shown in Equation (4).

$$\ln \sigma_i^2 = a_0 + a_1 \left[ \frac{1}{1 + PESR_i^R/100} \right] + a_2 \left[ \frac{1}{1 + HERR_i^R/100} \right]. \quad (4)$$

This specification captures the notion that chemical-control expenditures exhibit diminishing marginal risk-reduction effects. Initial applications may substantially reduce uncertainty by preventing severe pest and weed damage, whereas additional expenditures at already high levels generate progressively smaller reductions in production risk. If  $a_1 > 0$  and  $a_2 > 0$ , higher pesticide and herbicide expenditures are associated with lower production risk. Such a result would be consistent with the hypothesis that chemical inputs function as self-insurance mechanisms against adverse production shocks.

### 2.2.3 Risk Aversion and Chemical-Input Decisions

The economic rationale for treating pesticides and herbicides as risk-management inputs follows directly from expected utility theory. Profit per rai is defined as follows in Equation (5):

$$\pi_i^R = pY_i^R - r_L L_i^R - r_F CF_i^R - r_P PESR_i^R - r_H HERR_i^R, \quad (5)$$

where  $p$  denotes the output price and  $r_j$  denotes input prices. Under uncertainty, a risk-neutral farmer maximizes expected profit, whereas a risk-averse farmer maximizes expected utility. Using a mean-variance approximation, the farmer's objective can be expressed as Equation (6):

$$\max \left[ E(\pi_i^R) - \frac{\rho_i}{2} Var(\pi_i^R) \right], \quad (6)$$

where  $\rho_i$  measures the degree of risk aversion. This framework implies that chemical-input decisions depend not only on their effects on expected production but also on their ability to reduce variability. A risk-averse farmer may therefore choose a higher level of pesticide or herbicide expenditure than a risk-neutral farmer because reducing downside risk has economic value. Consequently, high chemical-input intensity should not automatically be interpreted as evidence of inefficient overuse. Instead, it may represent a rational response to production uncertainty, which emphasizes farmers' reliance on production and management decisions to reduce exposure to adverse production shocks.

#### 2.2.4 Risk-Adjusted Production Performance

The preceding framework suggests that farm performance should be evaluated not only by expected yield but also by the level of risk required to achieve that yield. To capture this trade-off, the study constructs a Farm Sharpe Ratio as shown in Equation (7):

$$FSR_i = \frac{\hat{Y}_i^R}{\hat{\sigma}_i}, \quad (7)$$

where  $\hat{Y}_i^R$  is fitted yield per rai and  $\hat{\sigma}_i$  is estimated farmer-specific production risk. The indicator measures expected production relative to risk exposure. Higher values indicate that a farmer achieves greater output per unit of risk, while lower values indicate weaker risk-adjusted performance. The Farm Sharpe Ratio extends the logic of risk-adjusted performance evaluation from financial economics to agricultural production by relating expected production outcomes to farm-specific production risk. Although inspired by the Sharpe ratio in finance, the measure is intended as a risk-adjusted agricultural performance indicator rather than a direct analogue of portfolio evaluation. The index should therefore be interpreted as a descriptive risk-adjusted performance measure rather than a welfare metric. By incorporating both expected production and uncertainty, it provides a more comprehensive assessment of farm performance than conventional yield measures alone.

### 3. Empirical Strategy and Data

The empirical objective is to examine whether pesticide and herbicide expenditures function as risk-reducing inputs and potential self-insurance mechanisms by reducing farm-level production risk. Consistent with the theoretical framework, the empirical specification separates the expected-output component of rice production from the conditional variance component. This distinction follows the stochastic production literature, which recognizes that agricultural inputs may influence both the mean and variance of output distributions (Just & Pope, 1978; Antle, 1983).

Let  $y_i = \ln(Y_i^R)$  denote the logarithm of rice yield per rai for farmer  $i$ . The conditional mean equation is specified as Equation (8):

$$y_i = X_i\beta + e_i, \quad (8)$$

where  $X_i$  contains the intercept, labor input per rai, and chemical fertilizer use per rai. The disturbance term  $e_i$  captures unobserved production shocks. Unlike conventional regression models that assume constant variance across observations, the present framework allows production risk to vary systematically across farmers. Specifically, the conditional variance is modeled as shown in Equation (9):

$$h_i = \sigma_i^2 = \exp(Z_i a), \quad (9)$$

where  $\mathbf{Z}_i$  contains the intercept and the transformed pesticide and herbicide expenditure variables. This specification permits farmer-specific production risk to depend directly on chemical-control expenditures and provides a direct test of the hypothesis that pesticides and herbicides act as risk-reducing inputs.

Assuming conditional normality, Equation (10) can be written as:

$$\mathbf{e}_i \sim N(\mathbf{0}, \mathbf{h}_i), \quad (10)$$

The model is estimated using heteroskedastic maximum likelihood. The log-likelihood contribution of observation  $i$  is given by Equation (11):

$$\ell_i = -\frac{1}{2} \left[ \ln(2\pi) + \ln \mathbf{h}_i + \frac{\mathbf{e}_i^2}{\mathbf{h}_i} \right]. \quad (11)$$

The parameter vector  $\theta = (\beta, a)$  is obtained by maximizing the sample log-likelihood across all observations. Robust sandwich standard errors are reported throughout to reduce sensitivity to potential departures from the assumed error distribution. Robust inference is employed because consistency of the coefficient estimates does not require correct specification of the conditional variance structure. The heteroskedastic specification is compared with a conventional homoskedastic benchmark using a likelihood-ratio test. A statistically significant improvement in model fit would indicate that production risk varies systematically across farmers and that modeling heteroskedasticity is economically meaningful. Such evidence would support the central premise of the paper that chemical-control expenditures influence not only expected production outcomes but also production uncertainty. As an additional robustness exercise, a Gaussian-kernel-weighted version of the heteroskedastic likelihood is estimated. The bandwidth is selected using a data-driven bandwidth selection procedure. The weighting scheme is constructed from a standardized index of chemical-control intensity based on pesticide and herbicide expenditures per rai. Observations near the center of the chemical-use distribution receive relatively greater weight, while extreme observations receive lower weight. The weighted model is not interpreted as the preferred specification because weighting changes the target estimand. Instead, it is used solely to assess the sensitivity of the estimated risk relationships to observations located at the tails of the chemical-use distribution.

The empirical analysis utilizes cross-sectional farm-level data collected by Chaovanapoonphol (2004) from rice farmers in Chiang Mai and Chiang Rai provinces in Northern Thailand. These provinces represent important rice-producing regions characterized by substantial heterogeneity in agroecological conditions, including variation in rainfall patterns, soil quality, pest pressure, and weed infestation. Such heterogeneity makes the setting particularly suitable for analyzing farmer-specific production risk. The unit of observation is the individual rice farmer. The primary outcome variable is rice yield per rai ( $ATP$ ), measured in kilograms per rai. Labor input per rai ( $LAMDR$ ) and chemical fertilizer use per rai ( $CFR$ ) enter the mean production equation, while pesticide expenditure per rai ( $PESR$ ) and herbicide expenditure per rai ( $HERR$ ) enter the variance equation as risk-management variables. Several additional variables are available in the dataset, including cultivated area, rice variety, seed use, and fuel expenditure. These variables are used primarily for descriptive analysis and robustness assessments. Baseline specification intentionally adopts a parsimonious structure to focus on the risk-management role of chemical-control expenditures and to maintain consistency with the theoretical framework.

The dataset is particularly suitable for the objectives of this study for three reasons. First, key production and input variables are measured on a per-rai basis, allowing comparisons across farms with different landholdings while avoiding scale-related distortions. Second, pesticide and herbicide

expenditures exhibit substantial cross-sectional variation, providing the identifying variation necessary to estimate farmer-specific risk relationships. Third, the diversity of production conditions across Northern Thailand creates meaningful differences in exposure to agricultural risk, making it possible to examine whether chemical-control expenditures are associated with reductions in production uncertainty.

**Table 1.** The Definitions of the Variables Used in the Analysis

| Variable     | Definition              | Measurement Unit                           |
|--------------|-------------------------|--------------------------------------------|
| <i>ATP</i>   | Rice yield/output       | Kilograms per rai                          |
| <i>LAMDR</i> | Labor input             | Workdays per rai                           |
| <i>CFR</i>   | Chemical fertilizer use | Kilograms per rai                          |
| <i>PESR</i>  | Pesticide expenditure   | Baht per rai                               |
| <i>HERR</i>  | Herbicide expenditure   | Baht per rai                               |
| <i>AMR</i>   | Rice cultivated area    | Rai                                        |
| <i>VMR</i>   | Rice variety indicator  | 1 = non-glutinous rice; 0 = glutinous rice |
| <i>SDR</i>   | Seed use                | Kilograms per rai                          |
| <i>FUR</i>   | Fuel expenditure        | Baht per rai                               |

Note: 6.25 rai equals 1 hectare.

## 4. Empirical Results

### 4.1 Descriptive Statistics

**Table 2.** Descriptive Statistics of Variables Used in the Analysis

| Variable     | Mean    | Std. Dev. | Minimum | Median  | Maximum  |
|--------------|---------|-----------|---------|---------|----------|
| <i>ATP</i>   | 627.759 | 186.181   | 37.333  | 630.000 | 1470.000 |
| <i>LAMDR</i> | 5.989   | 6.361     | 0.080   | 4.250   | 70.000   |
| <i>CFR</i>   | 31.944  | 29.632    | 0.000   | 30.000  | 620.000  |
| <i>PESR</i>  | 27.282  | 43.629    | 0.000   | 5.000   | 285.000  |
| <i>HERR</i>  | 51.856  | 60.597    | 0.000   | 45.000  | 790.909  |
| <i>AMR</i>   | 9.639   | 7.086     | 1.000   | 8.000   | 70.000   |
| <i>VMR</i>   | 0.357   | 0.480     | 0.000   | 0.000   | 1.000    |
| <i>SDR</i>   | 8.650   | 4.340     | 1.000   | 7.500   | 50.000   |
| <i>FUR</i>   | 62.250  | 99.416    | 0.000   | 35.000  | 900.000  |

Table 2 reports descriptive statistics for the 655 rice farmers included in the final sample. Average rice yield is 627.76 kg per rai, with a standard deviation of 186.18 kg per rai, indicating substantial heterogeneity in production performance across farms. Yield ranges from 37.33 kg per rai to 1,470.00 kg per rai, suggesting considerable variation in production conditions, managerial practices, and exposure to agricultural shocks. Labor use averages 5.99 workdays per rai, although the distribution is highly dispersed, ranging from 0.08 to 70 workdays per rai. Similarly, chemical fertilizer use exhibits substantial variation, with a mean of 31.94 kg per rai and a maximum value of 620 kg per rai. The presence of zero fertilizer observations is consistent with the existence of heterogeneous production systems, including potentially low-input or traditional cultivation practices. The variables of greatest interest for the present study are pesticide expenditure (*PESR*) and herbicide expenditure (*HERR*). Average pesticide expenditure is 27.28 baht per rai, while average herbicide expenditure is 51.86 baht per rai. However, the distributions are highly right skewed. The median

pesticide expenditure is only 5 baht per rai, compared with a mean of 27.28 baht per rai, indicating that a relatively small number of farmers account for a disproportionate share of pesticide spending. A similar pattern is observed for herbicide expenditure, where the median value of 45 baht per rai lies below the sample mean. These differences between means and medians suggest substantial heterogeneity in chemical-control strategies among farmers.

The wide dispersion in chemical-control expenditures is particularly important for empirical analysis. Pesticide expenditure ranges from zero to 285 baht per rai, while herbicide expenditure ranges from zero to 790.91 baht per rai. Such variation provides the identifying information necessary to examine whether differences in chemical-input intensity are associated with differences in farm-level production risk. From a theoretical perspective, if pesticides and herbicides function as risk-management inputs, farmers with higher chemical-control expenditures should exhibit lower estimated production risk, all else equal.

The remaining variables further illustrate the diversity of production conditions within the sample. Average cultivated area is 9.64 rai, although farm size ranges from 1 to 70 rai. Approximately 35.7% of farmers cultivate non-glutinous rice varieties, while the remainder produce glutinous rice. Average seed use is 8.65 kg per rai, and average fuel expenditure is 62.25 baht per rai. Together, these statistics highlight the heterogeneous nature of rice production in Northern Thailand and support the relevance of a modeling framework that allows production risk to vary across farms.

#### 4.2 Baseline Heteroskedastic Production-Risk Estimates

Table 3 reports the baseline heteroskedastic production-risk estimates. The results provide support for the central hypothesis that chemical-control expenditures are associated with lower farm-level production risk.

**Table 3.** Baseline and Robustness Estimates of Heteroskedastic Production Risk Models

| Variable                      | Baseline  | Kernel Weighted | Positive Fertilizer |
|-------------------------------|-----------|-----------------|---------------------|
| <b>Mean equation</b>          |           |                 |                     |
| Constant                      | 6.248***  | 6.430***        | 6.064***            |
| ln(Labor per rai)             | 0.093***  | 0.076***        | 0.087***            |
| ln(Fertilizer per rai)        | -0.002    | -0.029          | 0.054**             |
| <b>Risk equation</b>          |           |                 |                     |
| Constant                      | -3.749*** | -6.262***       | -3.604***           |
| Inverse pesticide expenditure | 1.025**   | 2.675**         | 0.872**             |
| Inverse herbicide expenditure | 0.995     | 1.781*          | 0.928               |
| Observations                  | 655       | 655             | 613                 |
| LR $\chi^2(2)$                | 31.60***  | -               | 23.83***            |

Notes: Robust sandwich standard errors are shown in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. The Gaussian-kernel-weighted model and the positive-fertilizer subsample are reported as a robustness check. The positive-fertilizer subsample excludes observations with CFR=0.

In the mean production equation, labor input exhibits a positive and statistically significant association with rice yield across all specifications. This finding is consistent with conventional

production theory and suggests that labor remains an important determinant of rice production performance. By contrast, the fertilizer coefficient is statistically insignificant in the baseline model and remains insignificant in the kernel-weighted specification. However, once observations with zero fertilizer use are excluded, the coefficient becomes positive and statistically significant. This pattern suggests that the pooled sample combines farms operating under different production regimes, thereby obscuring the productivity effect of fertilizer use. Rather than indicating fertilizer overuse, the result points to underlying technological heterogeneity between conventional and low-input production systems.

The principal findings emerge from the conditional variance equation. The coefficient on inverse pesticide expenditure is positive and statistically significant in all specifications. Because the risk function is specified inversely, this result implies that lower pesticide expenditures are associated with higher production risk, whereas greater pesticide expenditures are associated with lower output variability. The consistency of this finding across the baseline, kernel-weighted, and positive-fertilizer specifications provides strong evidence that pesticide expenditures contribute to production-risk reduction. Consequently, the results support Hypothesis 1 and suggest that pesticides may perform an economically meaningful risk-management role beyond their conventional productivity-enhancing function. The evidence regarding herbicide expenditure is more nuanced. Although the estimated coefficient is positive in all specifications, statistical significance is observed only in the kernel-weighted model. The consistent sign suggests that herbicide expenditures may also contribute to risk reduction, but the weaker statistical precision indicates that their influence is less robust than that of pesticide expenditures. One possible explanation is that pest-related shocks generate larger yield losses than weed-related shocks in the study area, causing farmers to rely more heavily on pesticides as a risk-management tool. Alternatively, variation in herbicide application practices across farms may weaken the precision of the estimated relationship.

Overall, the results indicate that chemical-control expenditures should not be interpreted solely as conventional production inputs. Instead, they appear to be consistent with a self-insurance interpretation by helping reduce exposure to adverse production shocks. This interpretation is consistent with the theoretical framework developed in Section 3. The observed patterns are also consistent with the possibility that farmers allocate resources toward chemical-control activities partly to stabilize production outcomes in addition to increasing expected output. In environments characterized by uncertain pest and weed pressure, the private value of risk reduction may therefore constitute an important component of chemical-input demand. Finally, the likelihood-ratio statistic strongly rejects the homoskedastic specification. This result indicates that production risk varies systematically across farmers rather than remaining constant throughout the sample. Such heterogeneity is economically meaningful because it reflects differences in production environments, management practices, and exposure to agricultural shocks. The significant improvement in model fit therefore validates the use of a heteroskedastic production-risk framework and demonstrates that modeling farmer-specific variance provides important information that cannot be captured by conventional mean-production models alone.

As robustness checks, first, the heteroskedastic model is re-estimated using Gaussian-kernel weights to reduce the influence of observations with extreme chemical-control expenditures. Second, the analysis is repeated using a positive-fertilizer subsample that excludes farmers reporting zero fertilizer use, thereby addressing potential technological heterogeneity between conventional and low-input production systems.

The results are broadly consistent across specifications. The coefficient on inverse pesticide expenditure remains positive and statistically significant, while the coefficient on inverse herbicide expenditure retains the expected positive sign. These findings indicate that the negative association between chemical-control expenditure and production risk is not driven by extreme observations or

by the inclusion of zero-fertilizer farms. The kernel-weighted model produces somewhat larger risk coefficients, suggesting stronger risk-reduction effects among farmers located near the center of the chemical-control expenditure distribution.

The positive-fertilizer subsample provides additional insight into the fertilizer effect. While the fertilizer coefficient is insignificant in the full sample, it becomes positive and statistically significant once zero-fertilizer observations are excluded. This result suggests that the pooled sample combines farms operating under different production technologies and that technological heterogeneity partly obscures the productivity effect of fertilizer use. Importantly, the estimated risk relationships remain stable across specifications, reinforcing the conclusion that chemical-control expenditures are systematically associated with lower production risk.

#### 4.3 Estimated Production Risk and Farm Sharpe Ratio

The heteroskedastic model generates farmer-specific estimates of *output variability* and risk-adjusted production performance. Estimated production risk ( $\hat{\sigma}_i$ ) ranges from 0.206 to 0.421, with a median value of 0.343. Although the range may appear modest in absolute terms, the distribution reveals substantial heterogeneity in risk exposure across farmers. Similarly, fitted yield per rai varies from 517.92 to 765.72 kilograms, indicating meaningful differences in expected production outcomes even within a relatively homogeneous rice-growing region. Combining expected production and estimated risk yields the Farm Sharpe Ratio, which ranges from 1,241 to 3,366 and has a median value of 1,768. The substantial dispersion in the index suggests that farmers differ not only in their expected production levels but also in their ability to convert production inputs into stable, risk-adjusted outcomes. Consequently, farmers with similar expected yields may exhibit markedly different production performance once risk is taken into account.

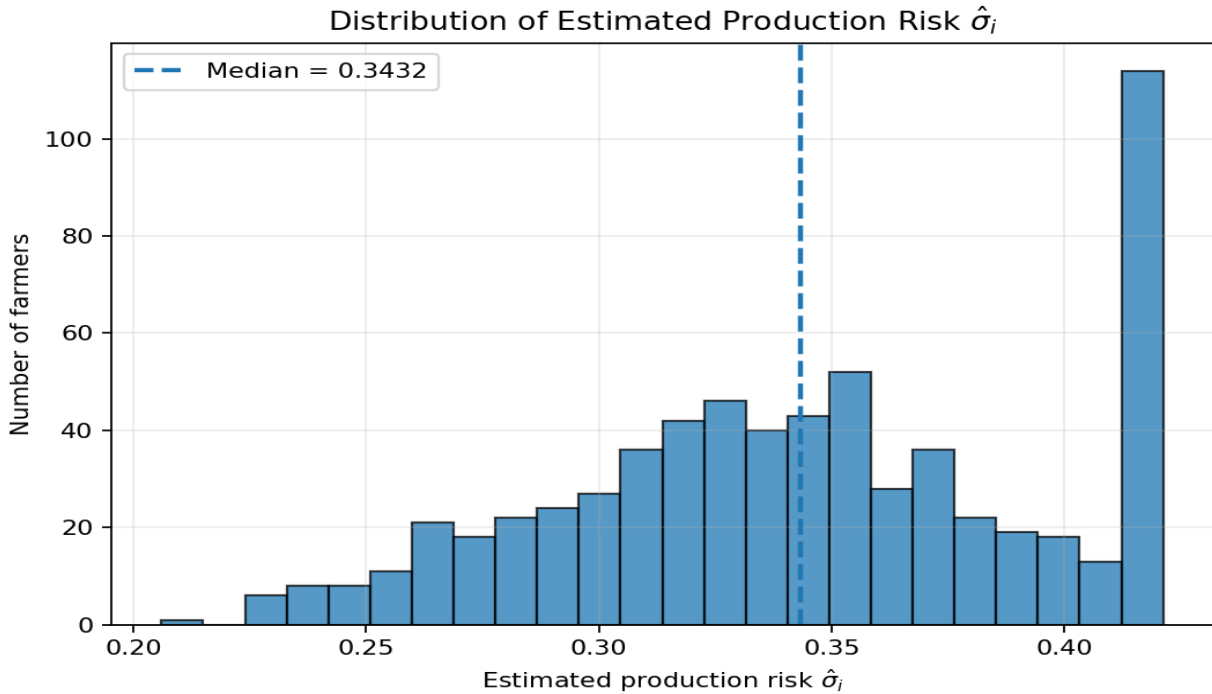


**Figure 1.** Distribution of Estimated Production Risk

Note: The figure shows the distribution of estimated farmer-specific production risk  $\hat{\sigma}$  from the baseline heteroskedastic model.

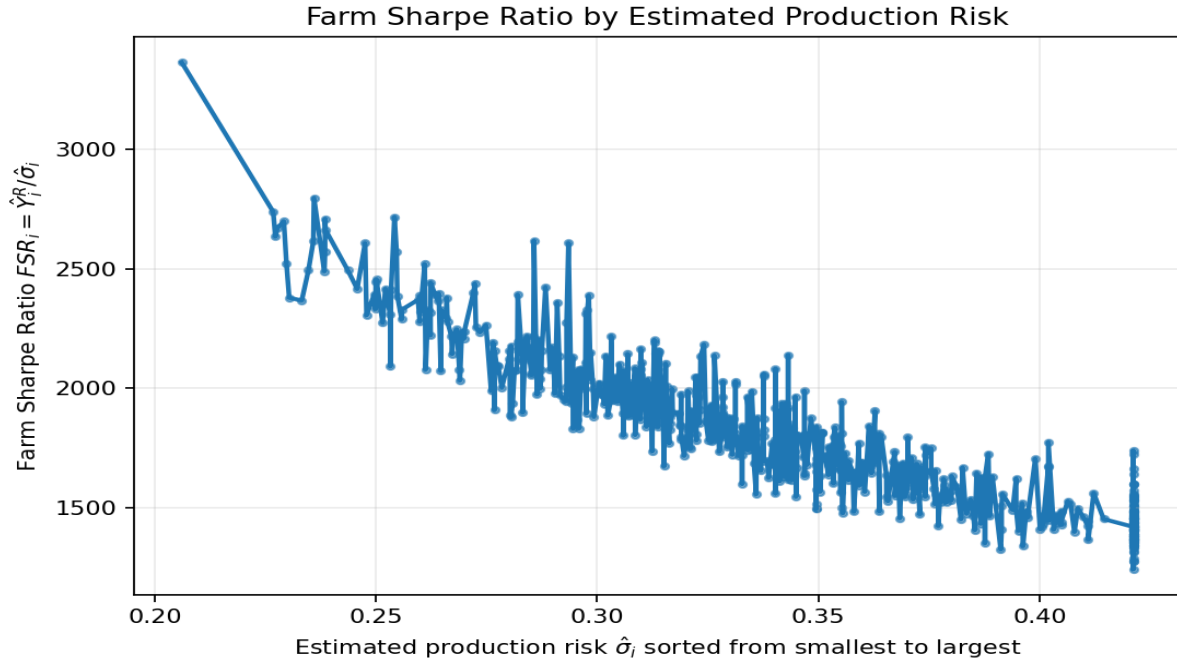


**Figure 2.** Farm Sharpe Ratio by Estimated Production Risk

Note: Farmers are sorted from the smallest to the largest estimated production risk. The vertical axis reports FSR.

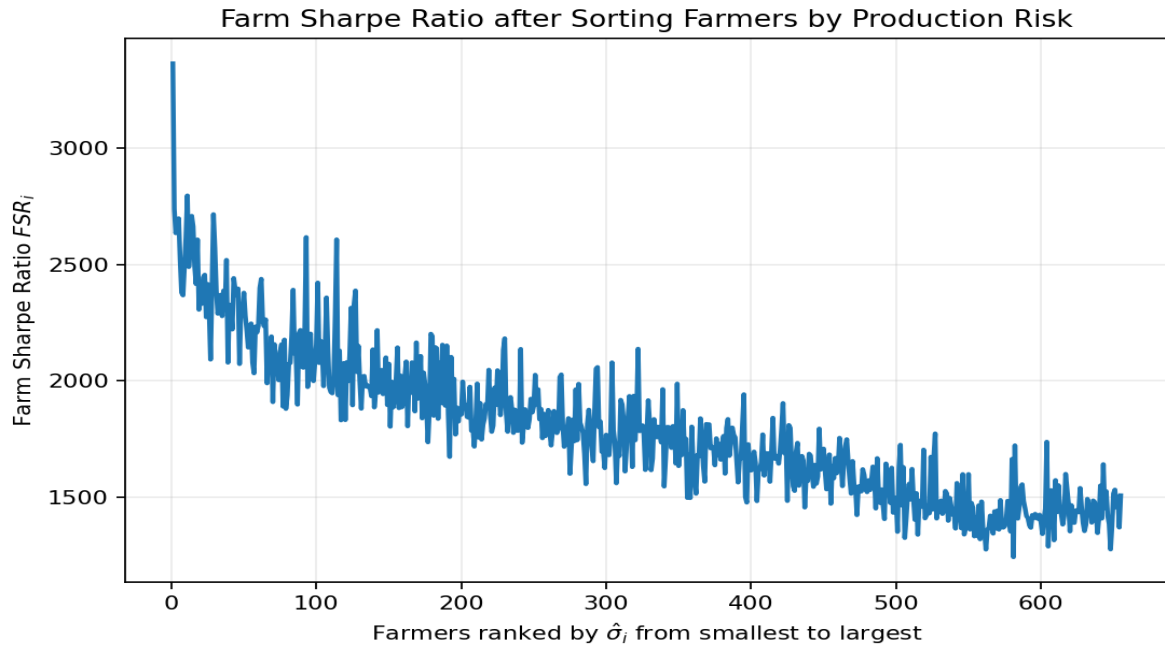


**Figure 3.** Farm Sharpe Ratio After Sorting Farmers by Production Risk

Note: The graph shows risk-adjusted fitted yield across farmers ranked by  $\hat{\sigma}$ .

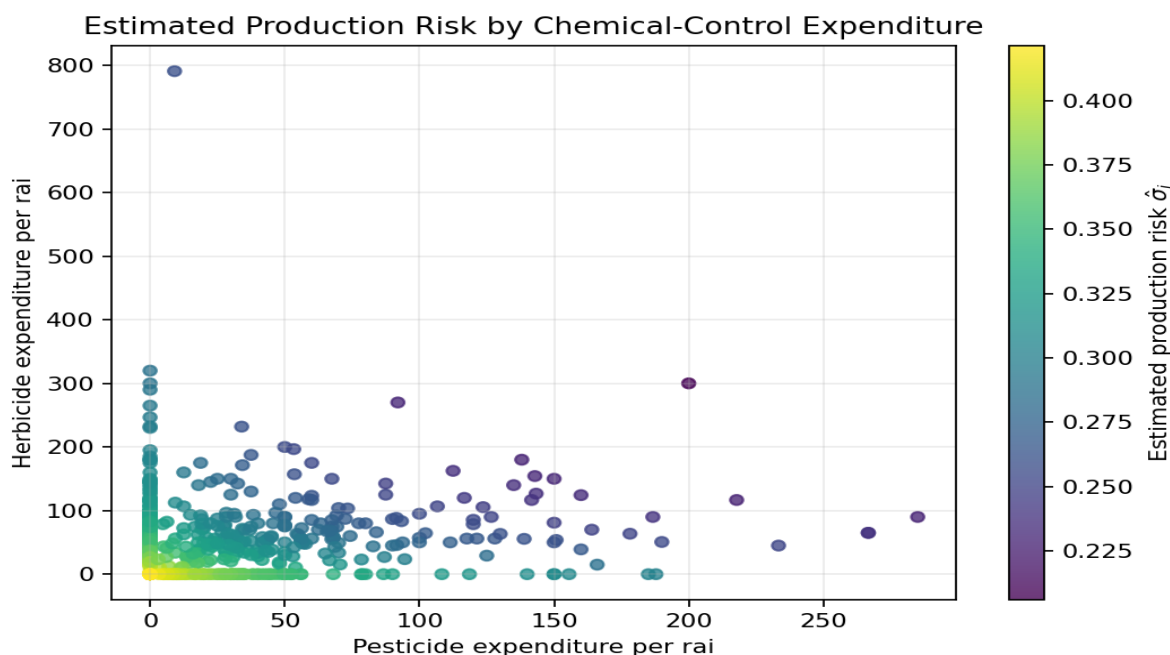


**Figure 4.** Estimated Production Risk by Chemical Control Expenditure

Note: The scatterplot relates pesticide and herbicide expenditure per rai to estimated production risk.

Figure 1 presents the distribution of estimated production risk. The distribution is concentrated around the sample median but exhibits noticeable dispersion, indicating that production uncertainty is not uniformly distributed across farms. This finding reinforces the results of the likelihood-ratio test reported earlier, which rejected the homoskedastic specification and demonstrated that production risk varies systematically across producers. The observed heterogeneity is consistent with differences in pest pressure, weed infestation, management practices, and local production conditions.

Figures 2 and 3 provide further insight into the relationship between production risk and risk-adjusted performance. Farmers are ranked according to their estimated production risk, and the corresponding Farm Sharpe Ratios are displayed. A clear negative relationship emerges as estimated production risk increases, risk-adjusted performance declines. Importantly, this pattern is not mechanically imposed by the construction of the index. The fitted-yield component also varies across farms, meaning that the observed decline reflects the combined effects of expected production and risk exposure. The results suggest that higher-risk farms face a substantial performance penalty once uncertainty is incorporated into the evaluation of production outcomes. This finding has important implications for agricultural performance assessment. Conventional analyses often compare farms solely based on observed or expected yields. However, two farmers achieving similar yield levels may differ substantially in the amount of risk required to achieve those outcomes. From a risk-management perspective, a production strategy that delivers slightly lower yields with substantially lower risk may be preferable to one that generates higher yields but exposes the farmer to considerable production uncertainty. The Farm Sharpe Ratio provides a descriptive way to capture this trade-off.

Figure 4 links estimated production risk to pesticide and herbicide expenditures. Several notable patterns emerge. First, the highest levels of estimated risk are concentrated among farmers with relatively low chemical-control expenditures. Second, farms exhibiting higher pesticide and herbicide expenditures generally appear within lower-risk regions of the distribution. Third, the relationship is nonlinear, with the most pronounced reductions in estimated risk occurring at lower

levels of expenditure. These patterns are consistent with the diminishing marginal risk-reduction effects assumed in the theoretical framework and estimated in the variance equation. Importantly, Figure 4 should not be interpreted as establishing a causal relationship between chemical-control expenditure and production risk. Rather, it provides a graphical representation of the associations identified by the heteroskedastic production-risk model. Nevertheless, the visual evidence aligns closely with the econometric results, particularly the statistically significant pesticide effect reported in Table 3. Together, the graphical and econometric evidence suggest that chemical-control expenditure is associated with more stable production outcomes and may provide private risk-management benefits to farmers.

Figures 1–4 strengthen the central argument of the paper. The evidence indicates that production risk varies substantially across farmers, that higher risk is associated with poorer risk-adjusted production performance, and that chemical-control expenditures are systematically related to lower estimated production risk. These findings suggest that agricultural chemical use cannot be evaluated solely through its effects on expected yields or external costs. At least part of the observed variation in pesticide and herbicide expenditures appears consistent with rational efforts to manage production uncertainty. As a result, policies aimed at reducing chemical input use should consider not only environmental objectives but also the risk-management services that such inputs provide within agricultural production systems.

#### 4.4 Additional Robustness Checks

As a further robustness check, the model is re-estimated by introducing a zero-fertilizer dummy in the mean production equation. The dummy equals one for farmers reporting no chemical fertilizer use and zero otherwise. This specification allows zero-fertilizer farms to operate under a different production regime rather than imposing a common production technology across all farmers.

**Table 4.** Technology-Regime Robustness: Zero-Fertilizer Production System

| Variable                      | Technology-Regime Model |
|-------------------------------|-------------------------|
| <b>Mean equation</b>          |                         |
| Constant                      | 6.063***<br>(0.103)     |
| ln(Labor per rai)             | 0.090***<br>(0.023)     |
| ln(Fertilizer per rai)        | 0.053**<br>(0.024)      |
| Zero-fertilizer dummy         | 0.261***<br>(0.098)     |
| <b>Risk equation</b>          |                         |
| Constant                      | -3.785***<br>(0.778)    |
| Inverse pesticide expenditure | 1.028***<br>(0.399)     |
| Inverse herbicide expenditure | 1.028<br>(0.686)        |
| <b>Model statistics</b>       |                         |
| Observations                  | 655                     |
| LR $\chi^2(2)$                | 32.80***                |

**Notes:** Robust sandwich standard errors are reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The zero-fertilizer dummy equals one for farms reporting no chemical fertilizer use and zero otherwise. The LR statistics test the null hypothesis of homoskedasticity against the heteroskedastic specification.

Table 4 reports the results. The zero-fertilizer dummy is positive and statistically significant, providing evidence that farms reporting no fertilizer use differ systematically from conventional fertilizer users. This finding supports the earlier interpretation that the insignificant fertilizer coefficient in the pooled sample reflects technological heterogeneity rather than fertilizer inefficiency. Consistent with this explanation, the fertilizer coefficient becomes positive and statistically significant once the distinct production regime is explicitly accommodated. More importantly, the production-risk results remain stable. The coefficient on inverse pesticide expenditure remains positive and statistically significant, while the inverse herbicide coefficient continues to exhibit the expected positive sign. The persistence of these findings indicates that the estimated relationship between chemical-control expenditures and production risk is not driven by differences between fertilizer and non-fertilizer production systems.

#### 4.5 Discussion

The findings provide consistent evidence that chemical-control expenditures are associated with lower farm-level production risk. Across the baseline model and all robustness specifications, higher pesticide expenditures are systematically linked to lower estimated production variance, while herbicide expenditures exhibit the expected risk-reducing relationship, although with weaker statistical precision. These results support the central proposition of the stochastic production literature that agricultural inputs may influence not only expected output but also the distribution of production outcomes (Just & Pope, 1978; Antle, 1983). In particular, the findings suggest that pesticides and herbicides appear to perform a dual role, contributing both to agricultural production and to the management of production risk. This interpretation is consistent with recent evidence emphasizing the risk-management role of agricultural inputs. Aleksandrova and Bojnec (2025) showed that chemical-input adoption reduces downside yield risk, while Vigani and Kathage (2019) argued that risk management is an important determinant of farm performance under uncertainty. The present results extend this literature by demonstrating that the association between chemical-control expenditures and production risk remains robust across alternative model specifications and sample definitions. In the context of Northern Thailand, where farmers face heterogeneous production conditions and limited formal insurance opportunities, chemical-control expenditures appear to be consistent with a self-insurance mechanism against adverse production shocks.

The results also contribute to the broader debate concerning agricultural chemical overuse. Existing studies have documented substantial environmental and health costs associated with pesticide use (Pimentel et al., 1992; Praneetvatakul et al., 2013), leading to widespread policy concern regarding excessive chemical dependence. The present findings do not challenge the existence of such external costs. Rather, they highlight an important dimension that is often overlooked in policy discussions: the private risk-reduction benefits associated with chemical-control expenditures. Consequently, observed pesticide or herbicide expenditures cannot automatically be interpreted as evidence of inefficient behavior or excessive input use. From the perspective of expected-utility theory, higher chemical expenditures may represent a rational response to production uncertainty rather than a deviation from optimal decision-making. This distinction is particularly important because policies aimed at reducing agricultural chemical use may generate unintended consequences if they fail to account for farmers' risk-management needs. Moschini and Hennessy (2001) emphasize that agricultural producers employ a variety of strategies to manage uncertainty, including diversification, insurance, contractual arrangements, and input choices. Where formal risk-management mechanisms are limited or costly, chemical-control expenditures may partially substitute for formal insurance mechanisms in some production environments. Policies designed to reduce chemical dependence may therefore be more effective when accompanied by alternative risk-management instruments such as integrated pest management programs, crop insurance schemes, improved extension services, pest monitoring systems, and access to risk-reducing technologies.

The Farm Sharpe Ratio provides an additional perspective on these issues by linking expected production outcomes to estimated production risk. The substantial variation in risk-adjusted performance observed across farms suggests that production success cannot be evaluated solely in terms of expected yield. Farmers with similar expected output levels may face markedly different levels of production uncertainty, implying that conventional yield comparisons may provide an incomplete assessment of farm performance. Incorporating risk into performance evaluation therefore offers a more comprehensive understanding of agricultural decision-making under uncertainty.

## 5. Conclusion

This study examines the relationship between chemical-control expenditures and production risk among rice farmers in Northern Thailand. Motivated by the growing policy concern surrounding agricultural chemical use, the analysis argues that evaluations of pesticide and herbicide use are incomplete when they focus exclusively on productivity effects or external costs while ignoring the role of production risk. Drawing on the stochastic production framework of Just and Pope (1978), the paper develops a heteroskedastic production-risk model that explicitly separates expected production outcomes from farmer-specific production variance.

The empirical results indicate that pesticide expenditures are consistently associated with lower estimated production variance and production risk across a range of specifications, while herbicide expenditures exhibit the expected risk-reducing relationship but with weaker statistical precision. These findings suggest that chemical-control expenditures may provide private risk-management benefits in addition to any effects they may have on expected production. The robustness of the results across kernel-weighted estimation, positive-fertilizer subsamples, and alternative technology-regime specifications strengthens confidence in this interpretation.

The results do not imply that greater chemical use is necessarily socially desirable. A substantial body of research has documented the environmental and health costs associated with pesticide use, and these concerns remain important. Rather, the findings suggest that observed chemical input intensity should not automatically be interpreted as evidence of inefficient or excessive use. At least part of the observed variation in chemical expenditure appears consistent with economically rational responses to production uncertainty. Consequently, policies designed to reduce agricultural chemical use may be more effective when combined with alternative risk-management mechanisms, including integrated pest management, extension services, pest-monitoring systems, and agricultural insurance programs. The results further align with recent discussions on agricultural resilience, which emphasize the importance of balancing environmental sustainability objectives with farmers' need for effective risk-management tools under increasing biological and production uncertainty.

Several limitations should be acknowledged. The analysis is based on cross-sectional data and therefore identifies associations rather than causal effects. In addition, expenditure measures do not distinguish among application timing, active ingredients, or chemical quality, and the study does not directly estimate environmental or health externalities. Future research could integrate production risk, environmental impacts, and farmer-specific risk preferences within a unified framework to provide a more complete assessment of agricultural chemical use.

## 6. Declarations

**Author Contributions:** Conceptualization, J.S., S.S. and Y.C.; Methodology, S.S., Y.C., and A.W.; Formal analysis, J.S. and Y.C.; Data curation, Y.C.; Investigation, Y.C.; Validation, Y.C., and A.W.; Writing—original draft preparation, J.S. and Y.C.; Writing—review and editing, Y.C., A.W., and S.S.; Supervision, Y.C., A.W., and S.S. All authors have read and agreed to the published version of the manuscript.

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**Clinical Trial Registration:** Not applicable. This study did not involve a clinical trial and therefore did not require registration in a clinical trial registry.

**Informed Consent Statement:** Informed consent was obtained from all individual participants involved in the study prior to data collection.

#### **Ethics Approval and Consent to Participate**

This study was conducted in accordance with the ethical principles for research involving human participants and was approved by the Human Research Ethics Committee (HREC), University of New England, Australia (Approval No. HE04/002), under the research project entitled "The Impact of Financial Services on the Performance of Rice Farmers in the Upper North of Thailand." Ethical approval was granted on 5 March 2004.

**Data Availability** The datasets generated and/or analyzed during the current study are not publicly available because they contain information that could compromise the privacy of research participants. The data are available from the corresponding author upon reasonable request for academic and research purposes, subject to institutional and ethical requirements.

**Conflicts of Interest:** The authors declare no conflict of interest.

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