Agricultural policy and its impact on fuel usage: Empirical evidence from farm household analysis

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\begin{abstract}
Off-farm work is a growing reality in the US agricultural sector as a whole. Another staple program in the US agriculture is the use of crop insurance. This paper assesses hitherto unaddressed issues of fuel consumption and hence pollution generated by farm households associated with off-farm work and crop insurance. We applied a quantile regression method on a unique national farm-level survey data to address the fuel consumption issues. Results indicate that off-farm work by operators tends to decrease fuel expenses. In contrast, households with crop insurance had higher fuel consumption thereby increasing fuel usage. Finally, our study shows that the net effect of these two activities resulted in an increase in the pollution level.
\end{abstract}

1. Introduction

Fossil fuel is consumed in food production both on and off the farm. For instance, fuel can be used on the farm by tractors during tillage, planting cultivation and harvesting, as well as in pest control, frost protection equipment, and irrigation pumps [1]. On the other hand, fuel can be used off the farm in the manufacture of machinery, nitrogen fertilizer, pesticides and plastics. Fuel uses have been recognized as one of the important farm production inputs related to the environmental quality [2]. Farming involves tillage of the soil which affects emission directly or indirectly. Direct emissions are due to the fuel usage for tillage (e.g., tractors), which depends on various factors including tractors size, implements uses, and depth of tillage. As stated in Collins et al. [3] and Lal [4], fuel requirement increases with an increase in depth of plowing and tractor speed and among the types of equipment used. Irrigation, spraying, fertilizer and pesticides are the most important secondary sources of emission.

Tailpipe emissions of volatile hydrocarbons from gasoline/diesel powered engines have been studied extensively [5,6]. These emissions have led to smog, acid rain and other types of air pollution (for example, particulate organic compounds and fine particle mass concentration) that are a concern to the environment and public at large. In farming, pollution concerns as well as recent fuel price hike have been a matter of concern to farmers. To reduce production costs and regulations to reduce emissions, some farmers are changing the allocation of family resources by employing more energy-efficient farming practices [1].

The crop insurance program, a federal risk reduction plan in the US, has impact on input use [7–9]. Evidence suggests that the crop insurance program may affect fuel uses on the farm and thereby impacting emissions from farm machinery. For instance, using the farm level household survey, Mishra et al. [10] examined the effects of crop insurance on fertilizer and pesticide use and concluded that any improved environmental outcomes due to crop insurance are likely due to the reduction in fertilizer use. On the other hand, crop insurance subsidies may lead to unintended environmental damage by inducing the conversion of land from pasture, range, and other uses to crop production.

In addition to crop insurance, off-farm work by farm operators, induced by farm program payments, may also affect the farm practice since working off the farm provides an alternative for farm households to reallocate their labors between farm and off-farm jobs. Mishra et al. [11] conclude that off-farm work by farm operators and spouses is a staple source of income in the farming community. Literature provides evidence [12–15] that farm program payments alter time allocation decisions of farm operators.
In particular, studies suggest that “decoupled” payments increase off-farm work whereas “coupled” payments reduce off-farm work by operators and spouses. In particular, Phimister and Roberts [16] in their study of England farmers conclude that fertilizer intensity may decline as off-farm labor increases while the use of crop protection per hectare increases with off-farm work. Although the impact of crop insurance on fertilizer or chemical uses has been documented, however, little is known about the extent to which participation in the crop insurance program may affect fuel consumption of farm households.

This paper assesses hitherto unaddressed issues of fuel consumption and hence potential pollution generated by farm households. The objective of this paper is to investigate how participation in off-farm work and crop insurance program may affect fuel expenses. Any reduction in fuel consumption (expenses), as a result of participation in crop insurance and off-farm work, may result in less pollution from agricultural production. We assume that farms are relatively homogenous in their use of fuel and farm machinery usage. Hence, higher fuel usage implies higher pollution emitted by the farm. We use a US national farm level household survey data to test our hypothesis.

2. Materials and methods

2.1. Data

Data used in this study were drawn from a unique national representative farm-level survey namely Agricultural Resource Management Survey (ARMS) in the US in 2003. The ARMS survey queried farmers on all types of financial, production, and household activities (such as labor allocation and consumption expenditures). Specifically, it is used to gather information about the relationships among agricultural production, resources, and the environment. It also helps in the determination of production costs and returns of agricultural commodities and in the measurement of net-farm income of farm businesses. Yet another aspect of ARMS’s important contribution is the information it provides on the characteristics and financial conditions of farm households, including information on management strategies and off-farm income.

In our analysis, only crop farm households are considered since they are eligible for the crop insurance program. We also limit our sample to the family farm households. After further deleting some observations with missing information, the final sample accounts for 1757 crop farm households. Since weather uncertainty is crucial in agricultural production and may impact the decisions to purchase crop insurance and off-farm work information on weather variability is included in the model. Specifically, variability in rainfall is calculated via coefficient of variation in rainfall. The coefficient of variation in rainfall calculated from the historical time series data in each county is used to represent weather uncertainty. In addition, a dummy variable is specified to indicate if the farm households are located in a county with low land quality.

The intensity of off-farm work and the decisions to purchase crop insurance and their effect on fuel expenses are summarized in Table 1. It appears that the likelihood of off-farm work is negatively associated with fuel expenses. For instance, operators who do not work off the farm spent $50 per acre on fuel/oil, on average, however, per acre expense drops to $29 for operators who reported two-thirds or more of their time working off the farm. The pattern between coverage by crop insurance and fuel/oil expense is not transparent. It appears that farm households with a higher proportion of farmland enrolled in crop insurance program have lower fuel expenses. However, the negative association is not very trivial.

Building on the findings of previous studies in crop insurance [18–20] and off-farm labor supply of farm operators [13–15], several variables reflecting the operator characteristics, farm and farm household factors, as well as the participations in government farm programs are specified. Variable definitions and summary statistics of the selected variables are presented in Table 2.

### Table 1 Sample distribution of off-farm work and crop insurance.

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<thead>
<tr>
<th>Off-farm work</th>
<th>Fuel/oil expenses</th>
</tr>
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<tr>
<td>0 No off-farm work</td>
<td>46% 50</td>
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<tr>
<td>1 Work off farm less than 1/3 of full time</td>
<td>6% 45</td>
</tr>
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<td>2 Work off farm between 1/3–2/3 of full time</td>
<td>17% 22</td>
</tr>
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<td>31% 29</td>
</tr>
<tr>
<td>Crop insurance</td>
<td></td>
</tr>
<tr>
<td>0 Did not purchase crop insurance</td>
<td>74% 45</td>
</tr>
<tr>
<td>1 Less than 1/3 acres covered with crop insurance</td>
<td>3% 37</td>
</tr>
<tr>
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Sample weight is included. 

### Table 2. Sample distribution of off-farm work and crop insurance.

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2.2. Econometric model

A profit maximizing farm chooses both its inputs and outputs to achieve maximum economic profits. We assume that a farm produces two outputs, corn and soybean, using three inputs, labor (L), fuel (F), and capital (K). One can obtain the input demand functions for fuel uses generated by considering the producer’s profit maximizing decision as:

\[
F = F(P_c, P_s, w, r, \phi) \tag{1}
\]

where \(P_c\) is the price of corn; \(P_s\) is the price of soybean; \(w\) is the price of labor; \(r\) is the rental rate of capital; and \(\phi\) is the price of fuel. Other factors (such as macroeconomic factors) that affect demand for fuel on the farm are represented by \(\phi\). The literature suggests that the demand for inputs such as fuel could also be affected by farmers’ participation in crop insurance programs [10,18,21]. Further, some studies have investigated the impact of off-farm work on the demand for farm inputs and on the intensity of production [16,22]. However, the inter-relationship between fuel demand and the decision to purchase crop insurance and off-farm work is not trivial.

To estimate the impact of crop insurance and off-farm work on fuel expenditures, a two-stage econometric estimation procedure is proposed. In the first stage, a bivariate ordered probit model that captures the potential inter-relationship between the intensity of off-farm work by a farm operator and the decision whether or not to purchase crop insurance. The second stage analysis is to examine the determinants of per acre fuel expense. A quantile regression method is utilized to examine the heterogeneity of these two decisions on the distribution of fuel expenses.

### 2.3. Estimating the off-farm work and crop insurance purchase equations

If \(y_1\) and \(y_2\) represent the observed discrete variable of the operator’s off-farm work and the decision to purchase crop insurance of the farm household, and it is also assumed that there are \(J_1\) and \(J_2\)
category that each discrete variable may fall into (J1 and J2 are equal to 3 in our case), a bivariate ordered probit model that capture the effects of the exogenous factors on off-farm work and crop insurance purchase of the farm household can be specified as:

\[
y_{1i} = X_{1i}\beta_1 + \epsilon_{1i} \\
y_{2i} = X_{2i}\beta_2 + \epsilon_{2i}
\]

\[
y_{1i} = \begin{cases} 1 & y_{1i} \leq U_{11} \\ 2 & U_{11} < y_{1i} \leq U_{12} \end{cases} \quad \text{and} \quad y_{2i} = \begin{cases} 1 & y_{2i} \leq U_{21} \\ 2 & U_{21} < y_{2i} \leq U_{22} \end{cases}
\]

where \(y_{1i}\) and \(y_{2i}\) are the unobserved latent variables of the operator's off-farm work decision and whether or not farm household \(i\) purchases crop insurance, respectively. \(X_{1i}\) and \(X_{2i}\) represent exogenous factors, and \(\beta_1, \beta_2\) are parameters of interest. \(U_i\) are unknown threshold parameters to be estimated. If the random errors \((\epsilon_{1i}, \epsilon_{2i})\) follow a standard normal distribution across individuals with a zero mean and unit variance, and the coefficient correlation, \(\rho\), the probability that \(y_{1i} = J_1\) and \(y_{2i} = J_2\) can be shown as [23]:

\[
\Pr(y_{1i} = J_1, y_{2i} = J_2) = \Pr(U_{1i} \leq 1 - y_{1i} \leq U_{1j}, U_{2i} \leq y_{2i} \leq U_{2j})
\]

\[
= \Phi((U_{1j} - X_{1i}\beta_1), (U_{2j} - X_{2i}\beta_2), \rho) - \Phi((U_{1i} - X_{1i}\beta_1), (U_{2j} - X_{2i}\beta_2), \rho) \\
- \Phi((U_{1i} - X_{1i}\beta_1), (U_{2i} - X_{2i}\beta_2), \rho) + \Phi((U_{1j} - X_{1i}\beta_1), (U_{2i} - X_{2i}\beta_2), \rho)
\]

where \(\Phi(\cdot)\) represents the standard cumulative density function of the standard bivariate normal distribution. Given the probability of each category, consistent estimators \((\beta_1, \beta_2, \rho)\) can be obtained by implementing the full information maximum likelihood method with the following log-likelihood function:

\[
\ln L_i = \sum \sum \sum \ln \Pr(y_{1i} = J_1, y_{2i} = J_2) \cdot \ln \Pr(y_{1i} = J_1, y_{2i} = J_2)
\]

where \(I(\cdot)\) is a binary indicator that specifies one of the \(J_1\) and \(J_2\) categories that each farm may fall into.

2.4. Estimating the fuel expense equation

The second stage examines the factors that are associated with fuel expenses. Since some farms report zero fuel expenses, a censored regression model is specified. If the variables \(F_i\) and \(F_i\) represent the unobserved latent and the observed input uses of \(i\)th farm household, respectively, the input expenditure equation can be specified as:

\[
F_i = \max(F_i, 0) = \max(K_i\alpha + X_{1i}\beta_1 d_1 + X_{2i}\beta_2 d_2 + e_i, 0)
\]

where the vector \(K_i\) represents the exogenous factors associated with the input use, and the vector \(\alpha\) represents parameters of interest. The scalars \((X_{1i}\beta_1, X_{2i}\beta_2)\) are the predicted value for the intensity of operator’s off-farm work and the decision to purchase crop insurance, respectively. They are calculated from the first stage estimation and then replace the observed counterparts in order to avoid the potential endogeneity between operator’s off-farm work, the decision to purchase crop insurance, and input expenses/use due to some unobserved heterogeneity. The parameters \((d_1, d_2)\) thus capture the effect of these two activities on input expenses. If the random error, \(e_i\) follows a normal distribution, the consistent estimators \((\alpha)\) can be obtained by estimating the Tobit model by the maximum likelihood method.
Although estimating a Tobit model on the input expenditure equation yields consistent estimates, the validation of the model relies on the normality assumption of the random error. If the random error is misspecified, the maximum likelihood method will lead to inconsistent estimations [24]. Additionally, the Tobit specification is not sufficient to investigate if the effects of exogenous variables are heterogeneous across the entire distribution of input use [25]. To investigate whether the magnitude of the marginal effects of the intensity of operator's off-farm work and the decision to purchase crop insurance of the farm household on input expenses/use are heterogeneous across the entire population, we apply the censored, quantile regression method proposed by Powell [26]. By characterizing the marginal response of input expenses/use at certain locations in the distribution, a more complete picture emerges with respect to the heterogeneity of economic behavior across the distribution.

Following Powell [25,26], the conditional censored quantile expectation of the input expenses/use can be specified as:

\[
Q_{\theta}(F_i|K_i, X_{i1} \beta_1, X_{i2} \beta_2) = \max(K_i \gamma_0 + X_{i1} \beta_1 d_{10} + X_{i2} \beta_2 d_{20} + e_{i1}, 0)
\]

where \(\theta\) indicates the conditional quantile of input demand \(F_i\), conditional on the exogenous vectors. Note that the distribution of the error term \(e_{i1}\) is left unspecified as certain distribution and the only requirement for the validation of Eq. (6) is to assume that the conditional mean evaluated at each quantile is zero. As such, the \(\theta_{0\%}\) sample quantile of the input use solves the following minimization problem [26]:

\[
\frac{1}{N} \sum_{n=1}^{N} \{F_i - \max(K_i \gamma_0 + X_{i1} \beta_1 d_{10} + X_{i2} \beta_2 d_{20} + e_{i1}, 0)\} \geq 0
\]

Finally, since the predicted values of off-farm work and the decision to purchase crop insurance are used in the input expenses/use equation, the variance–covariance matrix of the estimators in the input expenses/use equation is adjusted. In the empirical analysis, the reported standard errors of the estimated parameters in the input expenditures/use equation are based on the bootstrap method.4

3. Results and discussion

3.1. Effects of crop insurance and off-farm work on fuel expenses

Table 3 presents the effect of factors associated with fuel expenses (usage) as estimated in the censored quantile regression models.3 The estimations at 25th, 50th, and 75th percentiles are reported. To investigate if the off-farm work by farm operators and purchasing crop insurance may affect fuel use, a Wald test is conducted at each selected quantile. The test results of the Wald test under the null hypothesis that the coefficients of the predicted values of off-farm work by operators and crop insurance purchase decisions are equal to zero (\(H_0: \text{PRED\_OPWORK} = \text{PRED\_CROPINS} = 0\)) are rejected for all of the selected percentiles. These results indicate that the two decisions have some impacts on fuel expenses.

To better understand the effect of off-farm work and crop insurance decisions on the entire distribution of the fuel expenses, we summarize and plot the estimates in Fig. 1. Each plot in the figure depicts the coefficient estimates (PRED\_OPWORK and PRED\_CROPINS) on the 5th–95th percentiles of the censored quantile regression model. The solid line traces the estimated coefficient and the dashed lines represent the upper and lower bound of the 95% confidence intervals. Therefore, for a given quantile, if the confidence interval covers the zero-line (the horizontal axis), the coefficient estimates at that quantile is statistically insignificant at the 5% level or higher. As exhibited in Fig. 1, a negative association is found between the off-farm work of the farm operator and the fuel consumption of the farm household. Moreover, the negative association is more pronounced at higher percentiles (see the black line). For instance, the estimated effects are $1.04 and $1.34 per acre at the 25th and 50th percentiles, respectively (Table 3). However, the negative association is not statistically significant at the very highest percentiles.

The story is different for the effects of crop insurance on fuel expenses. In Fig. 1, since the 95% confidence interval does not cover the zero-line (see the dash-red lines), most percentiles indicating that the effect of crop insurance on fuel expenses is significant at most of the percentiles, but not at the very high end. The estimated effects of crop insurance on fuel expenses (usage) at the 25th, 50th and 75th percentiles are $3.77, $4.99, and $7.58 per acre, respectively. The positive association between crop insurance purchase decisions and fuel use is not inconsistent with the findings in previous studies. Agriculture is widely believed to be an industry in which risk plays a substantial role in production and crop insurance. Further, crop insurance and risk might be expected to affect input use as it relates to the problem of moral hazard as addressed in Horowitz and Lichtenberg [18]. In their study, a positive and significant relationship between crop insurance programs and chemical use was evident. In a similar vein as in Horowitz and Lichtenberg [18], findings from our study may also indicate another empirical evidence of moral hazard related to crop insurance. That is, farms who have crop insurance

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4 The detail of the introductive bootstrap method can be found in Horowitz [27].
5 To avoid the endogeneity, the predicted values of the off-farm work of the operator and the crop insurance participation are used in the fuel equation. These values are obtained from the estimates of a bivariate probit model. Since the discussions of the off-farm work and crop insurance participation are not the primary focus, the results of the bivariate probit model are not presented, and can be requested from the authors.

6 For interpretation of color in Fig. 1, the reader is referred to the web version of this article.
take fewer precautions on self-protection and may use more risky inputs, such as chemical or fuel inputs. Moreover, since the magnitudes of the positive association between crop insurance and fuel consumption is revealed, our findings may provide additional evidence by showing that the moral hazard problem is more substantial for farms at the higher tail of the fuel distribution.

Interestingly, the magnitude of the effect of crop insurance and off-farm work, in combination, seems to encourage the use of fuel, as indicated higher magnitude of the coefficients of crop insurance (PRED_CROPINS) than the coefficients of off-farm work (PRED_OPWORK). However, the magnitude of the coefficients differs within the distribution. Table 4 presents the overall net effects of crop insurance and off-farm work on the distribution of the fuel uses. Results indicate that both subsidized crop insurance program and off-farm work have resulted in higher usage of fuel on the farm. Using 2003 fuel prices and CO2 emissions data with our estimates shows a net increase in fuel usage, and this increase leads to higher carbon emissions about 56 and 121 lb at the 25th and 75th percentile, respectively.7

3.2. Other factors associated with fuel usage

The results of the censored quantile regression estimation (Table 3) also provide evidence that experience of the farm operator is an important factor in fuel use. Results indicate experienced farm operators (EXPER_OP) use less fuel throughout the distribution. For example, farm operators in the upper (75th) percentile decrease expenditures by $0.11 as compared to farmers in the lower tail of the distribution ($0.05 in 25th percentile). Results also show that large farmers use less fuel, and this result is significant across the entire distribution. Also, compared to full owners, part-owners (OWNER_P) and tenants (TENANT_F) are likely to use more fuel in the lower and medium tails of the distribution (25th–50th percentile). In addition, heterogeneous effects on fuel uses are also evident across different types of crop farms. Compared to other crop farms (the reference group), cash-grain farms uses less fuel. For example, farms in the 75th percentile specializing in cash grains would reduce their fuel expenses by $5.34 per acre in the 25th percentile as compared to other crop farms. In contrast, the coefficients on farms specializing in vegetable, fruit and nursery products are positive and significant across all selected percentiles.

Environmental characteristics are also important for fuel consumption. For instance, variability in rainfall is related to other agronomic conditions that are deemed necessary for a good crop cycle. Results in Table 3 indicate that an increase in rainfall variability (RAINFALL.CV) increases fuel expenses at the 75th percentiles by $27.25 per acre. On the other hand, fuel usage decreases with a decrease in land quality. For instance, the coefficient for LAND_QLTY is negative and significant for 75th percentile, indicating that fuel expenses for low quality land decreases by about $6.84 per acre. Regional location of the farm is also an important

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7 In the US, Environmental Protection Agency (EPA) reports that a gallon of fuel (diesel) produces about 19.4 lb of CO2 [29].
determinant of fuel expenditures. Results show that farms located in the Midwest and Southern regions use significantly less fuel at the 25th and 50th percentiles than farms located that were located in the Western US. Additionally, the magnitude of the coefficients increases at higher percentiles (Table 3). However, farms located in the Northern US are more likely to have higher expenditures on fuel compared to farms in the Western region. A possible reason could be that farms in the Northern region may have land of a lower quality as compared to other regions where crop insurance encourages Northern farmers to produce crops on marginal land.

4. Conclusion

Agriculture in developed countries is transforming rapidly. There are several factors contributing to this transformation, including risk management policies like crop insurance and self-insurance policy like off-farm work by farm operators and other family members. Recent increases in the price of crude oil and pollution created by operation of farm machinery, equipment, and other farming activities has caught the attention of farmers, researchers, and policymakers. However, participation in crop insurance programs and off-farms work may have a different effect on fuel expense or usage, consequently impacting the environment. In contrast to previous studies, this paper investigates how government subsidized crop insurance and policy induced off-farm work decision by the farm operator on fuel expenses.

Using a national farm-level survey of farm household in the United States, we first investigate the relationship between farm operator’s off-farm work and crop insurance purchase decisions. In what follow, we investigate the impacts of off-farm work and crop insurance purchase decisions on fuel expenses. With respect to the effects of operator’s off-farm work and crop insurance purchase decisions on fuel expenses, our results indicate that working off the farm leads to a decrease in fuel usage. The results are significant at the low and medium percentiles of the entire distribution of input use. One can conclude that off-farm work may result in an energy-saving practice of farm production. In contrast, crop insurance tends to increase fuel expenses. Moreover, the net effect of these two policies on fuel consumption/usage is positive—resulting in higher emissions of carbon and other pollutants to the environment.

Agricultural programs that stimulate production such as farm program payments (coupled payments that reduce off-farm work) and crop insurance can have unintended and undesired environmental consequences. The pollution concerns result from this study indicates that the government subsidized crop insurance program considered herein may have encouraged farmers to increase their fuel intensity thus contributing towards more emissions and air pollution (from increased use of farm machinery). On the other hand, farm program payments which decrease the likelihood of off-farm work (such as coupled farm program payments) by farm operators may also be contributing towards a higher use of fuel thereby increasing emissions. To reduce pollution and decrease the impact of higher fuel prices, policymakers could design policies that reduce government programs like farm program payments and subsidized crop insurance programs.

Conflict of Interests

None.

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References