Journal of Agribusiness 35, 1 (Spring 2017)

The Impact of Weather on Agricultural Labor Supply

Jaehyuk Lee, Denis Nadolnyak, and Valentina Hartarska

Recent work shows that the weather affects U.S. labor productivity and supply (e.g., Deryugina and Hsiang, 2016). Agricultural economists have been looking at the factors affecting farmers' allocation of labor between on- and off- farm work. We estimate the impact of temperature and precipitation on individual on-farm labor supply using 10 years of the Agricultural Resource Management Survey data. We find that temperature and farm operator labor supply have a parabolic relationship with a minimum at 61ºF. We compute that one 1ºF increase in annual temperature translates into 8.5 million hours of reduced country-wide farm operator labor valued at about $188 million. Precipitation has a significant but negligible marginal impact on the operator labor supply, consistent with the existing literature.

***Key words**:* Farm operator, labor supply, weather

There is a general belief that an advanced economy is less affected by the weather because economic agents have more resources to adapt to their environment (Kahn, 2005). Within agriculture, for example, it is believed that farmers can change the crops they plant to maximize profits under new weather patterns, or adopt new crop varieties resistant to adverse climates (Mendelsohn, Nordhaus, and Shaw, 1994; Olmstead and Rhode, 2011). However, the evidence is that U.S. crop yields continue to be highly sensitive to extreme heat, in spite of new genetic trait development and infrastructure improvements (Roberts and Schlenker, 2011). Moreover, over the past 40 years there has been little evidence of adaptation by U.S. producers to climate variability, possibly due to lack of incentives (Burke and Emerick, 2016). It is also possible that producers adapt to short-run climate variations by changing their labor input.

Experimental studies have shown that temperature affects labor productivity (Grether, 1973; Froom et al., 1993; Seppänen, Fisk, and Faulkner, 2003; Seppänen, Fisk, and Lei, 2006). In particular, research based on lab experiments confirms the empirical finding that labor productivity is highest in spring and fall, and lowest in summer and winter because of more extreme temperatures. Research on weather impact on agricultural labor supply and productivity, however, is limited at best (Zivin and Neidell, 2010). In this

Jaehyuk Lee is an assistant professor in the Department of Social Sciences, East Georgia State College, Swainsboro. Denis Nadolnyak and Valentina Hartarska are an associate professor and an Alumni professor, respectively, in the Department of Agricultural Economics and Rural Sociology, Auburn University, Alabama.
Any remaining errors are the sole responsibility of the authors.

paper, we focus exclusively on farm operators (owners and managers) in the United States and evaluate how weather affects their on-farm labor supply.

A related question is whether labor supply, in our case the hours worked on farm by farm operators, are positively correlated with weather-dependent productivity. While we don't measure productivity directly in this paper, a finding that extreme temperatures increase farm operator hours would suggest that decreased productivity is compensated with more labor input. Conversely, the opposite finding would be indicative of inter-temporal labor substitutability (i.e., work less when the productivity is low and more when it's higher), which is less likely in the farming business.

Zivin and Neidell (2010) estimate the link between temperature shocks and labor supply in the United States measured by time-use surveys and find a strong association in industries exposed to outdoor temperatures such as agriculture, forestry, construction, and transportation which, according to estimates by Houser et al., (20014) employ as much as 28% of the national workforce. Zivin and Neidell (2010) find that, at temperatures above 100ºF, labor supply drops by as much as 1 hour per day which is very close to temperature-exposed labor supply responses documented in the 1940s by Mackworth (1947). Deryugina and Hsiang (2016) also find that temperature reduces the productivity of workers and crops. Using within-county variation in weather and estimating the effect of daily temperature on annual income in U.S. counties over a 40-year period, they show that productivity declines roughly by 1.7% for each 1°C (1.8°F) increase in daily average temperature above 15°C (59°F) and that a weekday above 30°C (86°F) costs an average county $20 per person annually. These estimates are net of many forms of adaptation, such as factor reallocation, defensive investments, transfers, and price changes.

The literature on precipitation impacts on labor supply is scarcer. Connolly (2008), for example, finds that men increase working time by 30 minutes a day at the expense of leisure when it is raining. Other studies find that high temperatures may provoke costly personal conflicts even in wealthy populations (Hsiang, Burke, and Miguel, 2013). Studies also find that adaptation to extreme climatic events such as hurricanes remains only partial (Hsiang and Narita, 2012).

Weather conditions also seem to have an impact on the demand side of the labor market in agriculture. Some researchers argue that farmers and their family members tend to increase their supply of *off-farm* labor under unfavorable weather conditions in order to maintain consumption levels, which reduces the amount of time they allocate to on-farm work (Kochar, 1999; Rose, 2001; Cameron and Worswick, 2003; Ito and Kurosaki, 2009).

We use a more direct approach and look for a relationship between the farm operator *on-farm* labor supply and weather conditions. To the best of our knowledge, there are no papers that look at the impact of weather on the farm operator labor supply in the United States. Theoretically, an argument can be made for both positive and negative impacts of extreme temperatures on farm labor input. On the one hand, decreased labor productivity should result in increased labor use if the short-run substitutability between labor and other production factors is limited. On the other hand, there is inter-temporal substitutability of labor use, i.e., if the timing of labor input is flexible so one can wait for better weather which is less likely in agriculture, labor use can be negatively associated with temperature extremes.

The substitutability/complementarity between weather and labor use can also be helpful in explaining the relationship between aggregate agricultural output and weather. Some research attributes the lack of association between weather and farm incomes to the opposite impacts of the weather on output and prices (Deryugina and Hsiang, 2016). Other researchers have found that, while dairy production, for example, is negatively correlated with local average temperatures, there is no relationship between temperature *deviations* and dairy production (Key, Sneeringer, and Marquardt, 2014). One of the reasons for this observation might be that farmers work more hours when the weather is bad in order to compensate for the lower productivity during these times.

In this paper, we use a static labor supply model in which the farm operator maximizes utility subject to time and budget constraints. The budget constraint limits operator's consumption to earnings composed of on- and off-farm income. The weather variables enter the model through the production function. Total output is a function of weather, and so are the hours worked by the farm operator(s).

The rest of the paper is organized as follows. The second section describes the conceptual model and the empirical approach. The third section describes the data. The results are discussed in the fourth section. The fifth section provides conclusions.

Conceptual Model

We set out to measure the impacts of weather variables on on-farm labor supply decisions while controlling for prices and farm and operator individual characteristics. We use the static labor supply model (household model) following Ahearn et al. (2006). The farm operator maximizes utility in equation (1) subject to time and budget constraints in equations (2) and (4):

(1) $\mathrm{U} = \mathrm{U}(\mathrm{C}, \mathrm{L})$

where C is individual consumption and L is leisure. The price of the consumption good is normalized to one. The time is allocated among three activities: farm work, off-farm work, and leisure:

(2) $\mathrm{T} = \mathrm{L} + \mathrm{F} + \mathrm{J}$

where L, F, and J stand for leisure, farm work, and off farm work, respectively. The budget constraint has income from off- and on-farm work:

(3) $\mathrm{C} = \mathrm{wJ} + \mathrm{pQ}$

where w is the operator's wages from off-farm work and Q and p are the total farm output and its price. The variable "Hours worked by the Operator" enters the budget constraint through the production function:

(4) $\mathrm{Q} = \mathrm{f}(\mathrm{F}, \mathrm{X}, \mathrm{HC}, \mathrm{Weather})$

where X is physical production inputs, HC is the operator's human capital, and Weather represents the weather conditions described by temperature and precipitation.

Since all farm operators work non-negative number of hours on the farm (they are not considered farmers with less than $2,000 in revenue), we ignore the decision of whether to work on farm and focus on the interior solution for the on-farm labor supply:

(5) $F^{*} = \mathrm{F}(\mathrm{Weather}, \theta)$

where F^* stands for the utility maximizing time allocated to the farm work by the operator and Θ represents all the other variables in the model.

Econometric Model

The empirical counterpart of equation (5) is:

(6) $H_{ict} = C_{ct}\beta_1 + X_{ict}\beta_2 + \theta_t\beta_3 + \alpha_c + \gamma_t + \mu_{ict}$

where H_{ict} represents the hours worked by the operator of farm *i* in county *c* at year *t*.

The equation includes a set of county and annual dummies, α_c and γ_t. C_{ct} stands for weather variables, their squares, and their interaction. Specifically, we use county-level annual temperature and precipitation as measures of weather variability. θ_t represents the input and output price indices that consist of a number of categories of agricultural production inputs and outputs. The output price index for the "all farm products" category is used. For the input price index, we use the average of the price indexes for the production factor categories such as feed, seeds, fertilizer, chemicals, fuels, farm machinery, building materials, farm services, and labor. X_{ict} is a vector of farm and operator characteristics. More specifically, X_{ict} includes an indicator for whether the farm is a non-family or family-owned business. In addition, the land area of the farm and the farm operator's age, gender, and education level are included. The standard errors are clustered at the county level to correct for the possible correlation in unobservable characteristics of the farms located in the same county.

Data

The data are obtained from the U.S. Department of Agriculture (USDA)-Economic Research Service's (ERS) Agricultural Resource Management Survey (ARMS) dataset that consists of individual farm-level observations on farm characteristics and financial indicators. We construct a pooled cross-sectional dataset from the annual ARMS Phase III survey for a 10-year period between 2000 and 2009 in the 48 contiguous states.

The weather data are obtained from the National Oceanic and Atmospheric Administration Climate Prediction Center. County level annual averages are constructed from daily data. The input and output prices are obtained from the Monthly Agricultural Prices Summary of the USDA's National Agricultural Statistics Service (NASS). The price data are indexes of agricultural prices weighted by the 1990-1992 averages (100). Each index of input prices represents categories of all production inputs that include feed, livestock and poultry, seeds, fertilizer, chemicals, fuels, supplies and repairs, autos and trucks, farm machinery, building material, farm services, rents, interests, taxes, and wage rates. Since these indices are highly correlated with each other, an average input price index is used in our analysis.[1]

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[1] Kelly, Kolstad, and Mitchell (2005) also use an aggregate input price index for their agricultural profit analysis using a sample of five U.S. states: Illinois, Iowa, Kansas, Missouri, and Nebraska. They also use the same price indexes from the USDA-NASS.

Table 1. Variable Definitions.

Hours Worked	Annual on-farm working hours (hours)
Temperature	Annual average of the temperature (degrees in Fahrenheit)
Temperature Sq	*Temperature* ^2
Precipitation	Average annual precipitation (inches), county level
Precipitation Sq	*Precipitation* ^2
*Temp*Precip*	Interaction of *Temperature* and *Precipitation*
Input Price	Input price index of agricultural production (base: 1990-1992 = 100)
Output Prices	Output price index of agricultural production (base: 1990-1992 = 100)
Op.On-farm Income	Operator's income from on-farm work
Op.Off-farm Income	Operator's income from off-farm work
Acres	Acres operated
Non-family Farm	=1 if the farm is non-family farm, 0 otherwise
Operator Education	Operator's highest degree attained. 1 if less than high school, 2 if high school or GED, 3 if some college, 4 if associate degree, 5 if college degree or more.
Operator Age	Age of the primary operator
Operator female	=1 if the primary operator is female, 0 otherwise

Table 2. Summary Statistics.

Variable	Obs.	Mean	Std. Dev	Minimum	Maximum
Hours Worked	124,615	2,237	1,290	0	7000
Temperature	124,615	54.8	7.7	35.4	76.6
Precipitation	124,615	29.6	14.3	9.5	60.1
Op. Farm Income	124,615	3,470	18,819	0	***
Op. Off-farm Income	124,615	30,653	68,645	0	***
Acres	124,615	1,339	7,654	0	***
Input Prices	124,615	155	26	120	198
Output Prices	124,615	123	18	91	169
Family Farm	124,615	0.9	0.01	0	1
Operator's Education	124,615	2.7	1	1	5
Operator's Age	124,615	55.3	12.5	18	***
Operator Female (Share)	124,615	0.12	0.01	0	1

Maximum values of some variables are censored by USDA.

Table 1 presents variable definitions and Table 2 shows the summary statistics. All the variables are on an annual basis for the 10 years of data. The dependent variable is the operators' labor supply in hours per year. Most farms have one operator but there are farms that have more than one principal operator and the secondary operator is usually the spouse. The data shows an annual average of 2,237 hours worked on farm with a standard deviation of 1,290 and a maximum of 7,000 hours. This average is equivalent to one full-time employee working 5.4 days a week, 8 hours per day, 52 weeks a year, with the maximum equivalent to about 3 workers. These numbers suggest that, on average, there is a need for a constant, round-the-clock work on the farms and that at least one person works every day.

The main variables of interest are the weather measures: temperature and precipitation. Temperature is measured in Fahrenheit with the county level average of 54.5ºF and the minimum and maximum of 35ºF and 77ºF, respectively. Average annual precipitation nationwide is 29.6 inches with a standard deviation of 14.27, the highest and lowest precipitation is in Louisiana and Nevada, respectively.

The variable *Acres* is the operated acres (owned and rented) with an average of 1,340 acres and a large standard deviation of 7,650 acres indicating substantial variation.[2] The control dummy for the farm type takes the value of 1 if the farm is a family farm and zero otherwise, with the vast majority of farms being family farms.

The average statistics for the input and output price indexes show sufficient variation. The price of labor is important in our equation and we measure it through the operator on-farm and off-farm incomes. On average, the reported operator income from farm work is quite low at about $3,500 in year 2000 dollars suggesting hourly earnings of about $1.50, but the standard deviation of about $20,000 is very large. This can be attributed to the well-known fact that the self-employed underreport their labor earnings (Hurst, Li, and Pugsley, 2010). While this measure is problematic, the reported operator income is still the best proxy for the price of operators' on-farm labor. The off-farm income is more precisely reported averaging $30,650 but also with a large standard deviation of about $67,000. The data show that farmers were, on average, 55 years old, and the majority were men. Roughly half the operators have some college degree or higher.

Results

The results of the estimation of Equation (5) are presented in Table 3. We use OLS on the pooled cross-sectional sample and control for county and year fixed effects. Column 1 shows results from regressing on temperature and precipitation only, column 2 includes controls for farm characteristics and prices, and column 3 adds the controls for operator characteristics. All specifications include annual dummies and county fixed effects with standard errors clustered at the county level. From the regression diagnostics data, it is clear that, although statistically significant and sizeable in magnitude, the weather

[2] The largest number of operated acres is not shown as censored by the USDA.

variables alone explain only a small part of the variation in the labor supply which could partially be attributed to the pooled cross-sectional nature of the data. The weather coefficients estimates are consistent in magnitude across specifications and statistically significant.

Table 3. The Impact of Weather on Operator's On-Farm Labor Supply.

	(1)		(2)		(3)	
Variables	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Temperature	-39.806**	16.559	-42.751***	16.141	-38.241**	16.061
Temperature Sq	0.305**	0.151	0.348**	0.149	0.324**	0.149
Precipitation	1.478**	0.681	2.655***	0.646	2.726***	0.652
Precipitation Sq	0.053	0.196	-0.282	0.19	-0.187	0.185
Temp * Precip	-0.039***	0.013	-0.048***	0.012	-0.053***	0.012
Op. Farm Income			0.017***	0.001	0.017***	0.001
Op. Off-farm Income			-0.002***	0	-0.002***	0
Acres			0.076***	0.017	0.074***	0.016
Input Price			2.307***	0.438	0.11	0.506
Output Price			-5.088***	0.626	0.343	0.827
Non-family Farm					171.151***	24.155
Op-Education						
High School					-89.850**	36.976
Some College					-51.026	39.191
Associate's Degree					-103.793**	40.698
College or more					-284.865***	46.292
Op-Age					-9.483***	0.742
Op-Female					-354.030***	23.059
Year Dummy	yes		yes		yes	
County	yes		yes		yes	
Constant	2798.267***	453.849	2965.082***	434.187	3123.474***	433.111
Observations	124615		124615		124615	
R^2	0.035		0.082		0.107	
Adjusted R^2	0.033		0.08		0.105	

The dependent variable is the Annual Hours Worked by the Farm Operator. All regressions Include county fixed effects and year dummies. The descriptions and summary statistics of the variables are in Table 1 and 2, respectively. Standard errors are clustered at the county level.

, **, * are the 10, 5, and 1 % level of significance.*

The coefficients of the temperature variables are very consistent and close in magnitude in all regressions. The relationship between temperature and operator's labor supply is U-shaped with a minimum of 61ºF and the mean marginal of -4.29 hours or 0.2% of the mean total, shown in Figure 1. That is, the operator worked the least in counties and years when the average county-level temperature was around 60ºF. If optimal temperatures require less labor input from the operator/manager, this is consistent with the findings that the optimal temperature for most common crops to develop during the growing season is between 64 and 77 degrees Fahrenheit (Schlenker and Roberts, 2008; Deryugina and Hsiang, 2016).

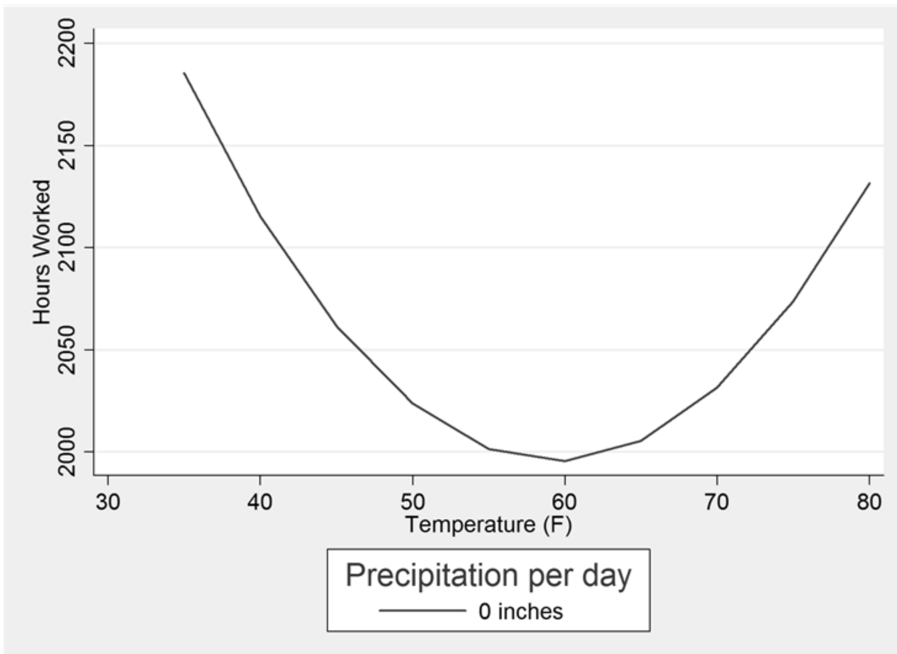

Figure 1. The Relationship Between Temperature and Operator's Labor Supply.

This result can also be related to existing research on weather impacts on productivity. Modern lab experiments show productivity loss in performing cognitive tasks of about 1.1% per 1ºF at temperatures above 77ºF (Grether, 1973; Seppänen, Fisk, and Faulkner, 2003; Seppänen, Fisk, and Lei, 2006). While we don't measure productivity directly in this paper, a finding that extreme temperatures increase farm operator hours would suggest that decreased productivity is compensated with more labor input. As farm operator labor involves both management and physical effort, our estimate of 0.2% per 1ºF seems comparable to the experiment results.

The small magnitude of the individual farm impact still translates into a sizeable variation in the aggregate operator labor input. With about 2,059,000 farms in the 48 states in 2015 (USDA-NASS, 2016) and the average hourly farm supervisor (operator) wage of $21.97 (USDA-ERS, 2016), a 1ºF temperature increase in the annual temperature from the mean of 54.8 translates into an 8.8 million fewer hours supplied by the farm operators, valued up to $194 million. This also indicates that the average temperature is below the operator labor input minimizing point, or labor productivity maximizing point if we assume the substitutability between on- and off-farm labor, level of 61.4°F. At more extreme temperature levels that are usually the focus of the research on economic effects of climate variability, the marginal impacts are higher. A 1°F increase in temperature from 85 (40) degrees Fahrenheit increases (reduces) individual operator labor input by 15.3 (13.9) hours representing 0.68% (0.62%) of the average total.

Precipitation is linearly related to the operator's labor supply because the coefficient at the squared value is insignificant and the coefficient on the interaction term is also statistically significant. A one-inch increase in the annual precipitation decreases annual hours worked by 0.16, which is unrealistically small but with a plausible sign suggesting wetter conditions lead to less labor input *ceteris paribus*.

The coefficients of the control variables are of the expected signs. The on-farm income reported by the operator is positively associated with the on-farm labor input but the relationship is very inelastic with an additional $1,000 in annual income associated with only 17 additional hours. As expected, an increase in the off-farm income is associated with a decrease in the on-farm labor but the magnitude is negligibly small. In this context, off-farm income can be viewed as non-labor income in the static labor supply model. This result also suggests that leisure is a normal good.

As expected, the larger the farm as measured by the acres operated, the larger the supply of labor. A 100-additional-operated-acres increases labor input by 70-80 hours a year. This increase is less than proportional (to the percentage change in acreage) suggesting either economies of scale or higher hired labor use on bigger farms.

Economic theory also suggests that variables that improve (harm) farm profits should increase (decrease) hours worked. The input and output prices also have plausible signs: increases in input prices and decreases in output prices reduce the hours worked, consistent with the utility maximization model result that increased profitability reduces labor input. However, this coefficient becomes insignificant when operator characteristics are added in the third specification.

Education is negatively associated with the number of hours worked. Relative to operators not completing high school, those who completed high school work on average 90 hours (roughly 2 weeks) less a year, those with some college work about the same, operators with an associate degree work 100 fewer hours (about 2 weeks), and those with college or higher education work 285 hours (6-7 weeks) less. We also observe that older farm operators work less by 1-2 days per year of age. Relative to male operators, female operators work 2 months fewer.

Summary and Conclusion

In this paper, we use a static labor supply model to estimate the impact of weather on the agricultural operators' on-farm labor supply. Our approach differs from previous work that tested this impact indirectly by directly estimating the impact on farmers' off-farm labor. The finding that unfavorable weather conditions are associated with more off-farm labor suggests a negative relationship between climate variability and on-farm labor. We draw parallels with the existing work on the impacts of temperature on labor productivity and test complementarity between labor productivity and labor input within the producer constrained utility maximization model that results in higher labor supply under more favorable weather conditions.

We use the ARMS (Agricultural Resource Management Survey) data to empirically test these hypotheses. The results show a U-shaped relationship between annual temperature and farmers' labor supply, when controlling for prices, farm and operator characteristics, and with county and annual fixed effects. Farmers' labor supply is minimized at a moderate temperature of 61ºF which suggests that, as long as extreme temperatures negatively impact productivity, the operator labor supply and productivity are complementary. This is consistent with the theoretical model. Precipitation has a positive and statistically significant but negligibly small impact on labor supply with the temperature interaction term also suggesting little impact of precipitation on temperature impacts.

On- and off-farm income has statistically significant but very small impacts on farm operator labor supply. Farm acreage increases labor input but less than proportionately to acreage increases suggesting economies of scale. Input and output prices have positive and negative impacts, respectively, which is consistent with the theoretical model of constrained utility optimization on which our empirical model is based.

Education reduces farm operator labor input suggesting higher efficiency of educated labor considering the (partly) managerial nature of it, with operators with a college degree working 6-7 weeks fewer a year compared to operators with less than a high school education. Farmers work about 9 hours less with an additional year of age. Female operators work about 9 weeks less a year which possibly reflects their higher opportunity costs.

Since we find that temperature affects individual operator's labor, exploring this relationship in future studies seems justified. Future work may need to control for use of hired labor which may substitute for own labor supply, as well as evaluate the impact on crop producing farmers as they are more likely directly affected by the weather.

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