COVER CROPS, DROUGHT, YIELD AND RISK: AN ANALYSIS OF U.S. SOYBEAN PRODUCTION

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Abstract

Besides a variety of production and environmental benefits, cover cropping has been promoted as a means to increase resilience to drought. I explore factors influencing farmers' adoption of cover crops and examine the effects of cover crops on soybean yield and their risk using USDA's 2018 ARMS Phase II Soybean Production Practices and Costs Report and Phase III Soybean Costs and Returns Report. Incorporating data on drought occurrence in the current year and the previous 5 years into our analysis, I find that the previous occurrence of drought did not affect farmers' adoption of cover crops and the effects of cover crops on yield and its risk are mixed. Under a drought condition, cover crops reduced soybean yield and increased yield variation; but in the meantime, they reduced the risk of crop failure, or made yield less negatively skewed. The insignificant effect of the previous drought on cover crop adoption and the mixture of positive and negative effects of cover crops on yield and its risk imply that farmers are divided over the use of cover crops to build resilience to drought.

Introduction

Climate change has caused increasing frequency and severity of drought stress in the U.S. Water scarcity has become one of the most severe constraints to agricultural production, adversely affecting crop yields and presenting a major challenge to sustainable food production. Along with prescribed grazing, mulching, micro-irrigation, and conservation tillage, cover cropping is among the five short- and long-term strategies for dealing with drought conditions that farmers can receive financial assistance for from the Natural Resources Conservation Service (NRCS) (USDA Climate Hubs 2021). Cover crops are defined by USDA NRCS in Cover Crop Termination Guidelines Version 4 (2019) as "*crops including grasses, legumes and forbs for seasonal cover and other conservation purposes. Cover crops are primarily used for erosion control, soil health improvement, weed and other pest control, habitat for beneficial organisms, improved water efficiency, nutrient cycling, and water quality improvement. A cover crop managed and terminated according to these Guidelines is not considered a "crop" for crop insurance purposes.*"

Legumes and grasses are currently the two most popular cover crop types (SARE 2015). Hairy vetch is the most widely used winter annual legume in northern regions because of its high N content, winter hardiness, and high productivity (Lu et al. 2000), and crimson clover is considered one of the best cover crops for southern regions due to its fast matureness and large N addition to the following crops (SARE 2015). Grass cover crops include annual cereals (such as rye, wheat, barley, and oats), annual or perennial forage grasses (such as ryegrass), and warm-season grasses (such as sorghum–Sudan grass) (SARE 2015). Besides legumes and grasses, buckwheat and Brassica (such as mustard, rapeseed, and forage radish) can also be used as cover crops (SARE 2018).

The use of cover crops as a cropping strategy is not new. It was practiced by people in ancient Greece, Rome, and China as early as 3,000 years ago (Langdale et al. 1991). Cover crops were first used in the U.S. in the 18th century and extensively expanded in the 19th century (Groff 2015), although their role by the time mainly as green manures. The affordability and ease of use of synthetic fertilizer at the end of World War II, however, attracted farmers to utilize more synthetic fertilizer instead of cover crops to further improve crop yields. The use of cover crops in conventional agriculture has gradually become less common since then (Groff 2015).

Currently, the adoption rate of cover crops is low and varies by agricultural commodity type. According to Agricultural Resource Management Surveys (ARMS) in years of 2010, 2016, 2017, and 2018, the adoption rate ranged from just over 5% of acreage on corn-for-grain (2016) to 8.4% on soybeans (2018), around 13% on cotton (2015), and over 24% on corn-for-silage (2016) (Wallander et al. 2021), in stark contrast to the adoption rate of conservation tillage, for example, which is 67% of soybean acreage (NASS 2019).

Cover crops can protect and improve soil between periods of regular crop production (Schnepf and Cox 2006). Besides a variety of production, soil health, and environmental benefits such as increasing weed and pest suppression, reducing runoff of sediments and nutrients into waterways, and reducing soil erosion and compaction, cover crops can improve water infiltration, reduce water evaporation, and increase soil's water holding capacity (e.g., USDA NRCS 2018; Mitchell et al. 2015; Blanco-Canqui et al. 2015; McDaniel, Tiemann, and Grandy 2014; Laloy and Bielders 2010; Dean and Weil 2009; Sainju et al. 2002, 2006).

There are, however, well-recognized tradeoffs and limitations in adopting cover crops as a conservation strategy (SARE 2017). In addition to the costs of soil preparation, seeds, and labor, there are challenges in implementation and management, such as the selection of cover crop species, planting and termination time—which may interfere with fall harvest or spring planting—, and producing too much surface residue (CTIC 2015; Sackett 2013; Miller, Chin, and Zook 2012; Snapp et al. 2005). Moreover, there are concerns that water needed by cover crops may reduce the amount of water available to the following main crop (SARE 2017; Clark et al. 1997; Corak et al., 1991; Ebelhar et al., 1984; Munawar et al., 1990).

Along with the above concerns, the effect on crop yield and risk is another important factor in farmers' adoption decision of cover crops as yield and risk directly affect farmers' economic returns. The Iowa Farm and Rural Life Poll in 2015 (Arbuckle 2016) reveals that 74% of the farmers believe that economic factors have a moderate to very strong influence on their changes in management practices. The 2017 Cover Crop Survey conducted by SARE (2017) also shows that the fear of a lack of economic returns (54% of respondents), increasing production risk (48% of respondents), and potential yield reduction (44%) are among the major concerns for non-users. Another cover crop survey conducted in 2015 shows that the potential yield benefit to cash crops is an important factor in decision making, especially for non-adopters (CTIC 2015). Therefore, an analysis of the effects of management practices on yield and its risk is essential to find effective supporting programs to promote good management practice adoption.

The results of existing studies of yield effects of cover crops are mixed. A meta-analysis of the response of corn yield to cover crops by Miguez and Bollero (2005) concludes that legume cover crops increase corn yield by 37%. Similarly, Andraski and Bundy (2005) and Munoz et al. (2014) find a positive effect of cover crop biomass on corn yields. Contrastingly, Reddy (2017) discovers lower soybean yield with cover crops compared with no cover crops. Nielsen et al. (2016) find that there was an average 10% reduction in wheat yield following a cover crop compared with following fallow, regardless of whether the cover crop was grown in a mixture or in a single-species planting; in addition, yield reductions were greater under drier conditions. In comparison, Acharya et al (2019), Smith et al. (2014), Hunter et. al (2019), and Acuna and Villamil (2014) locate no benefits of growing cover crops on subsequent crop yield. Note that all the findings are subject to certain conditions, such as soil types, other production practices (e.g., tillage), cover crop species, and precipitation.

Previous studies of yield effects of cover crops are mainly conducted in field experimental plots using agronomic models. A study based on a large number of fields with different agroecological characteristics and under varied weather is in need. In addition, increasing the frequency and severity of adverse events can expose farms to significant production uncertainty. Therefore, special attention is paid to downside risk exposure. In general, the downside risk is the risk associated with unfavorable events and located in the lower tail of the yield or return distribution (Kim et al. 2014). As pointed out by Hardaker et al. (2004), Kim et al. (2014), and OECD (2011), analyzing both the exposure to risk and levels of downside risk in agriculture is a key component in assessing welfare impacts. While cover cropping is recommended to farmers to deal with drought, its effects on farm yield risk and especially downside risk are not well documented. This study aims to fill the literature gap by analyzing the effects of cover crops on yield and its risk with varied weather, regional, and field characteristics.

In this study, we focus on U.S. soybean production. U.S. is the world's second-largest soybean producer and exporter, accounting for 31% of world total production and 36% of world total exports (USDA FAS 2022), respectively. U.S. farmers planted 87.2 million acres of soybeans in 2021, behind only corn. The growth and productivity of soybeans are adversely affected by various environmental stresses, among which drought stress is considered the most devastating event (Le et al. 2012; Shaheen et al. 2016). Drought stress, especially occurring at late vegetative stages, may cause significant soybean production losses of up to 40% (Specht, Hume, and Kumudin 1999; Le et al. 2012) by inhibiting increases in the soybean plant height and leaf area (Dong et al. 2019). Several studies find that cover crops improve soybean soil moisture (e.g., Acharya et al .2019; Chu et al. 2017), although some do not (Barker et al. 2018).

The paper makes three contributions. First, it explores the factors that affect the adoption of cover cropping. We consider not only land characteristics and farmers' demographics and concerns, but also droughts in previous years. This enables us to reveal whether farmers view cover cropping as an effective means of increasing resilience to drought. Second, the paper examines the effects of cover crops on yield variation and downside risk. We employ moments of yield distribution to evaluate the exposure to yield variation and downside risk. Disentangling the yield effects of adaptation is of paramount importance. It will reveal whether farmers who adopt cover crops are indeed getting benefits in terms of an increase in crop yield, a benefit crucial to broader adoption. Third, the paper utilizes a data set covering the majority of soybean fields in the U.S. with significantly different soil types and weather conditions. Two interplays, one between soil types and the adaptation strategy (namely, cover cropping), and the other between weather and the cover cropping practice are included in yield and its risk analysis. The interplay along with farmer demographics, farm characteristics, and input use allow us to examine the effectiveness of the managerial options for risk mitigation under varied soil and weather conditions, especially in the threat of drought.

The rest of the paper is organized as follows. The next section discusses the theoretical framework and empirical models, followed by a description of data and variables. Then estimation results are discussed, followed by conclusions at the end.

Theoretical Framework and Empirical Models

Consider a farmer who uses a vector of inputs $\mathbf{x}$ and drought adaptation strategies (e.g., cover cropping, mulching, or drought-resistant seeds) C to produce a single output Q through a technology described by a well-behaved (i.e., continuous and twice differentiable) production function $Q(\cdot)$. The farmer can choose to adopt (C = 1) or not (C = 0) a drought adaptation strategy. Use $\boldsymbol{e}$ to indicate random and uncontrollable factors reflecting production risk (e.g., drought effect) whose distribution is $F(\boldsymbol{e})$. The production technology can thus be represented by $Q = Q(\mathbf{x}, C, \boldsymbol{e})$. Use p to indicate the output price and $\boldsymbol{w}$ a vector of input prices. The net return is represented by $\pi = pQ(\boldsymbol{x}, C, \boldsymbol{e}\,) - \boldsymbol{wx}$.

Let $U(\pi)$ be a von Neumann-Morgenstern utility function that represents farmers' preferences regarding income. To simplify the analysis, I assume that the only risk that farmers are facing is production risk and both output and input prices are given or nonrandom. Being risk averse, farmers are assumed to maximize expected utility $EU(\pi)$, where $EU(\pi) = \int U(\pi) dF(\boldsymbol{e})$ with E as the expectation operator. For the decision on the drought adaptation strategy *C*, for example, if $EU(\pi|C = 1) - EU(\pi|C = 0) > 0$, then the farmer would choose to adopt the drought adaptation strategy; otherwise, the farmer would choose not to do so. In addition, the greater the difference between the expected utilities, the higher the probability of adoption. Very often there is a requirement of investment and/or possible uncertainty in profit due either to a lack of the exact performance of the adaptation strategy or to the higher probability of erring in the use of the adaptation strategy (Koundouri, Nauges, and Tzouvelekas 2006). In those cases, the farmer may choose to delay the adoption to achieve more information (Koundouri, Nauges, and Tzouvelekas 2006). Consequently, the farmer will choose the adaptation strategy *iff* $EU(\pi|C = 1) - EU(\pi|C = 0) > V$, where $V \geq 0$ is the value of new information essential for the farmer to make adoption decision which depends on the investment, the uncertainty related to the use of the strategy, and the farmers' characteristics (Koundouri, Nauges, and Tzouvelekas 2006). Therefore, drought adaptation strategies that require less investment and have less uncertainty in profit will have a higher level of adoption. For example, if technical assistance and extension service are provided to farmers for adopting an adaptation strategy, then the uncertainty in profit will be lower. Consequently, it is more possible that farmers will choose to adopt the strategy. In addition, farmers' characteristics such as their education level or their concerns about the environment may also play a role in the adoption decision. The more concerned the farmer is about an environmental issue, the higher probability of adopting a practice that can address the concern.

With differentiability of $U(\pi)$, $EU(\pi)$ can be approximated by taking the expectation of an *k*th-order Taylor series expansion of $U(\pi)$ at the mean net return $E\pi$ where $E\pi = \int \pi d\mathcal{F}(\boldsymbol{\epsilon}) = u_1$ and is written as

$$EU(\pi) \approx E[\sum_{j=0}^{k}(\frac{1}{j!}\frac{\partial^j U}{\partial \pi^j}(u_1) \times (\pi - u_1)^j)]$$

$$= U(u_1) + \sum_{j=1}^{k}[\frac{1}{j!}\frac{\partial^j U}{\partial \pi^j}(u_1) \times E(\pi - u_1)^j]$$

$$= U(u_1) + \sum_{j=2}^{k}[\frac{1}{j!}\frac{\partial^j U}{\partial \pi^j}(u_1) \times E(\pi - u_1)^j] \qquad (1)$$

Equation (1) shows that the expected utility depends on the mean net return u_1 and the *j*th ($j = 2,3,\ldots,k$) central moment of net return, $u_j = E[(\pi - u_1)^j]$. When *j*=2, u_j is the second moment or the variance, and when *j*=3, the third moment or the skewness of the net return. The skewness measures the asymmetry of the distribution around its mean, with a negative skewness implying a distribution skewed to the left; and a positive one implying a distribution skewed to the right. A lower skewness generates a greater exposure to downside risk.

By normalizing prices so that $p = 1$, a farm's net return can be expressed by $\pi = Q(\mathbf{x}, C, \mathbf{e}) - \frac{\mathbf{wx}}{p}$. The equation explicitly shows that the production function $Q(\mathbf{x}, C, \mathbf{e})$ provides all the relevant information for analyzing risk exposure on farms adopting drought adaptation strategies. To empirically investigate the impacts of cover crops on crop yield and yield risks, we start with the moment functions of crop yield.

Moment Representation of Production Function

Our empirical model is based on Antle's (1983) moment-based approach, which provides a flexible and convenient basis for evaluating exposure to production risk. As discussed in Antle (1983), a stochastic production function can be represented by a general parameterization of the moment functions. Using $\boldsymbol{\beta_1}$ to indicate a vector of technology parameters and as discussed above, the production technology can be represented by $Q = Q(\boldsymbol{x}, C, \boldsymbol{e}, \boldsymbol{\beta_1})$. The production function is stochastic given the random error term $\boldsymbol{e}$. Let the stochastic output Q have a cumulative distribution $F(\boldsymbol{e})$, then the first and the ith central moments of output Q can be represented, respectively, as

$$m_1(\boldsymbol{x}, C, \boldsymbol{\beta_1}) = E[Q(\boldsymbol{x}, C, \boldsymbol{e}, \boldsymbol{\beta_1})] = \int Q(\boldsymbol{x}, C, \boldsymbol{e}, \boldsymbol{\beta_1}) dF(\boldsymbol{e}) \quad (2)$$

$$m_i(\boldsymbol{x}, C, \boldsymbol{\beta_i}) = E[\{Q(\boldsymbol{x}, C, \boldsymbol{e}, \boldsymbol{\beta_1}) - m_1(\boldsymbol{x}, C, \boldsymbol{\beta_1})\}^i]$$

$$= \int (Q(\boldsymbol{x}, C, \boldsymbol{e}, \boldsymbol{\beta_1}) - m_1(\boldsymbol{x}, S, \boldsymbol{\beta_1}))^i dF(\boldsymbol{e}) \qquad for\ i \geq 2 \quad (3)$$

Here, E is the expectation operator; m_1 is the mean and m_i is the ith moment of output (for $i \geq 2$); and $\boldsymbol{\beta_i}$ is a vector of parameters. The models in (1) and (2) have the advantage of being flexible as there are no restrictions within or cross moments.

By rewriting equations (2) and (3), we get the following equations

$$\varepsilon_1 = Q(\boldsymbol{x}, C, \boldsymbol{\beta_1}) - m_1(\boldsymbol{x}, C, \boldsymbol{\beta}_1) \tag{4}$$

$$(\varepsilon_1)^i = m_i(\boldsymbol{x}, C, \boldsymbol{\beta}_i) + \varepsilon_i, \quad i \geq 2. \tag{5}$$

Here, $E(\varepsilon_j) = 0$ and $E(\varepsilon_j \varepsilon_{j'}) = 0$ (j=1, 2, …, n and $j \neq j'$).

As discussed by Kendall and Stuart (1977) and shown in many empirical analyses (e.g., Day 1965, Di Falco and Chavas 2009, Di Falco and Veronesi 2014, Tack, Harri, and Coble 2012, and Anderson, Dillon, and Hardaker 1980), the first three moments including location (mean), dispersion (variance), and skewness (the third moment) of a given distribution can adequately approximate the distribution. We, therefore, choose the first three moments to represent the distribution of yield in our analysis. While the variance (m_2) is a traditional measure of risk, the skewness of the output measure (m_3) captures the tail asymmetry of a yield distribution around its mean. A negative (positive) skewness implies a distribution skewed to the left (right). A lower skewness presents a greater exposure to the downside risk of unexpected low yield, i.e., crop failure.

From equations (4) and (5), we have the mean, variance, and skewness of yield as the following,

$$Q = m_1(\boldsymbol{x}, C, \boldsymbol{\beta}_1) + \varepsilon_1 \tag{6}$$

$$(\varepsilon_1)^2 = m_2(\boldsymbol{x}, C, \boldsymbol{\beta}_i) + \varepsilon_2, \tag{7}$$

$$(\varepsilon_1)^3 = m_3(\boldsymbol{x}, C, \boldsymbol{\beta}_i) + \varepsilon_3. \tag{8}$$

Here again, $E(\varepsilon_j) = 0$ and $E(\varepsilon_j \varepsilon_{j'}) = 0$ ($j = 1,2,3$ and $j \neq j'$). Empirically, if $\boldsymbol{\beta}_1^*$ is a consistent estimator of $\boldsymbol{\beta}_1$ from a sample of observed outputs, then $\varepsilon_1^* = Q(\boldsymbol{x}, C, \boldsymbol{\beta_1}) - m_1(\boldsymbol{x}, C, \boldsymbol{\beta}_1^*)$ is a consistent estimator of $\varepsilon_1 = Q(\boldsymbol{x}, C, \boldsymbol{\beta_1}) - m_1(\boldsymbol{x}, C, \boldsymbol{\beta}_1)$. It also suggests that $(\varepsilon_1^*)^i = m_i(\boldsymbol{x}, S, \boldsymbol{\beta}_i^*) + \varepsilon_i, i \geq 2$ is a consistent estimator of $(\varepsilon_1)^i$. The models in (5), (6), and (7) have no restrictions within or cross moments and thus are flexible.

The adoption of cover cropping *C* is variance increasing, variance neutral, or variance decreasing if $\frac{\partial m_2}{\partial C} > 0, = 0$, or < 0, respectively. For a risk averse farmer, $\frac{\partial m_2}{\partial C} > 0$ meaning that the adoption of cover crops creates a greater risk in output is undesirable. Similarly, the adoption of cover cropping C is skewness increasing, skewness neutral, or skewness decreasing if $\frac{\partial m_3}{\partial C} > 0, = 0$, or < 0, respectively. And, for a risk-averse farmer, $\frac{\partial m_3}{\partial C} < 0$ meaning that the adoption of cover crops increasing the exposure to a lower output is undesirable.

Some factors that are known by farmers but unknown to economists may affect both yield and the cover cropping decision. Consequently, when empirically estimating the yield equation as shown in (6), what arises is a concern that the adoption of cover crops may be endogenous. The endogeneity may result in inconsistent and biased estimates. To address the potential endogeneity issue, we use a two-stage method, which is one of the most potent and versatile tools available to treat endogeneity (Antonakis et al. 2014).

We will first estimate the use of cover crops with an instrumental variable approach. We model the adoption of cover crops in a logit model as follows:

Cover cropping: $\quad y_{cc}^* = \alpha' \boldsymbol{x} + \gamma Z + \epsilon$

$$y_{cc} = \begin{cases} 1 & \text{if } y_{cc}^{*} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Here y_{cc}^{*} is a latent continuous variable associated with the adoption of cover cropping; y_{cc} is the corresponding observed binary outcome with a value of 1 if cover cropping is adopted and 0 otherwise; α' is a transposed vector for parameters to be estimated; and Z is a vector of instrumental variables.

Data and Statistics

We apply our analysis to U.S. soybean production. We construct the data from the USDA's 2018 ARMS Phase II, Soybean Production Practices and Costs Report, and Phase III Soybean Costs and Returns Report. The phase II survey covers a cross-section of soybean fields in 19 states and collects information on production and management practices, input uses, and field characteristics. The phase III report provides information on farm operators and financial characteristics. Farm-level survey data provide us a good opportunity to look more closely at farm activities and the motives behind them (Dong, Hennessy, and Jensen 2010; Dong, Hennessy, Jensen, and Volpe 2016).

As conventional and organic production are significantly different in production practices, we only use data from conventional soybean growers. We delete all observations with missing values, leaving a total of 1,177 observations. ARMS has a complex survey design and is a probability-based survey with unequal probability sampling (National Research Council, 2008). To account for the survey design, we use the sampling weights (expansion factors) provided by USDA NASS to expand the sample to generate population estimates in the statistical analysis. With the survey weights applied to the sample observations, the weighted sample represents approximately 835,530 soybean fields in the United States.

Variables in Moment Equations

The dependent variables in equations (6) to (8) are the first three moments of the distribution of soybean yield per acre, respectively. Variable *phosphorus* measuring the use of phosphorus per acre is included along with its quadratic term. They are expected to increase the yield. Other independent variables include those on production practices, field characteristics, regional location, and weather/climate. To capture regional differences, indicator variables were constructed based on Farm Resource Regions (USDA-ERS 2000), which are defined based on farm, soil, and climate characteristics rather than state boundaries. The regional dummy variables (*Eastern Uplands, Heartland, Mississippi Portal, Northern Crescent, Northern Great Plains, Prairie Gateway, and Southern Seaboard*) are equal to 1 if the field locates in the corresponding region and 0 otherwise. Two variables (*PlantLate* and *ReplantPct*) are used to capture the impacts of adverse factors negatively affecting soybean yields at the start of the planting season. Variable *PlantLate* is equal to 1 if the planting date fell in the last 15% percentile of the state, and 0 otherwise. Variable *ReplantPct* is the proportion of fields that was replanted. Both might be resulted from adverse weather and result in shorter growing seasons for soybeans, and thus are expected to have a negative effect on yield. Dummy variable *manure* has a value of 1 if manure was applied to the field and 0 otherwise. Several field characteristics may affect yields such as soil texture and slope of the field (Butcher et al. 2018; Arora et al. 2011; Shane and Barker 1986; Kaspar et al. 2004; Jiang and Thelen 2004; Kravchenko, Bullock, and Boast 2000; Linkemer Board, and Musgrave 1998; Nelson and Meinhardt 2011) are also included in the yield moment functions. Soil texture is categorized into 5 types: loam, clay, sandy, mixed, and silty. Slope is categorized into 2 levels: nearly level and moderate/steep grade (even or variable). While the soybean growing season is from May to September, weather in both July and August is important for soybean yields (Westcott and Jewison 2013). The county-level U.S. Drought Monitor (USDM) indicator jointly produced by the National Drought Mitigation Center (NDMC), the National Oceanic and Atmospheric Administration (NOAA), and the U.S. Department of Agriculture is used. The USDM indicator has five categories: D0-D4, of which D0 indicates abnormally dry but not in drought while D1-D4 indicates moderate drought to exceptional drought. The USDM indicator is based on inputs including the Palmer Drought Severity Index (PDSI), the Standardized Precipitation Index (SPI), satellite-based assessments of vegetation health, and various indicators of soil moisture as well as hydrologic data (NDMC 2021). If on a weekly average over 10% of a county area is categorized as D1 or above in either July or August of 2018, then an indicator variable *drought18* is equal to 1 and 0 otherwise. Moreover, modified growing degree days (mGDD) and overheating growing days (ODD) for soybeans during July and August of 2018 are also included to explicitly capture temperature or heat effects on the growth and development of soybean plants. GDD is one of the most important factors influencing the rate of development in soybean (Major et al. 1975; Pedersen and Licht 2014; Kessler, Archontoulis and Lich 2020). Daily mGDD is calculated as

$$mGDD = \max\left(\frac{min(daily\ max\ temp,\ \ higher\ development\ threshold\ )+max(daily\ min\ temp,\ \ lower\ development\ thresholds\ )}{2} - 50\ ,0\right).$$

GDD depends upon the minimum and maximum temperatures which affect the plant's growth. The higher and lower development thresholds are 86 degrees Fahrenheit and 50 degrees Fahrenheit, respectively, for soybeans. Daily mGDD in July and August is accumulated to get mGDD for the two months. ODD is the count of days in July and August with a temperature over 89.6 degrees Fahrenheit and measures the heat stress for crops. Cover cropping is included in the function as a dummy variable. It is set equal to 1 if the cover cropping was adopted and 0 otherwise. In addition, interactions between cover cropping and drought status *drought18* are also included to capture the effects of the adaptation strategy on yield moments conditional on drought events. Survey population and sample summary statistics for variables used in the moment functions are reported in Table 1.

Variables in Logit Model

The instrumental variables used in the cover crop equation include farmers' concerns about soil and water-related issues. Seven dummy variables are constructed, indicating concerns on water-driven erosion, wind-driven erosion, soil compaction, poor drainage, low organic matter, water quality, and other concerns, respectively, and taking a value of 1 if a farmer had such a concern and 0 otherwise. We believe that farmers having concerns about soil erosion or soil quality may have more intention to adopt soil conservation practices. The variable of land ownership is included as another instrumental variable. The variable takes a value of 1 if the operator owned the land and 0 otherwise. We expect that land ownership may increase the likelihood of fields adopting cover crops as landowners may care more about soil erosion and soil quality on their own land and thus have more motivation to adopt conservation practices.

Farm size and some other field characteristics such as field size and whether any part of the field was classified as "highly erodible," and whether the field contained a wetland are also included in the cover crop equation given their possible effect on farmers' cover crop decision making (Ding, Schoengold, and Tadesse 2009; Vitale et al. 2011; Wandel and Smithers 2000). Highly erodible land is any land that can erode at an excessive rate due to its soil properties. Farmers are required to farm such land in accordance with a conservation plan or system approved by NRCS (USDA Risk Management Agency 2015). We expect that field classified as “highly erodible” is more likely to adopt cover crops for their vulnerability to soil erosion. Both farm and field sizes are measured in acres. We expect that larger farms and larger fields may be less likely to adopt cover crops given the time and labor requirements of cover crop implementation and management. Moreover, farmers’ age, education, years of experience in farming, and off-farm work are also included. We expect that older farmers or farmers with off-farm work may be less likely to adopt cover crops given the time and labor investment needed for cover crop implementation and management.

Several studies have found evidence that extreme weather affects farmers’ adoption of practices. We use the variable *drought5yr* to indicate the number of years in which a D1 degree or above drought happened in at least 10% of the county areas during July and August in the last five years. Survey population and sample summary statistics for variables used in the logit model are reported in Table 2. To avoid forbidden regression, all exogenous variables in yield moment equations are also included in the estimation of the cover crop equation. However, since many of them do not have realistic meanings (e.g., phosphorus use should not affect cover crop adoption), we only report several of their estimates, including regional dummy variables, soil texture, and slope of the field in the next section.

Estimation Results

Utilizing a two-stage method, we estimate the logit model specified in equation (9) in the first stage to address the endogeneity issue. We explore the determinants of cover crop adoption with a focus on the effects of climate change, farmers’ demographic information, and field characteristics. In the second stage, we estimate the moment equations of (6), (7), and (8).

Results of Logit Model for Cover Crop Adoption

The logit model estimation results are reported in Table 3. The results show that there existed regional differences in the adoption of cover cropping. Compared to fields in Heartland, those in Northern Crescent, Northern Great Plains, Prairie Gateway, and Mississippi Portal were less likely to adopt cover crops while those in Eastern Uplands and Southern Seaboard were more likely to do so. The higher adoption rate of cover crops in Heartland, Eastern Uplands, and Southern Seaboard comparting to that in other regions can be attributed to several factors. In addition to federal programs such as the Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP), many states in Heartland, Eastern Uplands, and Southern Seaboard have implemented state incentive programs, which have been found positively correlated with the adoption of cover crops (e.g., Fleming 2017; Lichtenberg, Wang, and Newburn 2018; Wallander et al. 2021). The top seven state-funded cover-crop programs in terms of acreage in the U.S. are all in the three regions (Wallander et al. 2021). In addition, tax credits, reduction on crop insurance premiums, and programs that rent out or loan equipment related to cover cropping in the three regions (Wallander et al. 2021) may also contribute to their higher adoption rates. Moreover, access to technical assistance and extension service may also cause variations in cover crop adoption across regions. Regional differences in the adoption of cover crops or other conservation practices have been found in other studies. Unger and Vigil (1998) find that the decision on adopting cover crops may vary from semiarid regions to humid/sub-humid regions depending on whether water is scarce or not. Given that western regions had a lower adoption rate than Heartland, Eastern Uplands, and Southern Seaboard, concerns about cover crops depleting soil water for the following main crops probably dominated in those drier western regions. In addition, as suggested in some other studies (e.g., Davey and Furtan 2008, Ding, Schoengold, and Tadesse 2009, and Claassen et al. 2018), a higher rate of adoption in Eastern Uplands and Southern Seaboard may reflect the concern about soil erosion given more rainfall in the regions.

The likelihood of cover crop adoption was also affected by farmers' concerns. Farmers who had concerns over wind-driven erosion, soil compaction, water quality, or other concerns were more likely to adopt cover crops than those who did not have such concerns. The result aligns itself with the benefits that cover crops are supposed to provide. In contrast, farmers who had concerns over water-driven erosion, poor drainage, or low organic matter were less likely to adopt than those without such concerns. Steele, Coale, and Hill (2012) did not observe consistent differences in total organic matter and labile organic matter between the winter cover crop and control soils in an experiment with 13 years of cover crop use. Our finding on the effect of concerns over low organic matters is consistent with Steele, Coale, and Hill's (2012) finding. While plenty of studies have found a positive effect of cover crops on soil organic matters and erosion by water (e.g., Shanks, Moore, and Sanders 1998; Ding et al. 2006; Dube, Chiduza, and Muchaonyerwa 2012;), many studies have concluded that cover crops' effect on organic matter may vary with cover crop species, soil type, and other practices, such as tillage and rotation (e.g., Wulanningtyas et al. 2021, Abdollahi and Munkholm 2014, Dube, Chiduza, and Muchaonyerwa 2012, and Motta et al. 2007). Our results imply that cover crops might either have not practically worked well on improving water-driven erosion, poor drainage and organic matter conditional on commonly used management and practices in soybean production or complexities of management and implementation of cover crops as well as its interactions with other practices have discouraged its adoption to address those concerns.

Field characteristics also affected the adoption of cover crops. As expected, if a field was classified as "highly erodible", it was more likely to adopt cover crops; fields with slopes were also more likely to adopt cover crops since they are more vulnerable to soil erosion. Whether a field contained wetland did not statistically significantly affect the adoption. Soil texture also affected farmers' decisions on cover crop adoption. Compared to loam soil, fields with clay or mixed soil were more likely to adopt cover crops and fields with sandy soil were less likely to do so. There was, however, no statistically significant difference between loam soil and silty soil in cover crop adoption. Larger farms and larger fields were less likely to adopt cover crops. This is expected since the larger the farm/field, the more labor and time are needed for the implementation and management of cover crops.

Farmers' demographic characteristics played an important role in practice adoption decisions. Older farmers or farmers working at least 50% off farms were less likely to adopt cover crops. This might be due to the labor and time requirements of cover crop implementation and management, as discussed previously. In addition, more educated farmers were more likely to adopt cover crops as they might better understand the importance of cover crops in the environment and agricultural sustainability. Consistent with expectation, farmers who had land ownership were more likely to adopt cover crops as they care more about their own land.

Drought in the last five years did not affect the likelihood of cover crop adoption. This might be due to the same reason as discussed above. Cover crops' drought mitigating effect may interact with other factors such as cover crop species, planting and termination time, tillage, rotation, soil type, etc. Proper combinations of the use of cover crops and other practices conditional on soil and weather conditions are required and many farmers might not have observed desired results of the use of cover crops as a drought adaptation strategy.

Results of Yield Moment Functions

Results of the first moment yield equation are presented in Table 4. As expected, more mGDD increased the soybean yield while more ODD decreased the soybean yield. If the year had a drought in July or August, the mean yield decreased. Regional differences were shown in soybean yield. Fields in Heartland, which includes Illinois, Indiana, Iowa, and parts of Missouri, Nebraska, South Dakota, Minnesota, Ohio, and Kentucky, had the highest yield among all regions. Unsurprisingly, if soybeans were planted late or a bigger proportion of fields were replanted, the field had a lower yield, resulting from shortened vegetative and reproductive intervals. Inputs of fertilizer did help increase the yield. The more phosphorus was applied, the higher the yield. With the small parameter for the quadratic term, the effect of phosphorus on yield was close to linear. The application of manure also helped improve yield by adding more nutrients to the soil. Without cover crops, soybean yield in loam soil was higher than in clay, sandy, or mixed soil, but not significantly different from that in silty soil. This is consistent with the findings of previous studies such as Radocaj et al. (2020) and He et al. (2014).

Regional differences also showed in yield variance and skewness. Compared to Heartland, soybean yield in Southern Seaboard had lower variations, and it had higher variations in the Northern Great Plains, Prairie Gateway, Eastern Uplands, and Mississippi Portal. In addition, Northern Crescent, Prairie Gateway, and Mississippi Portal had higher downside risk; in contrast, Northern Great Plains, Eastern Upland, and Southern Seaboard had lower downside risk. The higher percentage of field replanted, the more variation and the lower downside risk in yield, probably resulting from the replacement of damaged plants, for example by frosts. If soybeans were planted late, their yield varied less but had a higher downside risk, probably due to a shorter growing season or higher probability of frost before harvest. At the mean application level, phosphorus inputs reduced the variation in yield, but manure application did not. In addition, more mGDD increased the variance while more ODD decreased the variance. Both did not change the downside risk. As expected, a drought that occurred in July or August increased the variance of yield and in the meantime increased the risk of crop failure. Yield moments also showed a heterogeneous effect on soil texture. Compared to loam soil, clay and sandy soils had higher variance; clay and silty soils had lower skewness or higher downside risks.

Given the interaction terms with soil texture and weather, marginal effects of cover crops were calculated and presented in Table 5. Standard errors are calculated using the delta method. As shown in Table 5, if there was no drought in July and August that year, then cover crops statistically significantly increased the yield of soybeans planted in sandy, silty, or mixed soil; but there was no statistically significant effect on soybean yield in loam and clay soils. This is consistent with many studies and experiments finding that cover crops help increase cash crop yield. In the meantime, cover crops increased yield variance in loam and clay soils, but decreased yield variance in sandy and silty soils and had no significant effect in mixed soil. In addition, planting cover crops reduced downside risk in loam soil while increased downside risk in all other types of soils. From the above, we can see that the effects of cover crops depend on soil types when there was no drought. And there was always a tradeoff between the mean, the variation, and the downside risk of yield, i.e., there was no simultaneous positive effect of cover crops on the three moments of yield, which affected farmers' expected utility.

With droughts in July and August, cover crops reduced soybean yield in all soil types, although the effects in sandy and mixed soil were not statistically significant. This implies that cover crops consumed water in the soil for their own growth and reduced water available for the following cash crops. When drought occurred, the water supply worsened to a point where crop yield decreased. In addition, cover crops increased yield variance but reduced the risk of crop failure in all types of soils when drought occurred. The mixture of positive and negative effects of cover crops on yield moments is somewhat consistent with the finding in the first stage that previous droughts did not affect farmers' adoption of cover crops, implying a divided acceptance of cover crops as a drought adaptation strategy among farmers.

Conclusions and Discussions

We explored factors affecting farmers' adoption of cover crops by a logit model and examined the effects of cover crops on soybean yield and its risk by three moment functions. By incorporating two interplays between cover crops and soil type, and cover crops and drought, we were able to explore the varying effects of cover crops in drought and different soil types. While we found that the adoption of cover crops varied in regions and soil types and was affected by field properties and farmers' demographic characteristics and concerns, we did not find a significant effect of previous droughts on the adoption. The results from the moment functions of soybean yield confirmed what the results in the first stage suggest. When there was a drought, cover crops reduced yield and increased yield variance. However, cover crops also reduced the downside risk of crop failure in the meantime. The mixed effects of cover crops on yield and its risk associated with an occurrence of drought support the statistically insignificant effect of the previous drought on cover crop adoption, implying that farmers were divided in the acceptance of cover crops as a means to build resilience to drought. The mixed effect of cover crops also warrants a further study to calculate the certainty equivalent of net economic return of soybeans with cover crops, which requires information on cover crop seed, planting, and termination cost as well as additional or saved fertilizer and pesticide costs. The certainty equivalent of net economic returns of soybeans with cover crops may provide more information on economic impediments to farmer adoption.

The low adoption rate of cover crops may also be related to complex interactions between management and cultural practices including species selection, planting and termination date, rotation, and termination method. Achieving desired benefits requires significant training, learning, and adjustments in many aspects of the farming system (Wallander et al. 2021). As shown in the National Cover Crop Survey 2020 (Conservation Technology Information Center 2020), roughly 70% of respondents said that they typically used their own experience of trial and error for cover cropping. About 67% and 60% of the respondents considered the two approaches, i.e., local farm tours to see how cover crops worked and one-on-one technical assistance to select, plant, or manage cover crops, very helpful or moderately helpful, respectively, in encouraging them to try cover cropping. Therefore, programs that provide necessary training and showcase cover crop management to farmers are clearly in need.

Greater soil and environmental benefits can be achieved when cover crops are utilized in conjunction with other practices (Wallander et al. 2021), such as conservative tillage, irrigation, crop rotation, nutrient management, and adoption of drought tolerant seeds—which are currently available for maize. A broader range of research that finds proper combinations of cover crops and other practices conditional on soil types and weather are crucial for establishing practice guidance for farmers. Such guidance can help farmers achieve desired results by using cover crops as a drought adaptation strategy as well as a tool for improving soil and environmental benefits along with a suite of other conservation practices.

The recent increase in cover crop adoption has been accompanied by financial incentives. Given financial support, cover crop acres enrolled in the Environmental Quality Incentives Program (EQIP) increased from 312.6 thousand acres in 2009 to 2,443.1 thousand acres in 2020 (Climate Hubs, USDA, 2021). In 2018, about one-third of the acreage planted with a cover crop received a financial assistance payment for cover crop adoption from either federal, state, or other programs, ranging from $12 per acre to $92 per acre (Wallander et al. 2021).

The USDA NRCS recently announced a program to promote the use of soil health practices especially cover crops. The initiative sets a goal of doubling the number of corn and soybean acres using cover crops to 30 million acres by 2030 (USDA 2022). Given the mixed effects of cover crops on soybean yield and yield risk found in this study, financial incentives can help improve the certainty equivalent of net returns and thus encourage more risk-averse farmers to adopt cover crops. In addition, farmers have recently been paid to plant cover crops by large seeds, chemical, and food companies to generate carbon credits to offset their environmental footprints (Reuters 2022). The payments, however, are generally not as much as those from EQIP and CSP. In addition, the current carbon credit market lacks transparency and liquidity (Ag Decision Maker 2021). It is facing several challenges including setting up protocols to ensure the additionality and permanence of net greenhouse gas (GHG) reductions (Blaustein-Rejto, 2021).

We conclude the paper by recognizing a key limitation of this study: it does not consider the long-term effects of sustainable practice adoption by using cross-sectional data. Cover crops have multiple benefits to soil and the environment. Cover crops can not only be used as a drought adaptation strategy, but also to reduce soil erosion, enhance weed control, improve soil health, increase carbon storage, improve water quality through reduced nutrient and sediment runoff, and increase biological diversity. While solely comparing the cost of seed, seeding, and management to the impact on the yield of the following main crop may show a loss in the first few years, cover crops may possibly improve the efficiency and resiliency of the entire farm over time, resulting in a net benefit from the broad, holistic standpoint (Myers, Weber, and Tellatin, 2019). Myers, Weber, and Tellatin (2019), for example, show that the adoption of cover crops may have negative net returns in the first year, negligible net returns in three years, but about $18 net returns in 5 years. In addition, if cover crops are used to address more than one yield-limiting factor in a field such as for grazing, improving soil health, and weed impression, then the net return can be larger and faster. This can be applied to many other sustainable practices. For example, the payoffs from investments in improving soil fertility and reducing soil erosion are cumulative and may take several years. And the subsequent improvement in soil fertility and reduction in soil erosion can reduce future expenses for crop nutrients, irrigation, and energy (Lee 2005; Tilman et al. 2001). If such long-term positive net returns can be demonstrated by more farmers who are supported financial assistance from federal and state programs to offset a portion of upfront investments— which have been proved very useful in increasing the adoption (Bowman and Lynch 2019)—, then the adoption of cover crops, as well as other drought adaptation strategies, may surge.

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Table 1. Survey Means and Standard Errors of Variables in Moment Functions

Variable and unit	Survey Mean	Std. Err
Yield (bushels/acre)	52.354	0.097
Heartland (0/1)	0.498	0.003
Northern Crescent (0/1)	0.141	0.003
Northern Great Plains (0/1)	0.066	0.001
Prairie Gateway (0/1)	0.054	0.001
Eastern Uplands (0/1)	0.053	0.002
Southern Seaboard (0/1)	0.105	0.002
Mississippi Portal (0/1)	0.083	0.001
PlantLate (0/1)	0.129	0.002
ReplantPct	0.041	0.002
Manure (0/1)	0.043	0.001
Phosphorus (lbs/acre)	25.550	0.229
drought18 (0/1)	0.175	0.002
Soil texture: loam (0/1)	0.369	0.003
Soil texture: clay (0/1)	0.170	0.003
Soil texture: sandy (0/1)	0.069	0.002
Soil texture: mixed (0/1)	0.369	0.005
Soil texture: silty (0/1)	0.019	0.001
Growing degree days (Celsius)	3304.675	4.396
Overheating degree days (days)	30.778	0.133
Cover crops	0.100	0.003

Table 2. Survey Means and Standard Errors of Variables in the Logit Model

Variable and Unit	Survey Mean	Std.Err
Cover crops (0/1)	0.100	0.003
Heartland (0/1)	0.498	0.003
Northern Great Plains (0/1)	0.141	0.003
Prairie Gateway (0/1)	0.066	0.001
Eastern Uplands (0/1)	0.054	0.001
Southern Seaboard (0/1)	0.053	0.002
Mississippi Portal (0/1)	0.105	0.002
Northern Crescent (0/1)	0.083	0.001
Fields having moderate or steeper slope (0/1)	0.556	0.004
Soil texture: loam (0/1)	0.369	0.003
Soil texture: clay (0/1)	0.170	0.003
Soil texture: sandy (0/1)	0.069	0.002
Soil texture: mixed (0/1)	0.369	0.005
Soil texture: silty (0/1)	0.019	0.001
Concern about water-driven erosion (0/1)	0.262	0.003
Concern about wind-driven erosion (0/1)	0.080	0.002
Concern about soil compaction (0/1)	0.261	0.004
Concern about poor drainage (0/1)	0.232	0.004
Concern about low organic matter (0/1)	0.109	0.003
Concern about water quality (0/1)	0.066	0.002
Other concerns (0/1)	0.025	0.001
Field classified as "highly erodible" (0/1)	0.180	0.003
Field contains wetland (0/1)	0.041	0.002
Age (years)	57.730	0.100
Years of experience (years)	33.326	0.121
College education (0/1)	0.251	0.002
Off-farm work (0/1)	0.185	0.004
Land ownership (0/1)	0.491	0.004
Farm size (acres)	1348.206	11.558
drought5yr (years)	0.764	0.007
Field size (acres)	50.015	0.328

Table 3. Estimates of Parameters of the Logit Model

parameter	Estimation	Bootstrapped Std. Err.
Northern Crescent	-1.049***	0.157
Northern Great Plains	-3.100***	0.212
Prairie Gateway	-0.605***	0.205
Eastern Uplands	2.363***	0.129
Southern Seaboard	2.788***	0.172
Mississippi Portal	-1.187***	0.202
slope	0.520***	0.057
Soil texture: clay	0.711***	0.114
Soil texture: sandy	-0.249*	0.144
Soil texture: mixed	0.413***	0.087
Soil texture: silty	0.330	0.277
Concern about water-driven erosion	-0.413***	0.121
Concern about wind-driven erosion	0.532***	0.102
Concern about soil compaction	0.223*	0.129
Concern about poor drainage	-0.218**	0.105
Concern about low organic matter	-0.793***	0.121
Concern about water quality	0.901***	0.112
Other concerns	0.976***	0.142
Field "highly erodible"	0.545***	0.120
Field contains wetland	0.355	0.531
age	-0.024***	0.006
Years of experience	-0.005	0.005
College education	0.551***	0.078
Off-farm work	-0.258**	0.109
Land ownership	0.230*	0.080
Farm size	-9.280E-05***	3.160E-05
drought5yr	-0.089	0.068
Field size	-0.003***	0.001
Constant	-3.119***	0.667

Note: statistical significance at 1%, 5%, and 10% are denoted as ***, **, and *, respectively.

Table 4. Estimates of Parameters of Yield Moment Equations.

	First moment (Mean) equation		Second moment (variance) equation		Third moment (skewness) equation	
Parameter	Estimation	Bootstrapped Std. Err	Estimation	Bootstrapped Std. Err	Estimation	Bootstrapped Std. Err
Cover crops	-3.890	2.720	48.337***	9.092	2868.821***	341.341
Drought×cover crops	-20.160***	4.452	223.235***	21.604	16562.100***	1050.960
Cover crops×clay soil	6.869***	2.517	4.441	32.237	-12716.120***	1430.358
Cover crops×sandy soil	17.406***	2.509	-79.215***	17.073	-6299.486***	559.366
Cover crops×mixed soil	18.586***	1.655	-48.293***	18.088	-8944.720***	667.661
Cover crops×silty soil	14.110***	1.926	-154.608***	23.123	-4624.771***	793.497
Northern Crescent	-2.994***	0.314	-3.153	2.946	-263.873**	110.773
Northern Great Plains	-9.363***	0.472	19.329***	4.805	377.511***	146.329
Prairie Gateway	-4.436***	0.603	103.903***	7.312	-1081.599***	259.667
Eastern Uplands	-17.638***	1.147	39.311***	6.498	1982.181***	286.687
Southern Seaboard	-25.983***	0.819	-20.231***	4.326	932.423***	131.663
Mississippi Portal	-4.093***	0.668	153.902***	12.949	-2364.662***	500.023
PlantLate	-4.934***	0.256	-20.423***	-20.423***	-461.056***	77.673
ReplantPct	-6.639***	1.069	42.540***	11.625	4547.295***	499.821
Manure	1.956***	0.440	3.777	4.742	547.647***	184.636
Phosphorus	0.020***	0.004	-0.569***	0.062	-3.022	1.899
Phosphorus ^{2}	1.735E-04***	2.680E-05	0.003***	0.001	0.003	0.012
Drought18	-3.696***	0.401	30.540***	4.323	-856.462***	151.164
Soil texture: clay	-1.507***	0.389	7.641**	3.275	-788.829***	113.448
Soil texture: sandy	-10.515***	0.477	71.824***	5.500	2274.254***	211.552
Soil texture: mixed	-3.742***	0.243	-17.207***	2.521	446.028***	84.746
Soil texture: silty	0.485	0.429	1.400	10.029	-1525.396***	389.240
mGDD	0.013***	0.001	0.041***	0.007	-0.314	0.242
ODD	-0.184***	0.016	-0.650***	0.189	-5.393	6.670
Constant	23.424***	1.390	7.472	18.158	1100.763*	648.716
R^2	0.334		0.095		0.112	

Note: statistical significance at 1%, 5%, and 10% are denoted as ***, **, and *, respectively.

Table 5. Marginal effects of cover crops under different situations

			yield equation		second moment (variance) equation		third moment (skewness) equation	
	Soil type	Drought	Estimation	Std.Err	Estimation	Std.Err	Estimation	Std.Err
cover crops	loam	No	-3.890	2.720	48.337***	9.092	2868.821***	341.341
		Yes	-24.049***	4.579	271.572***	26.449	19430.921***	1244.251
	Clay	No	2.980	3.108	52.778*	31.177	-9847.299***	1426.819
		Yes	-17.180***	3.826	276.013***	31.774	6714.801***	1166.486
	sandy	No	13.516***	2.349	-30.878**	13.859	-3430.665***	391.965
		Yes	-6.643	4.586	192.357***	23.436	13131.435***	1080.542
	mixed	No	14.696***	2.375	0.045	13.002	-6075.899***	461.852
		Yes	-5.463	4.216	223.280***	17.548	10486.201***	701.112
	silty	No	10.220***	1.839	-106.271***	21.328	-1755.950***	709.924
		Yes	-9.940***	4.234	116.964***	26.404	14806.150***	981.327

Note: statistical significance at 1%, 5%, and 10% are denoted as ***, **, and *, respectively.