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Off-Farm Income, Technology Adoption, and Farm Economic Performance

Jorge Fernandez-Cornejo, with contributions from Ashok Mishra,
Richard Nehring, Chad Hendricks, Malaya Southern
and Alexandra Gregory



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Ashok Mishra, Richard Nehring, Chad Hendricks,
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Abstract

The economic well-being of most U.S. farm households depends on income from both onfarm and off-farm activities. Consequently, for many farm households, economic decisions (including technology adoption and other production decisions) are likely to be shaped by the allocation of managerial time among such activities. While time allocation decisions are usually not measured directly, we observe the outcomes of such decisions, such as onfarm and off-farm income. This report finds that a farm operator's off-farm employment and off-farm income vary inversely with the size of the farm. Operators of smaller farm operations improve their economic performance by compensating for the scale disadvantages of their farm business with more off-farm involvement. Off-farm work reduces farm-level technical efficiency, but increases household-level technical efficiency. And adoption of agricultural innovations that save managerial time is associated with higher off-farm income.

Keywords: Off-farm income, farm households, economic performance, managerial time, scale economies, scope economies, technical efficiency, technology adoption, farm size.

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Summary

U.S. farmers must make a host of decisions relating to their farms' operation, including what to grow, when to grow it, in what quantities, and by what methods. Often overlooked in this calculation, but factoring heavily in the diversity of U.S. farms and farm households, is the fact that most operators split their time between farm and nonfarm activities. Large farms are typically able to economize on inputs and better coordinate stages of production. Smaller farms, though often unprofitable from a farm business perspective, have endured by being part of household enterprises that combine farm and off-farm activities. Their operators' onfarm decisions, from choice of technology to choice of specialty, are often influenced by off-farm commitments and income.

What Is the Issue?

Onfarm and off-farm activities compete for limited managerial time (mainly of the operator and spouse). How farm operator households allocate their time largely affects production decisions (such as technology adoption), economic performance, and the household's economic well-being.

The extent of off-farm work and its relationship with farm economic performance may have important policy implications. For example, government policies for agriculture (via conservation, research and development, extension, and commodity programs) may affect farm households differently, depending on the relative importance of onfarm versus off-farm income. And the effectiveness of policies promoting adoption of farm technologies might be improved by taking into account the different demands on managerial time and the relative ability of the farm household to accommodate those demands.

What Did the Study Find?

Operators of smaller farms typically participate more in off-farm employment, work more hours off the farm, and have higher off-farm income than operators of larger farms. In 2004, farm households with farm sales less than \$10,000 had average off-farm earned income of \$54,600, while households with farm sales of \$500,000 – \$1 million averaged only \$30,100. More than 58 percent of operators with farm sales less than \$10,000 reported off-farm hours worked in 2004, versus less than 20 percent for operators of farms with sales of \$500,000-\$1 million.

As previous studies have shown, **off-farm work is less likely on farms with labor-intensive enterprises** such as dairy. Moreover, dairy farmers who do work off the farm tend to require higher compensation to do so than farmers producing other commodities. Off-farm work has also been shown to be positively related to urban proximity and to the education and experience of the operator and spouse.

Including off-farm income-generating activities improves the overall economic performance of the farm household. Off-farm income clearly adds to total household income, but it can also improve efficiency and other

measures of performance of the farm household. Our estimates for corn and soybean farms show that households engaged in off-farm income-generating activities together with the production of traditional farm outputs have cost savings of 24 percent relative to carrying out those activities separately. The savings likely arise from the sharing of managerial expertise (and its many components, such as accounting and information processing skills, sales expertise, administrative and technical know-how, etc.) between onfarm and off-farm activities. For example, management skills acquired in farming might be applicable to (and shared with) a nonfarm business, and vice-versa.

From a farm business perspective, operators of smaller farms have a greater **incentive to expand**. However, from a household perspective (including off-farm income-generating activities), operators of small farms have a reduced tendency to increase their farm size.

Large farms are generally more efficient than smaller farms in transforming farm inputs into outputs, given the technology at their disposal. But focusing on farm inputs and outputs alone is misleading because off-farm income-generating activities are increasingly important in determining economic performance of the farm household.

When off-farm activities are included, farm household-level efficiencies are higher than farm-level efficiencies across all farm sizes, and efficiency gains from integrating off-farm work into the output portfolio are relatively greatest for smaller farms. As a result, household-level efficiencies of smaller farms are comparable to farm-level efficiencies of larger farms. This suggests that households operating small farms have partially adapted to shortfalls in farm-level performance by increasing their off-farm income.

In addition to its links with the farm business, as traditionally examined, farmers' technology choices are closely related to off-farm income. Higher off-farm income is significantly related to the adoption of technologies that economize on management time (management saving such as herbicide-tolerant crops, conservation tillage). For example, a 16-percent increase in off-farm household income is associated with a 10-percent increase in the probability of adopting herbicide-tolerant (HT) soybeans. Household income from onfarm sources is not significantly associated with adoption of these technologies, but total household income (including income from off-farm sources) is. On the other hand, lower off-farm income is significantly related to adoption of managerially intensive technologies (such as precision farming). For example, an 8-percent decrease in off-farm income is associated with a 10-percent increase in the probability of adopting yield monitors, a key component of precision agriculture. These findings corroborate a tradeoff between household/operator time spent in onfarm and off-farm activities. Households operating small farms devote more time to off-farm opportunities and are more likely to adopt management-saving technologies.

How Was the Study Conducted?

To examine the relationships between off-farm income, farm and household characteristics, and economic performance of U.S. farm households, we developed econometric models and estimated them using USDA's Agricultural Resource Management Survey (ARMS) data for several years (1996-2001). To examine the relationship between off-farm work and economic performance of farm households (including economies of scale and scope, and economic efficiency), we compared estimates obtained using traditional farm-level models to estimates obtained using household-level models (including off-farm income-generating activities along with traditional farm outputs such as crops and livestock). To examine the relationship between off-farm income and technology adoption, we developed a model that incorporates the adoption decision into the agricultural household framework. We examined the interaction of off-farm work and adoption of agricultural technologies of varying managerial intensity, including herbicide-tolerant crops, precision agriculture, conservation tillage, and Bt (*Bacillus thuringiensis*) corn, after controlling for other factors.

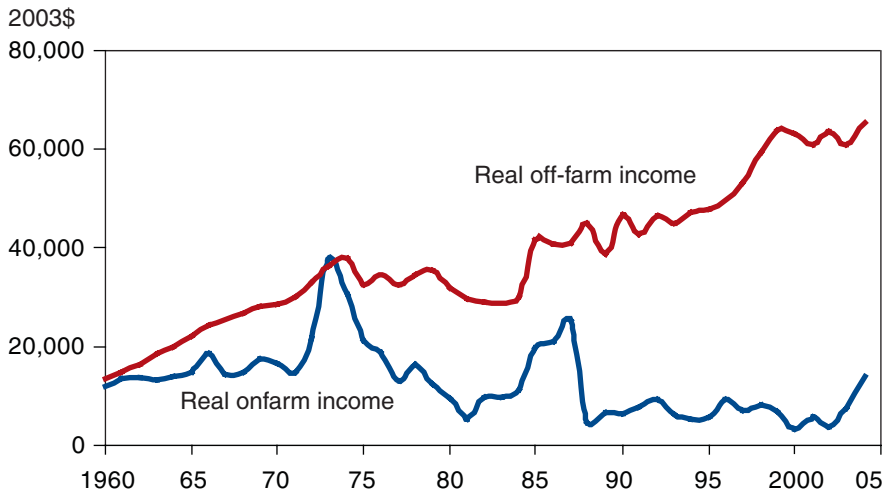
Introduction and Overview

Decisionmakers (mainly farm operators and their spouses) are a major determinant of farms' economic performance. The effort and ability to manage land, water, machinery, and other inputs— as well as adoption of technologies and production practices—can help secure farm business success and the economic well-being of a farm household. However, many farm operators (and other household members) use a large share of their time in off-farm income-generating activities. Consequently, for many farm households, economic decisions (including technology adoption and other production decisions) are likely to shape and be shaped by the allocation of managerial time to such activities. While time allocation decisions are usually not measured directly, we observe the outcomes of such decisions, such as onfarm and off-farm income.

Off-farm income (largely earned income from employment and off-farm business income) received by U.S. farm operators and their spouses has risen steadily over recent decades and now constitutes the largest component of farm household income (fig. 1a, b). The impact of off-farm income is felt particularly by households operating small farms, allowing many of them to survive and even flourish to an extent not thought possible 20 or 30 years ago (Gardner, 2005). In addition, the growth in off-farm income over the last 40 years reduced income inequality among farm households and helped U.S. farmers' average incomes overtake those of the nonfarm population (Gardner, 2002).

This report examines the empirical relationships between off-farm income, farm household characteristics, production decisions (particularly technology adoption), and various measures of economic performance for U.S. farm households. This research provides insights into farmers' choices in the context of farm/household integration and helps improve our under-

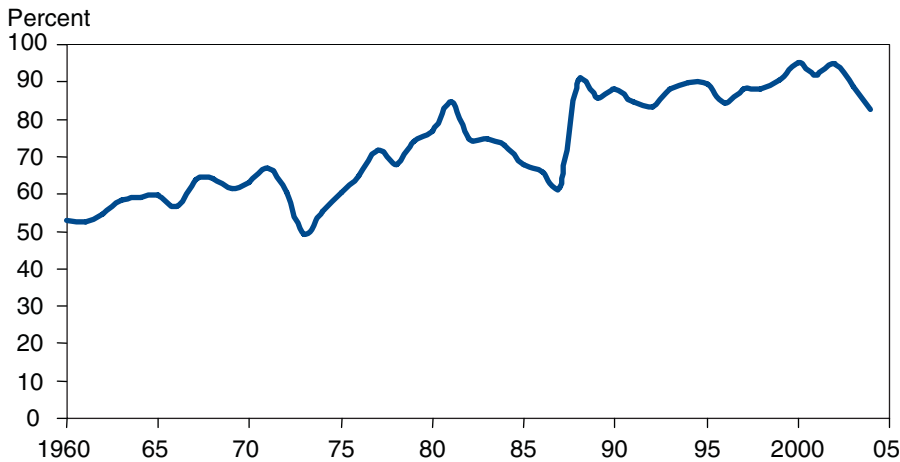
Figure 1a
Farm household income, U.S. average 1960-2004



Sources: USDA, ERS. Deflator used to calculate real income is the consumer price index (CPI-U) from the Bureau of Labor Statistics.

Figure 1b

**Off-farm income share of total farm household income,
U.S. average, 1960-2004**



Sources: 1960-2003: USDA farm household income estimates over time, ERS farm structure briefing room, <http://www.ers.usda.gov/Briefing/FarmStructure/Data/historic.htm>; 2004: Covey et al., 2005.

standing of the pace of technological innovation and its relation to the structure of agriculture.

The report also suggests the need to analyze the economics of the farm business and farm household in an integrated framework and describes two approaches for doing so. We summarize statistics of off-farm work and income in U.S. farm households and examine the relationship between off-farm income and farm size, location, and household characteristics.

Our main research focus is to examine how off-farm work influences the economic performance of the integrated farm business and household. To do this, we expand traditional concepts of economic performance, such as economies of scale and efficiency, to incorporate onfarm and off-farm income-generating activities of household members. In addition, we examine the relationship between off-farm income and the adoption of agricultural technologies of varying managerial intensity, namely herbicide-tolerant crops, precision agriculture, conservation tillage, and Bt (*Bacillus thuringiensis*) corn.

An Integrated Approach

While increasing household income, off-farm activities also compete for managerial time (mainly of farm operators and their spouses), which may affect the economic performance of the farm business. Consequently, economic decisions (including technology adoption and other production decisions) are likely to shape and be shaped by the underlying allocation of time within the farm operator household. So, rather than examining the farm business or farm household in isolation, an integrated approach captures the interplay of farm and nonfarm considerations and contributions.

Despite its importance, the role of off-farm income has been largely neglected in empirical analyses of farm economic performance and technology adoption.¹ Some exceptions include Gardner (2001), Boisvert (2002), Goodwin and Mishra (2004), Fernandez-Cornejo et al. (2005), Nehring et al. (2005), Paul and Nehring (2005), and Chavas et al. (2005).² One reason for this lack of studies may be the modeling and data challenges in moving from the traditional unit of analysis (the farm business) to the farm household.

While agricultural economists have made major contributions in understanding farm production functions, they may not have exploited as fully the concept of the household production function (Offutt, 2002). In this context, the allocation of time (and money) of household members to production, consumption, and other activities is particularly important. An integrated firm-household perspective was suggested back in 1952 by E.O. Heady, who observed that “the firm-household complex is important not only to defining the organization of resources and family activities which will maximize utility at a given point in time but also in helping to explain uncertainty precautions, capital accumulation, soil conservation, and other production-consumption decisions, which relate to time.”³

Approaches To Integrate Off-Farm Work and Farm Production

Two approaches are used in this report to model the interaction of off-farm income-generating activities with traditional farm production activities. The unifying notion underlying the two approaches is that managerial time is a key resource in both onfarm and off-farm activities.

In one approach, we expand the agricultural household model to include the technology adoption decision together with the off-farm work decisions by the operator and spouse. The agricultural household model describes how a farm household allocates its time (and other resources) among producing commodities, earning off-farm income, leisure, and home production.⁴ The model assumes that the farm household maximizes its utility subject to constraints on its time (including work and leisure), income, and production technology (production function). Household members derive utility from goods purchased for consumption, leisure, and factors exogenous to current household decisions, such as human capital, household characteristics, and weather. Using this model, we examine the interaction of off-farm work and the adoption of agricultural innovations (both management saving like herbicide-tolerant crops, and management using like precision agriculture or integrated pest management—IPM), then obtain empirical estimates of the relationship between adoption of these technologies and farm household income.

Though the agricultural household model has intuitive appeal in modeling farm household behavior, it requires much in the way of assumptions and data (Offutt, 2002). Parameter estimation for the models spawned by the household production function often requires hard-to-get data, including consumption expenditures, farm and off-farm labor supply, farm and nonfarm outputs and inputs, assets, and prices for all goods, inputs, and labor. Also needed is information on technologies and participation in

¹Economic researchers have been examining farm economic performance focusing on the farm business for several decades (Heady; Griliches; Dawson and Hubbard; Hallam). Another line of research has focused on the farm household and the labor allocation decisions by the operator and their spouses (Huffman, 1980, 1991; Lass, Findeis, and Hallberg, 1989; Lass and Gempesaw, 1992; Kimhi, 1994, 2004).

²Boisvert (2002) stressed not only the growing links between farming activities and off-farm labor markets but also the links between farm household activities, conservation payments, and agricultural pollution.

³Loosely, utility is a measure of satisfaction. Economists assume that people act if doing so gives them utility.

⁴The household model initially received a great deal of attention in studies of developing countries' agriculture because of the relative importance of consumption activities in such households. Agricultural economists have also applied these models in developed countries to examine how household members make decisions about the allocation of labor both on and off the farm (Huffman, 1980, 1991; Sumner, 1982; Lopez, 1985; Singh et al., 1986; Lass et al., 1989; Lass and Gempesaw, 1992; Kimhi, 1994, 2004; Mishra and Goodwin, 1997; Goodwin and Holt, 2002). Other analysts have examined income and wealth distributions and links between income instability and consumption/investment (El-Osta and Morehart; Mishra and Morehart). Lopez is one of the few to have considered labor supply and farm production decisions simultaneously. In a very recent application, Chavas et al. used a farm household model to investigate the economic efficiency of farm households in Gambia (Chavas et al., 2005).

government programs, as well as demographic data. For these reasons, it is sometimes necessary to use alternative methods. In this approach, we expand the concept of scope economies to include as output all income-generating activities, on or off the farm, in addition to the traditional farm outputs such as corn, soybeans, and livestock (Nehring et al., 2005). In addition, we estimate scale economies and technical efficiency, and compare results at the farm and household levels.

Scale and Efficiency

Scale Economies

A farm is said to have economies of scale (or increasing returns to scale) if the average cost declines as output (scale of production) increases. If a farm is subject to economies of scale, it is cost effective for that farm to increase all outputs simultaneously while holding the mix of outputs constant (costs would rise less than proportionally). Thus, the existence of scale economies suggests that farms can achieve lower average costs by becoming larger. Economists have established (under reasonable conditions) the equivalence between the information provided by the costs and the production technology (Carlton and Perloff, 2000). Based on the production technology, economies of scale may be viewed from an output or input perspective.

From an output perspective, the term elasticity of scale is used to measure the percent increase in output generated by a 1-percent increase in all inputs (Varian, 1992). There are increasing returns to scale if the elasticity is greater than 1; that is, an increase in overall inputs generates a more than proportionate increase in output. For example, a scale elasticity of 1.15 means that a 1-percent increase in inputs leads to a 1.15-percent increase in output. Conversely, if the elasticity is lower than one there are decreasing returns to scale; that is, an increase in overall inputs generates a less than proportionate increase in output. For example, a scale elasticity of 0.8 means that a 1-percent increase in inputs leads to a 0.8-percent increase in output. Constant returns to scale means that a 1-percent increase in overall inputs generates a 1-percent increase in output; in this case the elasticity of scale is equal to 1.

From an input perspective, a similarly defined scale elasticity measures the percent increase in inputs required to support a 1-percent increase in all outputs. In this case, returns to scale are increasing when the input-oriented scale elasticity is less than one. For example, if the scale elasticity of a farm is 0.75, it means that a 0.75-percent increase in inputs will be needed to support an output increase of 1 percent. This suggests that there is an incentive for the farm to grow larger. If the elasticity is equal to one (constant returns to scale), there are no scale economies available. In this report, we use an input perspective (input distance function, appendix 1).

Technical Efficiency

Economic efficiency can be decomposed into technical efficiency and allocative efficiency. A farm is technically efficient if it uses the minimum possible levels of inputs to produce a given level of output, given the technology. An allocative efficient farm produces a given output using the best (minimum cost) input proportions given prevailing input prices. Unless specified otherwise, the efficiency results discussed in this report involve technical efficiency.

Technical efficiency is the ratio of current to maximum possible or “best practice” production and it is calculated in this study using an input distance function (see appendix 1). Technical efficiency is defined relative to an “efficient frontier” and all farms operating on the efficient frontier are classified as 100 percent efficient with an efficiency score equal to 1. Farms using more inputs to produce a given output level than those on the efficient frontier are inefficient and their efficiency score is less than 1. Technical efficiency is often associated with managerial ability and experience.

Off-Farm Work and Income in U.S. Farm Households

Off-farm income received by farm operators and their spouses has risen steadily over recent decades (fig. 1a) as job opportunities have grown and technological progress, such as mechanization, has lessened onfarm labor needs. The off-farm income share of total household income of U.S. farmers rose from about 50 percent in 1960 to more than 80 percent over the past 10 years (fig. 1b). Most of the off-farm income was earned. On average, a farm household earned about \$48,800 from off-farm sources in 2004, received about \$18,500 in unearned income (Social Security, interest, etc), and netted nearly \$14,200 from farming activities (Covey et al., 2005).⁵ Fifty-two percent of farm operators worked off farm in 2004 (up from 44 percent in 1979). The share of spouses working off farm grew from 28 percent of spouses in 1979 to 45 percent in 2004 (Mishra et al., 2002; 2004 ARMS data).

The trend is similar in terms of hours worked (table 1). Average hours worked off farm by farm operators has increased (from 830 hours per year in 1996 to 1,022 in 2004), while the hours devoted to farm work did not change markedly (1,525 hours in 1996 and 1,574 in 2004). Similarly, the number of hours worked off the farm by spouses increased from 690 in 1996 to 809 in 2004.

Farmers' Motivations To Work Off Farm

Once seen as a “temporary response to the Great Depression,” off-farm employment is now regarded as a “regular feature of almost all farming societies” (Fuller, 1991; Bartlett, 1986; Bessant, 2000). More than half of U.S. farm operators now work off the farm.⁶ Moreover, off-farm income appears to smooth out household income flows (Mishra and Goodwin, 1997; Mishra and Sandretto, 2002), and most farmers view off-farm employment as a permanent rather than a temporary or transitional (into or out of farming) pursuit (Ahearn and El-Osta, 1993).⁷ Farm operators in a 1982 survey felt that full-time farming provided inadequate income (91 percent of the respondents), and that farm income was risky (70 percent) and offered no fringe benefits such as pensions and health insurance (55 percent). Capital and land constraints were considered less important disadvantages to full-time farming (42 and 30 percent) (Barlett, 1991). More

Table 1

Operator and spouse hours worked on and off farm, 1996-2004

Item	1996	2000	2004
Operator hours worked:			
On farm	1,525	1,433	1,547
Off farm	830	1,011	1,022
Total	2,355	2,443	2,596
Spouse hours worked:			
On farm	366	337	877
Off farm	690	751	809
Total	1,056	1,089	1,686

Sources: 1996: Hoppe (2001, p. 29); 2000: Mishra et al. (2002, p. 50); 2004: ARMS data.

⁵Across all farms, operators earned 64 percent of all household off-farm earned income in 2001, spouses earned close to 33 percent, and other members earned 3 percent (O'Donoghue and Hoppe, 2005).

⁶There are, however, some issues regarding the definition of a farm. Since the USDA definition of a farm is not adjusted for inflation, the number of small operations that get defined as farms may increase over time, which may also increase the share of operators working off the farm.

⁷A minority of farmers (18.4 percent of the total in 1987) may be considered as a transitional group, i.e., full-time farmers who worked off farm because they faced heavy losses and high debts. Some of these farmers expected to return to full-time farming when their financial situation was resolved (Bartlett, 1991). Moreover, using agricultural census data spanning 1982 to 1997, ERS researchers identified 644 (out of over 5,000) small part-time farms that managed to grow into large commercial operations. These farms are called emergent adaptive farms (EAF). Off-farm work provided financial support during the early years of the typical EAF, but EAF operators spent more time on farm activities as their businesses expanded: 35 percent of EAF operators worked at least 200 days off the farm in 1987, but that share declined to 16 percent by 1997 (Newton, 2005).

recently, the 2004 ARMS asked operators and spouses to list the two main reasons for seeking off-farm work. The primary reason given by 35-50 percent of the operators and 44-63 percent of the spouses (depending on farm size and occupation of the farm operator) was “to increase income” of the farm household. Other reasons cited were to obtain fringe benefits (such as health insurance) and personal satisfaction (Covey et al., 2005).

So most operators and spouses report working off farm primarily to increase income for the farm household, but how was the additional income used? Contrary to conventional wisdom, most farm operators and spouses did not work off the farm to directly support their farm business. USDA surveys indicate reasons unrelated to the farm business, from buying groceries to funding a retirement account (Hoppe, 2001).

Farmers and spouses hold a variety of off-farm jobs, but especially in private businesses (54.1 percent of operators with off-farm jobs), self-employment (22.3 percent), and government (16.0 percent). Only 3.3 percent worked on another farm (Mishra et al., 2002). Spouses with off-farm work are most likely to be employed in the private sector (55.1 percent) and government (28.4 percent), with less than 1 percent working on another farm.

Opportunity Cost of Labor for Farm Operators

Opportunity cost is an important economic concept that measures the economic cost of an action or decision in terms of what is given up (opportunity forgone) to carry out that action. In the case of farm labor, for example, the opportunity cost of labor for the operator (or spouse) labor is often measured in terms of the wage that the operator (or spouse) can obtain working off farm. As the United Nations’ Economic Commission for Europe notes: “In conventional accounting systems, ‘unpaid’ family labour does not usually appear as an explicit cost of production. Consequently, there is no explicit ‘wage’ paid to the labour that the farmer and his family [contribute to] production.”

Farm household labor is a critical input in agricultural production. In the corn/soybean-producing States, farm household members provide more than 80 percent of all labor hours.⁸ A significant proportion of those labor hours is not valued directly in the marketplace (e.g., through wages). Studies have estimated the opportunity costs of farm labor by using predicted off-farm wages (El-Osta and Ahearn, 1996).

Alternatively, a simplified approximation of the opportunity cost of labor for farm operators and their spouses can be obtained directly from ARMS data. The (nominal) opportunity costs for corn/soybean operators and spouses appear not to have increased over 1996-2000. The cost for the operator (\$21.07 per hour for 2000) appears to run about 20 percent higher than that of the spouse, and both are higher than the actual wage rate for hired farm labor.⁹

It is also interesting to compare the opportunity cost of labor for corn/soybean farmers with those of dairy farmers. The cost for U.S. dairy farmers in 2000 was econometrically estimated at \$27.58 per hour for oper-

⁸Corn/soybean-producing States are defined as those that account for most of the U.S corn and soybean production. States included are Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin.

⁹The opportunity cost of labor varies with the farm’s region, size, and specialization, the operator’s human capital (education and experience); and household characteristics (El-Osta and Ahearn). In addition, opportunity cost estimates may vary with the characteristics of the labor markets, the methodology used, and data sources.

ators (30 percent higher than for corn/soybean farmers) and \$19.36 for spouses (18 percent higher) (Lovell and Mosheim, 2005). Given that labor requirements in dairy production are high and inflexible (El-Osta and Ahearn), dairy farmers likely require a higher “wage” to work off the farm than farmers working in other enterprises.

Table 2

Opportunity cost of labor for corn/soybean farm operators and spouses, and actual hired farm wage rate, 1996-2000

Year	Operator	Spouse	Hired
<i>Dollars per hour</i>			
1996	22.88	17.87	7.42
1997	26.72	19.06	8.01
1998	22.14	18.77	8.30
1999	22.19	17.96	8.67
2000	21.07	17.47	8.99

Source: ERS estimates based on ARMS data for corn/soybean States analyzed (Nehring, Fernandez-Cornejo, and Banker, 2005).

Off-Farm Income and Farm/Household Characteristics

Like their nonfarm counterparts, many farm households are dual career. While operators and spouses across all sizes and typologies work off-farm or manage nonfarm businesses, the level of off-farm income varies with farm size, region, farm type, and the human capital of operators and spouses.

Off-Farm Income and Farm Size

Off-farm income varies inversely with farm size; operators of smaller farms have higher off-farm incomes, both earned and total.¹⁰ Farm households with gross farm sales less than \$10,000 had total off-farm income averaging nearly \$74,000 in 2004 (\$54,600 of which was earned), while households with farm sales between \$250,000 and \$499,999 had total off-farm income averaging about \$45,000 (\$33,200 earned) (table 3). While off-farm income constitutes the largest component of farm household income on average, its share decreases with farm size. For farms with gross sales higher than \$250,000 (less than 8 percent of U.S. farms), off-farm income is no longer the largest component of household income (table 4).

Off-farm household income earned by the operators is more variable across farm sizes (\$27,500 for operators of smaller farms versus less than \$10,000 for operators of the largest farms) than that earned by spouses (between \$12,000 and \$14,000 across all sizes in 2004). Off-farm income earned by other household members averages around \$1,000.

To a large extent, the inverse relationship between off-farm earned income and farm size is due to greater off-farm employment (and more hours worked off the farm) by operators of smaller farms. More than 55 percent of operators with farm sales less than \$100,000 reported off-farm hours in 2004 versus 20 percent or less for operators of farms with sales above \$250,000 (table 4). On the other hand, off-farm income earned by farm operators who work off-farm does not vary much with size, averaging \$47,000 for operators of the smallest farms and \$39,000 for operators of the largest farms.

¹⁰Smaller farms represent a very large share of farm population but a small share of the farm sales. For example, about 44 percent of the farms have sales less than \$10,000 and more than 80 percent of the farms have sales below \$100,000 (table 3). This distribution, however, is dependent on the definition of farm. In the United States, a farm is currently defined, for statistical purposes, "as any place from which \$1,000 or more of agricultural products were sold or normally would have been sold during the year under consideration." (USDA, 2005).

Table 3
Off-farm household income by farm size, 2004

Farm sales	Share of farms	Income earned by the operator	Income earned by the spouse	Income earned by other members	Off-farm business income	Total earned income	Unearned income	Total off-farm income
	Percent	Dollars						
\$9,999 or less	43.7	27,457	14,756	1,219	11,209	54,641	19,392	74,033
\$10,000-\$99,999	40.7	24,295	13,095	1,142	9,889	48,422	19,549	67,971
\$100,000-\$249,999	7.9	11,074	14,722	1,158	8,493	35,445	11,467	46,913
\$250,000-\$499,999	4.2	7,559	13,439	836	11,404	33,238	11,633	44,870
\$500,000-\$999,999	2.0	7,790	12,816	1,110	8,371	30,086	21,991	52,077
\$1,000,000 or more	1.5	4,898	12,017	612	10,744	28,271	12,811	41,082
All farms	100.0	23,318	13,943	1,156	10,402	48,818	18,461	67,279

Source: 2004 ARMS data.

Table 4

Farm household income by farm size, 2004

Farm size (annual sales)	Number of farms	Share of farms income	Total household farming	Income from income	Share of farm	Off-farm income
	<i>Number</i>	<i>Percent</i>	<i>Dollars</i>	<i>Dollars</i>	<i>Percent</i>	<i>Dollars</i>
\$9,999 or less	901,333	43.7	71,155	-2,878	-8.9	74,033
\$10,000-\$99,999	838,912	40.7	72,061	4,091	11.7	67,971
\$100,000-\$249,999	162,782	7.9	80,912	33,999	18.9	46,913
\$250,000-\$499,999	86,087	4.2	124,386	79,516	23.4	44,870
\$500,000-\$999,999	41,424	2.0	168,844	116,766	16.5	52,077
\$1,000,000 or more	30,284	1.5	411,266	370,184	38.3	41,082
All farms	2,060,822	100.0	81,480	14,201	100.0	67,279

Farm size (annual sales)	Earned off-farm income	Share of operators reporting off-farm hours	Off-farm earned income by operators who worked	Off-farm earned income of operators	Share of spouses reporting off-farm hours	Off-farm income earned by spouses	Off-farm earned income of spouses who worked off-farm
	<i>Dollars</i>	<i>Percent</i>	<i>Dollars</i>	<i>Dollars</i>	<i>Percent</i>	<i>Dollars</i>	<i>Dollars</i>
\$9,999 or less	54,641	58.7	27,457	46,775	44.1	14,756	33,460
\$10,000-\$99,999	48,422	55.5	24,295	43,775	45.5	13,095	28,780
\$100,000-\$249,999	35,445	31.1	11,074	35,608	54.4	14,722	27,063
\$250,000-\$499,999	33,238	20.4	7,559	37,054	45.2	13,439	29,732
\$500,000-\$999,999	30,086	18.6	7,790	41,882	44.8	12,816	28,607
\$1,000,000 or more	28,271	12.6	4,898	38,873	37.2	12,017	32,304
All farms	48,818	52.1	23,318	44,756	45.4	13,943	30,711

Source: 2004 ARMS data.

The inverse relationship between farm size and off-farm work still holds after controlling for other factors, as demonstrated econometrically by many researchers (Lass et al., 1989, 1991; Yee et al., 2004). In addition, Goodwin and Bruer (2003) and Fernandez-Cornejo et al. (2005) showed that the inverse relationship holds for both operator and spouse.

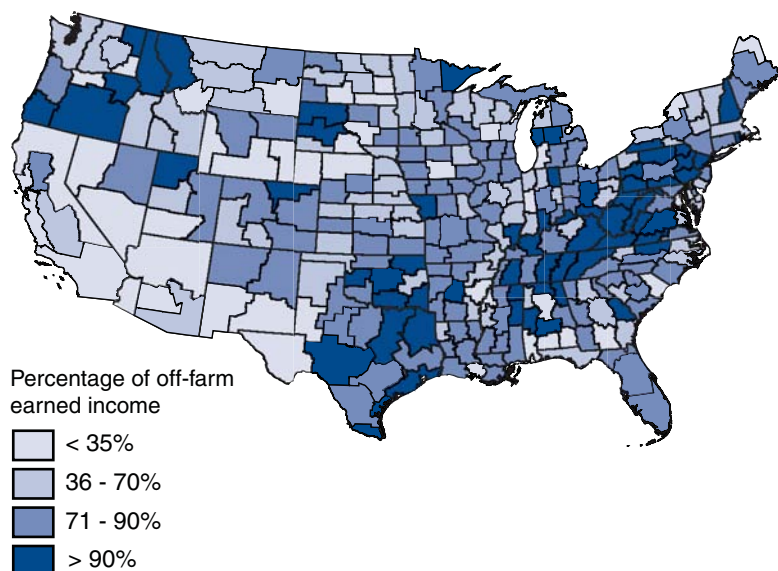
Time allocation between onfarm and off-farm activities by household members appears to be the underlying reason for the inverse relationship between farm size and off-farm work. This relationship appears to be valid regardless of the sequence in which time is allocated between farm and off-farm work. As Olfert (1984) notes, it may be the case that farmers choose farm size and type after knowing the time commitments required by an off-farm job, or farmers may choose the type and amount of off-farm work after taking into account the nature of the labor requirements on the farm.¹¹

Off-Farm Income and Farm Location

Off-farm employment also varies geographically, with widely differing shares of off-farm income (to total income) even within States (fig. 2). In general, high ratios of off-farm earned income to total income are exhibited in the four regions—the Northeast, Appalachian, Southern Plains, and Northwest—where job opportunities tend to be highest or farm income lowest. In many cases, one family member may focus on the farm operation while the spouse and children work off the farm. In other situations, the farm operation may be a side job and a refuge from urban stress. The supply of off-farm labor has been shown to be positively related to urban proximity (Lass et al., 1991). Moreover, Gardner (2001) found that farmers’ income growth is inversely related to the rural share of a State’s population. Gardner observed that this finding supports Schultz’s (1950) hypothesis that “a larger presence of nonfarm people in a State is good for

¹¹The tradeoff between time spent in onfarm and off-farm activities also manifests itself in Conservation Reserve Program (CRP) participation. Boisvert and Chang (2006) found empirical evidence that a household’s decision to participate in the CRP and to work off the farm are made jointly rather than independently. Participation in off-farm work with higher wages provides an incentive for operators to work less on the farm and to take land out of production and commit it to the CRP. As a result, participation in the CRP and off-farm work increase household income.

Figure 2
The importance of off-farm income by ASD*, 2001
(off-farm earned income/total income)



*ASD = Agricultural Statistics District.
 Source: 2001 ARMS data.

the growth of farmers' incomes, because it increases their off-farm earnings opportunities and increases the demand for the goods and services that farmers produce." This may be particularly true for agricultural States with large urban populations such as Texas, where off-farm opportunities increase near one of that State's four major cities—Dallas-Fort Worth, Houston, San Antonio, and Austin.

Off-Farm Income, Type of Enterprise, and Human Capital

Off-farm work is less likely on farms with labor-intensive enterprises such as dairy (Leistriz et al., 1985) and other livestock (Lass et al., 1991; Goodwin and Bruer, 2003). Moreover, dairy farmers who do work off the farm tend to require higher "wages" (the opportunity cost of labor is higher) to work off farm than farmers working in other enterprises.

The supply of off-farm labor has also been shown to be positively related to human capital such as education and experience of the operator and spouse (Lass et al., 1991). The number of children is positively associated with off-farm employment for farm men, but the association is negative for farm women. More children may imply more need for additional income but also additional child care at home.

Off-Farm Work, Scale and Scope Economies, and Efficiency

The importance of off-farm income to all U.S. farmers is widely acknowledged, and the relative dedication to off-farm work is related to farm size, location, specialty, and operator characteristics. However, is off-farm work actually helping farm households in general, and those operating small farms in particular, to improve their economic performance? Since scale and scope economies, as well as economic efficiency, are key concepts used by economists to examine economic performance, this section introduces those concepts as they relate to off-farm work.

A farm is said to have economies of scale (or increasing returns to scale) if the average cost of production declines as output (scale of production) increases (see box, p. 4). This decline in per-unit costs as output increases suggests that smaller farms can achieve cost advantages by becoming larger. The concept of economies of scale is an important one. For example, farms with lower average costs are better able to cope with higher input prices (Kumbhakar, 1993). On the other hand, increasing returns to scale in production may lead to consolidation of firms with potential effects on competition (Hallam, 1991).

With multiple outputs, the measurement of scale economies becomes more complicated. In addition to changes in costs that occur as output expands, there are also changes in costs due to the product mix (Hallam, 1991). If it is cheaper to produce several outputs in one operation than it is to produce them in separate operations, economies of scope are said to occur (see box, p. 14).

Off-Farm Work and Scale Economies

We estimated the scale economies for corn and soybean farms for 1996-2000, from an input perspective. Scale economies both at the farm level (the measure traditionally reported) and at the household level (including off-farm income-generating activities as an output) are considered. At the farm level, the elasticity of scale ranges from about 0.56 for smaller farms (gross sales less than \$100,000), to about 0.8 for the larger farms (sales greater than \$500,000) (table 5). This means that to support a 10-percent increase in outputs, smaller farms would require a 5.6-percent increase in all inputs, while larger farms would require an 8-percent increase in inputs. Thus, the greater scale economies available for smaller operations provide a major inducement to increase farm size (compared with the larger farms whose scale elasticities are closer to 1).

However, at the household level, with off-farm income-generating activities included, the scale economies available are lower (scale elasticity is closer to 1; that is, closer to constant returns to scale). Thus, the scale elasticity is higher for all sizes, ranging from 0.73 to 0.96 (table 5). So for smaller farms, a 10-percent increase in all outputs requires a 7.3-percent increase in inputs, while larger farms require a 9.6-percent increase in inputs.¹² More importantly, the difference between the scale elasticities at the household and farm levels is larger for the smaller farms (30 percent)

¹²The scale elasticity increases (moves closer to constant returns to scale) when off-farm income is included because of the theoretical relationship between scale and scope economies in multi-product firms: “the presence of scope economies ‘magnifies’ the extent of overall economies of scale beyond what would result from a simple weight sum of product specific economies of scale” (Baumol et al., 1982).

Table 5

Scale economies for corn/soybean farms, 1996-2000

Farm type ¹	Gross sales	Elasticity of scale	
		Farm level (Excluding off-farm income)	Household level (Including off- farm income)
Farming occupation/ lower sales	< \$100,000	0.56	0.73
Farming occupation/ medium sales	\$100,000-\$249,999	0.74	0.88
Large family farms	\$250,000-\$499,999	0.77	0.94
Vary large family farms	>\$500,000	0.80	0.96
All farms		0.66	0.83

¹Excluding limited-resource farms and retirement/residential farms. Limited-resource farms are small farms with gross sales less than \$100,000, total farm assets less than \$150,000, and total operator household income less than \$20,000. Limited-resource farmers may report farming, a nonfarm occupation, or retirement as their major occupation. Retirement/residential farms are small farms whose operators report they are retired or engaged in a major occupation other than farming) (Hoppe et al., 1999)

Source: Nehring et al., 2005.

than for the larger farms (around 20 percent). Thus, households operating smaller farms may compensate for the scale disadvantages of their farm business activities with the advantages of off-farm income-generating activities. This advantage may also support the notion that integrated farm and nonfarm labor markets are enabling many small farms to survive and flourish to an extent not thought possible three decades ago (Gardner, 2005).

Off-Farm Work and Economies of Scope

Scope economies measure the cost savings due to simultaneous production of outputs relative to the cost of separate production (see box, p. 14). The concept of economies of scope is useful in assessing the advantages of output diversification. Given the importance of off-farm income to U.S. farm households, scope economies may be expanded to include as output any income-generating activities on or off the farm (household-level scope economies) (see appendix 1).¹³ Our estimates for corn and soybean farms show substantial household-level scope economies, 0.24 on average. This means that farm households engaged in off-farm income-generating activities together with the production of traditional farm outputs have cost savings of 24 percent relative to carrying out those activities separately.¹⁴ The cost savings are likely to arise from the sharing of managerial expertise (of the operator and spouse) between onfarm and off-farm activities. Economic evaluations of the farm business alone, then, provide an incomplete view because they exclude off-farm activities, which are an important means of output diversification.

¹³Farms that produce the two output groups separately are those that either produce conventional outputs and no off-farm income or else generate off-farm income but no conventional outputs. While our sample includes farm households that produce conventional outputs with no off-farm activities, it technically does not include households with zero traditional outputs. However, the sample does include many farm households with very small revenues from traditional outputs because, for statistical purposes, in the U.S., a farm is currently defined “as any place from which \$1,000 or more of agricultural products were sold or normally would have been sold during the year under consideration” (USDA, 2005). We consider five outputs (corn, soybeans, other crops, livestock, and operator/spouse off-farm labor) and five inputs (hired labor, operator labor, spouse labor, miscellaneous inputs, and pesticides). The method of calculating scope economies, as well as the underlying cost function, is shown in appendix 1.

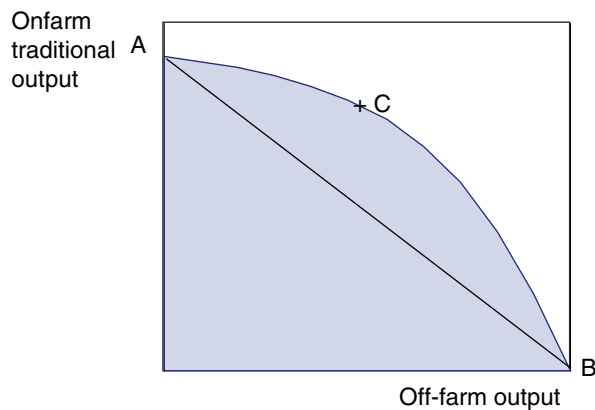
¹⁴This result is valid on the average, not necessarily for all the corn/soybean farms studied. For example, it is not likely to be valid for the largest farms in the sample (whose operators are less likely to work off the farm, table 4). As shown in appendix 1, the underlying cost function is a function of the output quantities (and, thus, gross sales), and so are scope economies. The values reported here are calculated at the means of the sample.

Scope Economies

Scope economies measure the total cost savings due to simultaneous production of outputs relative to the costs of separate production (appendix 1). Given scope economies, it is less costly to produce several outputs in one operation than to produce each output in separate operations (or joint production in one operation generates more output than separate production in two different operations using the same resources). An often-cited example of scope economies is fast food outlets, where savings are obtained by sharing storage, cooking facilities, and customer service in the production of many food products. In general, scope economies may arise from the presence of public inputs or from sharing of imperfectly divisible quasi-fixed inputs in the production of different goods (Fernandez-Cornejo et al., 1992). In our context, farm households achieve scope economies by diversifying or pursuing off-farm activities in addition to the onfarm production of traditional commodities.

To illustrate the possible advantages of “producing” onfarm and off-farm outputs in a farm household, we may use the example of a production possibilities curve (often used in economics). When the production possibilities curve (ACB) is shaped as in the figure, it is advantageous to produce onfarm and off-farm outputs together. As the figure shows, total output produced by a farm household at point C (a combination of onfarm and off-farm outputs) is higher than output produced either at A or B (or a linear combination of both, line AB) while using the same amount of resources.

Diagram of a production possibilities curve



Scope economies for farm households are likely to arise from the sharing of managerial expertise (and its many components, such as accounting and information processing skills, sales expertise, administrative and technical know-how, etc.) between onfarm and off-farm activities.¹⁵ The expertise of many farm operators and/or their spouses is used in off-farm jobs in private businesses and Government, and in self-employment (Mishra et al., 2002). A USDA survey shows that the largest share of off-farm work done by operators and their spouses is accounted by work in executive, administrative, and managerial positions, service occupations, administrative support, and sales (Covey et al., 2004).

¹⁵As is well known, diminishing marginal labor productivity is a determinant in the allocation of labor between onfarm and off-farm activities. In addition, labor requirements for crop production are often concentrated in very few months of the year. Thus, the marginal productivity of managerial labor for the rest of the year is often very low or negligible (Olfert, 1984).

Off-Farm Work and Efficiency

Technical efficiency measures how well a farm transforms inputs into outputs given the technology at its disposal (Kumbhakar and Lovell, 2000). Efficiency is of great importance to prevent the waste of resources. Technically inefficient farmers fail to produce the maximum attainable output with the amount of inputs used, and therefore can increase output with the existing level of inputs and available technology.

Two types of technical efficiency are examined here: traditional (farm-level) technical efficiency of the farm business in the production of commodities; and technical efficiency at the household level, which considers both on- and off-farm activities.¹⁶

Efficiency of the Farm Business

Kumbhakar et al. (1989) examined the effect of off-farm income on farm-level efficiency for dairy farmers. They reasoned that the larger the off-farm component of the operator's income, the less time the operator would spend managing the farm, eroding farm-level efficiency. Indeed, they found that farm-level efficiency of Utah dairy farmers in 1985 was negatively related to off-farm income and that the negative effect was strongest for the smallest farms, which had the largest off-farm incomes.¹⁷ Fernandez-Cornejo (1992) calculated that the farm-level technical efficiency of vegetable farms in Florida was negatively related to off-farm work carried out by the operator. Similar results were obtained by Aigner et al. (2003) for the farm-level efficiency of U.S. corn farmers using 2001 data.

More recently, Goodwin and Mishra (2004) analyzed the relationship between farm-level efficiency and off-farm labor supply. With data collected from 7,699 farms in USDA's 2001 Agricultural Resource Management Survey (ARMS), they used gross cash income (appendix table 1) over total variable costs as an operational measure of farm-level economic efficiency. Greater participation in off-farm labor markets was shown to be significantly associated with lower farm-level efficiency. An additional 1,000 hours engaged in off-farm work would tend to lower the farm-level efficiency ratio by 0.17 with respect to the mean, which was \$1.93 of cash farm income per dollar of variable cost. This effect, while not large, was statistically and economically significant. Such findings support the notion hypothesized by Smith (2002) that off-farm work may hinder "smart farming" and confirm a negative relationship between farming efficiency and the supply of labor to off-farm employment. As theory predicts, more efficient farmers are less likely to work off the farm, reflecting the higher opportunity cost for their labor. Furthermore, the statistical tests performed by Goodwin and Mishra suggest that off-farm labor supply and farm-level efficiency are jointly determined.¹⁸

Household-Level Efficiency

Rather than estimating the influence of off-farm work on the efficiency of the farm business, we estimated the household-level technical efficiency (including on- and off-farm activities), compared it with farm-level effi-

¹⁶We have adopted the terminology of "farm-level" and "household-level" efficiency following a recent publication by Chavas et al. (2005). Our earlier terminology (as used in Nehring et al., 2005) was less transparent.

¹⁷In a subsequent article, Kumbhakar (1993) showed that lower efficiency is the main reason that small farms are less profitable than medium and large farms; another reason being their higher returns to scale (lower scale economies).

¹⁸There is a two-way relationship between the two variables rather than a cause-and-effect relationship (in economic jargon, each variable is endogenous to the other).

ciency, and examined how those efficiencies vary with farm size. The technique used in this research isolates the best-practice farm within any size class, and measures technical efficiency by how close other farms are, on average, to the best-practice farms, which are assigned a technical efficiency equal to 1 and said to be on the “frontier.”¹⁹

At the farm level, technical efficiencies of corn/soybean farms increase with size from 0.87 to 0.93 (table 6).²⁰ However, technical efficiencies at the household level (when off-farm income is included) are higher (around 0.95) and the measures of technical efficiency do not vary across size groups. Moreover, while the beneficial effect of off-farm income occurs at all sizes, it is stronger for smaller farms, whose household-level efficiency levels are comparable with the farm-level efficiencies of the larger farms. This suggests that small corn/soybean farmers have adapted to shortfalls in farm-level efficiency by increasing off-farm income.

Also, the higher household-level efficiencies are consistent with the positive scope economies found. Both findings reflect the more efficient use of resources at the household level, particularly the use of managerial labor (operator and spouse) shared between onfarm and off-farm activities.

Moreover, as Smith (2002) observes, as farm operators and other household members engage in off-farm activities, they have less time available for farm management. This may inhibit their adoption of management-intensive agricultural innovations and lead to less efficient farming.

Table 6

Technical efficiency of corn/soybean farms, 1996-2000

Farm type ¹	Gross sales (\$)	Technical efficiency scores	
		Farm level (excluding off-farm income)	Household level (including off-farm income)
Farming occupation/ lower sales	< \$100,000	0.87	0.95
Farming occupation/ medium sales	\$100,000-\$249,999	0.91	0.95
Large family farms	\$250,000-\$499,999	0.91	0.95
Very large family farms	> \$500,000	0.93	0.95
All farms		0.91	0.95

¹Excluding limited-resource and retirement/residential farms.

Source: Nehring et al., 2005

¹⁹The analysis uses several econometric techniques, including the estimation of an input distance function and stochastic frontier estimation (appendix 1; Nehring et al., 2005) to estimate technical efficiency at the farm (excluding off-farm income-generating activities) and at the household level (including off-farm income-generating activities). Data used were 1995-2003 survey data of corn/soybean farms from 10 States (Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin), that account for most U.S corn and soybean production.

²⁰A farm unit with an efficiency score of 0.8 is said to be 80 percent as efficient as the farms on the ‘frontier,’ i.e., the best performing farms in the data set.

Off-Farm Work and the Adoption of Agricultural Innovations

Technological change has been acknowledged as a critical component of productivity and economic growth (Solow, 1994; Griliches, 1995). The rapid adoption and diffusion of new technologies in U.S. agriculture has sustained growth in agricultural productivity and ensured an abundance of food and fiber (Huffman and Evenson, 1993). Technological innovations and their adoption have also changed the way farm households regard employment choices (Binswanger, 1974, 1978). Labor-saving technologies, in particular, have allowed farm household members to increase income by seeking off-farm employment (Mishra et al., 2002).²¹

While profitability (i.e., the extent of yield increases and/or reduction in input costs from an innovation relative to the costs of adoption and current management practices) plays a key role in technology adoption, most studies acknowledge that heterogeneity among farms and farm operators often explains why not all farmers adopt an innovation in the short or long run (Batte and Johnson, 1993; Feder and Umali, 1993; Khanna and Zilberman, 1997; Lowenberg-DeBoer and Swinton, 1997; Rogers, 1961, 1995) (see box, “Factors Influencing Technology Adoption”).

Still, assessments of technology adoption using the traditional economic tools pioneered by Griliches (1957) have proven insufficient to explain differing adoption rates for many recent agricultural innovations. The standard measures of farm (accounting) profits, such as net returns (to management), give an incomplete picture of economic returns because they usually exclude the value of management time (Smith, 2002). For example, herbicide-tolerant soybeans were rapidly adopted despite showing no significant advantage in net returns over conventional soybeans. On the other hand, adoption of technologies such as integrated pest management (IPM) has been rather slow despite explicit economic and environmental advantages (Fernandez-Cornejo and McBride, 2002; Smith, 2002). This led to the hypothesis that adoption is driven by “unquantified” advantages, such as simplicity and flexibility, which translate into reduced managerial intensity, freeing time for other uses. An obvious use of managers’ time is off-farm employment.

Off-Farm Work as a Factor in Early Studies of Technology Adoption

Early studies of technology adoption viewed off-farm income as influencing adoption of “conservation” practices by providing “supplemental income” to finance conservation expenditures (Blase, 1960). Ervin and Ervin (1982), on the other hand, argued that “off-farm income could reflect the need for supplemental income for family living expenses and essential farm production expenses other than conservation and less time to implement and maintain unfamiliar practices.” Survey results on farmers’ motivation to seek off-farm income and their view of such employment as permanent rather than temporary, suggest that motivation is closer the view of Ervin and Ervin.

²¹Off-farm employment was also facilitated by economic growth in the nonfarm economy, improved infrastructure (communications and transportation), as well as education level of farm household members (Banker and MacDonald, 2005).

Factors Influencing Technology Adoption

Rural sociologists recognized early that essential differences among farmers can explain why they do not adopt an innovation at the same time. In addition, the characteristics (perceived or real) of an innovation are widely known to influence the adoption decision (Rogers, 1995; Batz et al., 1999). Economists and sociologists have made extensive contributions to the literature on the adoption and diffusion of technological innovations in agriculture (e.g., Griliches, 1957, Feder et al., 1985; Rogers, 1962, 1995). Such research typically focuses on the long-term extent of adoption and the factors that influence the adoption decision.

Farm Structure/Size

A basic hypothesis regarding technology transfer is that the adoption of an innovation will tend to take place earlier on larger farms than on smaller farms. Just et al. (1980) show that, given the uncertainty and the fixed transaction and information costs associated with innovations, there may be a critical lower limit on farm size that prevents smaller farms from adopting. As these costs increase, the critical size also increases. It follows that innovations with large fixed transaction and/or information costs are less likely to be adopted by smaller farms. However, Feder et al. (1985) point out that lumpiness of technology can be offset by the emergence of a service sector (i.e., custom service or consultant). Disentangling farm size from other factors hypothesized to influence technology adoption has been problematic. Feder et al. (1985) caution that farm size may be a surrogate for other factors, such as wealth, risk preferences, and access to credit, scarce inputs, or information. Moreover, access to credit is related to farm size and land tenure because both factors determine the potential collateral available to obtain credit.

Human Capital

The ability to adapt new technologies for use on the farm clearly influences the adoption decision. Most adoption studies attempt to measure this trait through operator age, formal education, or years of farming experience (Fernandez-Cornejo et al., 1994). More years of education and/or experience is often hypothesized to increase the probability of adoption whereas increasing age reduces the probability. Factors inherent in the aging process or the lowered likelihood of payoff from a shortened planning horizon over which expected benefits can accrue would be deterrents to adoption (Barry et al., 1995; Batte and Johnson, 1993). Younger farmers tend to have more education and are often hypothesized to be more willing to innovate.

Risk and Risk Preferences

In agriculture, the notion that technological innovations are perceived to be more risky than traditional practices has received considerable support in the literature. Many researchers argue that the perception of increased risk inhibits adoption (Feder et al., 1985). Hiebert (1974) and Feder and O'Mara (1981) show that uncertainty declines with learning and experience. Innovators and other early adopters are believed to be more inclined to take risks than are the majority of farmers.

Tenure

While several empirical studies support the hypothesis that land ownership encourages adoption, the results are not unanimous and the subject has been widely debated (e.g., Feder et al., 1985). For example, Bultena and Hoiberg (1983) found no support for the hypothesis that land tenure has a significant influence on adoption of conservation tillage. The apparent inconsistencies in the empirical results are due to the nature of the innovation. Land ownership is likely to influence adoption if the innovation requires investments tied to the land. Presumably, tenants are less likely to adopt these types of innovations because the benefits of adoption will not necessarily accrue to them.

Credit Constraint, Location, and Other Factors

Any fixed investment requires the use of own or borrowed capital. Hence, the adoption of a non-divisible technology, which requires a large initial investment, may be hampered by lack of borrowing capacity (El-Osta and Morehart, 1999). Location factors—such as soil fertility, pest infestations, climate, and availability or access to information—can influence the profitability of different technologies across different farms. Heterogeneity of the resource base has been shown to influence technology adoption and profitability (Green et al., 1996; Thrikawala et al., 1999). Irrigation may also influence adoption. Irrigation generally increases yields and profitability and reduces production risk. However, irrigation may also increase risk; for example, it may encourage certain pest populations (Harper and Zilberman, 1989). Contractual arrangements for the production/marketing of the crop are also believed to influence the adoption of certain technologies. Contracts often specify the acreage to be grown or quantity and quality of product to be delivered and may also require the application of certain inputs and practices.

McNamara et al. (1991) used empirical evidence from peanut producers to conclude that integrated pest management (IPM) required substantial time for management and that off-farm employment may present a constraint to IPM participation. Fernandez-Cornejo et al. (1994), Fernandez-Cornejo (1996, 1998), and Fernandez-Cornejo and Jans (1996) found similar results for vegetable and fruit producers. Wozniack (1993) considered livestock feeding innovations and showed that off-farm wage income was inversely related to the likelihood of early adoption and acquiring information.²² More recent survey results show that operators of high-sales, large, and very large farms—which depend on farm revenues more (and therefore less on off-farm employment) than smaller farms—tend to adopt more management-intensive technologies. For example, around 18 percent of the operators of larger farms adopted precision farming in 1998. In contrast, only 3 percent of the operators of smaller farms (who worked more off-farm hours) adopted precision farming (Hoppe, 2001).

Weaknesses of Early Studies

While insightful, early studies failed to model the interaction of technology adoption and off-farm employment decisions based on the underlying economic theory and consistent with farmers' optimization behavior. Rather, they simply included some measure of off-farm work as one explanatory variable in the adoption decision. Early studies also had some econometric problems, such as not accounting for simultaneity of the off-farm work and adoption decisions and the possibility of self-selection (see appendix 2).²³ Finally, earlier studies did not examine the relationship between technology adoption and household income from farm and off-farm sources.

Modeling the Interaction Between Off-Farm Work and Adoption Decisions

To address these issues, we examine the interaction of off-farm income-earning activities and adoption of four agricultural technologies (see box, p. 22) of varying managerial intensity, including herbicide-tolerant crops (Fernandez-Cornejo and Hendricks, 2003; Fernandez-Cornejo et al., 2005), precision agriculture (Fernandez-Cornejo and Southern, 2004), conservation tillage (Fernandez-Cornejo and Gregory, 2004), and Bt (*Bacillus thuringiensis*) corn (Fernandez-Cornejo and Gregory, 2004). We also estimated empirically the relationship between the adoption of these innovations and farm household income from onfarm and off-farm sources.

For this purpose, we expanded the agricultural household model to include the technology adoption decision together with the off-farm work participation decisions by the operator and spouse (appendix 2).²⁴ We developed an econometric model to examine the interaction of off-farm work and adoption of agricultural technologies, as well as the impact of technology adoption on farm household income (from onfarm and off-farm sources) after controlling for such interaction (appendix 2). The model used data from nationwide surveys of corn and soybean farms in 2000-2001.

²²Measures used included off-farm income as a percentage of total household income (Ervin and Ervin, 1982) or days (or hours) per year that the operator worked off-farm (Fernandez-Cornejo, 1996, 1998; Fernandez-Cornejo and Jans, 1996).

²³Self-selection occurs because farmers are not assigned randomly into groups (e.g., farmers that work off farm or not, adopt or not) but make the choices themselves. Therefore, group members may be systematically different, and these differences may manifest themselves in farm performance and could be confounded with differences due purely to working off farm (or adoption). This situation, called self-selection, may bias the statistical results unless it is corrected (appendix 2).

²⁴The agricultural household model (Singh et al., 1986; Huffman, 1980, 1991; Lass et al., 1989; Lass and Gempeasaw, 1992; Kimhi, 1994, 2004) combines in a single framework all important economic decisions of the farm household.

We hypothesize that adoption of managerial-saving technologies (such as herbicide-tolerant (HT) soybeans) frees up management time for use elsewhere (notably off-farm employment), leading to higher off-farm income. On the other hand, managerially intensive technologies (such as precision agriculture) would result in less time available for off-farm activities, leading to lower off-farm income.

It is also possible that farmers already working off farm may be more disposed to adopt managerial-saving technologies. This may lead to additional off-farm work and result in even higher off-farm income. Similarly, farmers who are working off farm may be reluctant to adopt managerially intensive technologies.²⁵

In either case, we anticipated that adoption of managerial-saving technologies would be associated with higher off-farm income and adoption of managerially intensive technologies would be related to lower off-farm income. (In this report, we show only the empirical validity of the relationship, but not the direction of the causality.)

A two-stage econometric estimation method was used to estimate the empirical model (appendix 2). The first stage, the decision model, examines the factors influencing off-farm work participation and technology adoption decisions. The second stage is used to estimate the relationship between technology adoption and household income.

Technology Adoption and Off-Farm Income

We find that the relationship between the adoption of herbicide-tolerant (HT) soybeans and *off-farm* household income is positive and statistically significant (table 7). The elasticity of off-farm household income with respect to the probability of adoption of HT soybeans (calculated at the mean) is +1.59.²⁶ That is, after controlling for other factors, a 15.9-percent increase in off-farm household income is associated with a 10-percent increase in the probability of adopting HT soybeans. The adoption of HT soybeans is also positively and significantly associated with total household income (from off-farm and onfarm sources). A 9.7-percent increase in total household income is associated with a 10-percent increase in the probability of adopting of HT soybeans. On the other hand, adoption of herbicide-tolerant soybeans did not have a significant relationship with household income from farming (table 7).

Results for adoption of conservation tillage are similar to those obtained for HT soybeans, but of a lesser magnitude (table 7). Controlling for other factors, the association between the adoption of conservation tillage and off-farm household income is positive and statistically significant (elasticity +0.98). An increase in *off-farm* household income of 9.8 percent is associated with a 10-percent increase in the probability of adopting conservation tillage. The association of adoption of conservation tillage and total household income (including both off-farm and onfarm sources) is positive and statistically significant. The elasticity of total household income with respect to the probability of adopting conservation tillage is +0.46.

²⁵As Olfert observes: “Given the nature of nonfarm jobs, where commitments to specific timeframes are frequently more precise than is the case in farming, it is possible that a nonfarm job receives first priority in the allocation of time with farm production undertaken as a second priority.” However, Olfert adds: “It may also be the case that the decision regarding time allocation to farm and nonfarm work is made simultaneously or that the off-farm employment decision influences the type and size of farm that is optimal. Farm enterprises that are less demanding in their commitments may be chosen to permit nonfarm employment. Knowing the time commitments required by the nonfarm job, the farm size and type will be organized to accommodate that schedule. Similarly, given the nature of labour requirements on the farm, a choice will be made about the type and amount of nonfarm work.”

²⁶Results are expressed in terms of elasticity—the percent change in a particular variable (e.g., household income) relative to a small percent change in adoption of the technology from current levels, controlling for other factors. The elasticity results can be viewed in terms of the aggregate change in a particular variable (across an entire agricultural region or sector) relative to aggregate increases in adoption (as more and more producers adopt the technology). However, in terms of a typical farm—that has either adopted or not—the elasticity is usually interpreted as the (marginal) farm-level change associated with an increase in the probability of adoption, away from a given, or current, level of adoption. As shown in appendix 2, the regression model controls for farm location and typology, operator age, education, and experience, number of children, price of the crop, a measure of specialization on soybean/corn production, a measure of the extent of livestock operations, farm size, and proxies for local labor market conditions.

Table 7

Elasticities of farm household income with respect to the probability of adopting technologies of differing managerial intensity

Elasticity of	With respect to adoption of:			
	Yield monitors	Bt corn ¹	Conservation tillage	Herbicide-tolerant (HT) soybeans
Onfarm household annual income	0 ²	0 ²	0 ²	0 ²
Off-farm household annual income	-0.84	0 ²	+0.98	+1.59
Total household annual income	0 ²	0 ²	+0.46	+0.97

¹Bt = *Bacillus thuringiensis*)

²Statistically insignificant underlying coefficient. The underlying coefficients and their standard errors are shown in appendix 2.

On the other hand, the relationship between the adoption of yield monitors (an important component of precision agriculture) and off-farm household income is negative and statistically significant (elasticity = -0.84) when we control for other factors. That is, a decrease in off-farm household income by 8.4 percent is associated with a 10-percent increase in the probability of adopting yield monitors. Adoption of yield monitors did not have a statistically significant association with either farm household income or total household income. These results are quite different from those for HT soybeans and conservation tillage. This empirical evidence suggests that yield monitoring techniques are management-intensive compared with the other two technologies, which spare management time.

Finally, the relationship between the adoption of Bt corn with either off-farm or onfarm household income was not statistically significant, indicating that Bt corn may be managerially neutral.

These results are consistent with anecdotal evidence (see box “Selected Agricultural ...”) that herbicide-tolerant soybeans save managerial time because of the simplicity and flexibility of weed control. Conservation tillage is also believed to save managerial labor, but to a lesser degree than HT soybeans. Our results for yield monitoring are also consistent with anecdotal evidence that precision farming techniques in general are managerially using. Before the commercial introduction of Bt corn in 1996, most farmers accepted yield losses rather than incur the expense and uncertainty of chemical control. For those farmers, the use of Bt corn was reported to result in yield gains rather than pesticide savings, and savings in managerial time were small.

Selected Agricultural Technologies and Their Managerial Intensity

Herbicide-tolerant (HT) soybeans contain traits that allow them to survive certain herbicides that previously would have destroyed the crop along with the targeted weeds. This allows farmers to use more effective postemergent herbicides, expanding weed management options (Gianessi and Carpenter, 1999). The most common herbicide-tolerant crops are resistant to glyphosate, a herbicide effective on many species of grasses, broadleaf weeds, and sedges. Adoption of HT soybeans has risen rapidly since commercial availability in 1996. HT soybean use rose quickly to about 17 percent of U.S. soybean acreage in 1997 and reached 87 percent in 2005 (Fernandez-Cornejo and McBride, 2002; USDA, NASS, 2003).

Herbicide-tolerant soybeans save managerial time because of the relative simplicity and flexibility of the weed control program. The herbicide-tolerant technology allows growers to apply one herbicide product over the soybean crop at any stage of growth, instead of using several herbicides, to control a wide range of weeds “without sustaining crop injury” (Gianessi and Carpenter, 1999). In addition, using HT soybeans is said to make harvest easier (Duffy, 2001).

Conservation tillage is defined as “any tillage or planting system that maintains at least 30 percent of the soil surface covered by residue after planting” (Conservation Technology Information Center, 2004). It includes no-till, ridge-till, and mulch-till techniques. The impact of conservation tillage in controlling soil erosion and soil degradation is well documented (Edwards, 1995; Sandretto, 1997). By leaving substantial amounts of residue evenly distributed over the soil surface, conservation tillage reduces soil erosion by wind/water, increases water infiltration and moisture retention, and reduces surface sediment and chemical runoff. Adoption of conservation tillage was estimated at 2 percent of planted acreage in 1968 and grew fastest during 1975-85, reaching nearly 28 percent in 1985 (Schertz, 1988). It reached about 37 percent of planted acreage in 2002 (Conservation Technology Information Center, 2004). Conservation tillage is used primarily to grow corn, soybeans, small grains, and cotton.

Conservation tillage is believed to save managerial labor (Sandretto, 1997; USDA, 1998). While it is accepted that adoption of conservation tillage leads to labor savings, its slower rate of adoption compared

with HT crops may be because the managerial savings are less.

Bt crops carry the gene from the soil bacterium *Bacillus thuringiensis* (Bt) and are able to produce proteins that are toxic to certain insects. Bt corn, originally developed to control the European corn borer, was planted on 35 percent of corn acreage in 2005, up from 24 percent in 2002. The recent upswing may be due to the commercial introduction in 2003/04 of a new Bt corn variety that is resistant to the corn root-worm.

Before the commercial introduction of Bt corn in 1996, chemical pesticide use was often not profitable to control the European corn borer (ECB) and timely application was difficult (Fernandez-Cornejo and Caswell, 2006). Many farmers accepted yield losses rather than incur the expense and uncertainty of chemical control. For those farmers, the use of Bt corn resulted in yield gains rather than pesticide savings, and managerial time savings were minimal.

Precision agriculture (PA) is often characterized as a suite of technologies used to monitor and manage subfield spatial variability. It includes, for example, global positioning systems, grid soil sampling, yield monitors, and input applicators that can vary rates across a field (Daberkow et al., 2002). These technologies can be used independently or as a package of technologies that includes, for example, the use of grid soil sampling, a variable-rate input applicator, and a yield monitor. PA has been growing relatively slowly. Yield monitors, which provide farmers site-specific data to allow them to vary input application and production practices, are the most extensively adopted PA component. Yield monitors were used in about 33 percent of total corn acreage in 2001 and in about 25 percent of soybean acreage. Adoption of other components of PA is even slower. Adoption of variable-rate applicators reached just 10 percent of corn acreage for fertilizer and 3 percent for pesticides or seeds in 2001 (Daberkow et al., 2002).

Unlike herbicide-tolerant soybeans, which provide savings in management time (and therefore allow operators to obtain higher income from off-farm activities), yield monitors (and precision agriculture in general) are generally believed to be human capital-intensive (Griffin et al., 2004).

Conclusions

As onfarm and off-farm activities compete for scarce managerial time in U.S. farm operator households, economic decisions (including technology adoption and other production decisions) are likely to shape and be shaped by time allocation within the household. Time allocation decisions are usually not measured directly, but their outcomes, such as onfarm and off-farm income, are observable.

Our research finds that the farm-level efficiency of farm households decreases as off-farm activities increase. Smaller farms, which average the highest off-farm incomes, obtain the lowest farm-level efficiencies. These results support the hypothesis that farm operators who devote more time to off-farm activities have less time to manage the farm. However, examining efficiency from a wider perspective, we find that household-level efficiency (including off-farm income-generating activities) is higher across all farm sizes than farm-level efficiency alone. Moreover, the beneficial effect of off-farm income is higher for smaller farms. In fact, farm households operating small farms achieve efficiency levels comparable to those operating larger farms when off-farm income is included. These results, therefore, suggest that farm households operating small farms have adapted to shortfalls in farming performance by increasing off-farm income.

By including off-farm income-generating activities in the household output portfolio (in addition to the traditional farm products), many farm households, especially those operating smaller farms, are able to enhance diversification. The advantages of such diversification, measured by the household-level economies of scope, are substantial. These results suggest that off-farm employment may enhance onfarm diversification, especially for households operating small farms.

The economic inducement of smaller farms to increase their size (measured by the economic concept of scale economies) is reduced when we include off-farm income. Household-level scale economies (which include off-farm income-generating activities) are closer to constant returns to scale than are farm-level scale economies (which only consider the farm business). However, the beneficial effect of off-farm activities in improving scale economies is more pronounced for households operating smaller farms. These findings provide a different way of measuring the role of off-farm work in improving the economic condition of farm households, particularly those operating small farms.

The adoption of agricultural innovations is also linked to off-farm income through managerial time. For example, the adoption of managerial time-saving technologies is significantly related to higher off-farm household income for U.S. corn/soybean farmers, after controlling for other factors. On the other hand, managerially time-intensive technologies are associated with significantly lower off-farm income.

In a broader sense, these findings confirm the tradeoff between time spent on farm and off-farm activities or, in economic terms, the substitution of economies of scope (derived from engaging in multiple income-generating activities, on and off the farm) for economies of scale.

A number of implications follow. Each of these implications reinforces the importance of understanding farmers' decisions in the context of the farm household rather than the farm operation alone. First, our research provides empirical confirmation of Smith's suggestion that households operating small farms, which lack economies of scale, are more likely to devote time to off-farm opportunities, more likely to adopt management-saving technologies (like herbicide-tolerant crops), and less likely to adopt management-intensive technologies (such as integrated pest management).

The relationship between off-farm work and economic performance also suggests that a farm household's dependence on off-farm income has an effect on the distributional consequences of government policies. Government policies affecting agriculture—such as conservation, research and development, extension, and farm support—may affect farm households differently depending on the relative importance of onfarm and off-farm income-generating activities. Thus, the consequences of government policies depend on the diversity of U.S. farm households, particularly regarding their income sources. For example, a policy promoting the adoption of management-intensive agricultural techniques (such as IPM) may not be fully effective unless it takes into consideration the demands in managerial time imposed by IPM adoption.

This research also has implications for private agricultural research and development (R&D). While innovators often base their economic evaluations of returns to R&D on the expected profitability of potential innovations for farmers (i.e., the extent of yield increases and/or input cost reduction resulting from an innovation relative to the costs of adoption and current management practices), this report shows that there is an important additional element to be included in such evaluations: the value of management time.

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Appendix 1—Economies of Scale and Scope and Technical Efficiency

This discussion uses two different but related methodologies and data sets and follows the analysis described in Nehring et al., 2005. First, using 1996-2000 survey data, we use an input distance function to estimate scale economies and technical efficiency, and compare these performance measures at the farm and household levels. Second, using 2000 survey data, we set up a multi-activity cost function to analyze labor allocation decisions within the farm operator household and estimate scope economies. We interpret off-farm income-generating activities as outputs, along with corn, soybeans, livestock, and other crops. For both estimations, we use detailed survey information of the farm operator household from USDA's Agricultural Resource Management Survey (ARMS).

Economies of Scale and Technical Efficiency

The analysis of production structure and performance requires representing the underlying multi-dimensional (input and output) production technology. This may be formalized by specifying a transformation function, $T(X, Y, R) = \theta$, which summarizes the production frontier in terms of an input vector X , an output vector Y , and a vector of external production determinants R . This information on the production technology can also be characterized via an input set, $L(Y, R)$, representing the set of all X vectors that can produce Y , given the exogenous factors R .

An input distance function (denoted by superscript I) identifies the least input use possible for producing the given output vector, defined according to $L(Y, R)$:

$$(1) \quad D^I(X, Y, R) = \text{Max} \{ \rho : (x/\rho) \in L(Y, R) \}.$$

This multi-input, input-requirement function allows for deviations from the frontier. It is also conceptually similar to a cost function, if allocative efficiency is assumed, in the sense that it implies minimum input or resource use for production of a given output vector (and thus, implicitly, costs). However, it does so in a primal/technical optimization or efficiency context, with no economic optimization implied.

For the farm-level model, the Y vector contains Y_1 = crops (corn, soybeans, and other crops), Y_2 = livestock, and, for the household-level model, Y_1^* = crops and livestock, and Y_2^* = off-farm income-generating activities, as farm "outputs." With Y_2^* included, one might think of Y as a multi-activity rather than a multi-output vector. The components of X are defined as X_1 = land (LD), X_2 = hired labor (L), X_3 = operator labor (including hours worked off-farm)(K), X_4 = spouse labor (including hours worked off-farm) (E), X_5 = capital (F), and X_6 = materials (M).

The scale economies measure may be computed from the estimated model via derivatives or scale elasticities: $-\epsilon_{DIY} = -\sum_m \partial \ln D^I(X, Y, t) / \partial \ln Y_m = \epsilon_{X_I Y}$ for M outputs Y_m (similar to the treatment in Baumol et al. (1982) for a multiple-output cost model, and consistent with the output distance function

formula in Färe and Primont (1995). However, the inverse measure is more comparable to the cost literature, where the extent of increasing returns or scale economies is implied by the shortfall of the measure from 1. Again, this measure is based on evaluation of (scale) expansion from a given input composition base.

The distance function can be approximated by a translog functional as follows:

$$(2) \ln D_{it}^I / X_{P,it} = \alpha_0 + \alpha_t t + \sum_m \alpha_m \ln X_{mit}^* + 0.5 \sum_m \sum_n \beta_{mn} \ln X_{mit}^* \ln X_{nit}^* \\ + \sum_k \alpha_k \ln Y_{kit} + 0.5 \sum_k \sum_l \alpha_{kl} \ln Y_{kit} \ln Y_{lit} + \sum_k \sum_m \delta_{km} \ln Y_{kit} \ln X_{mit}^* ,$$

or

$$(3) -\ln X_{P,it} = \alpha_0 + \alpha_t t + \sum_m \alpha_m \ln X_{mit}^* + 0.5 \sum_m \sum_n \beta_{mn} \ln X_{mit}^* \ln X_{nit}^* \\ + \sum_k \alpha_k \ln Y_{kit} + 0.5 \sum_k \sum_l \alpha_{kl} \ln Y_{kit} \ln Y_{lit} + \sum_k \sum_m \delta_{km} \ln Y_{kit} \ln X_{mit}^* - \ln D_{it}^I ,$$

where i denotes farm and t time period. This functional relationship, which embodies a full set of interactions among the X , Y and t arguments of the distance function, can more succinctly be written as: $-\ln X_{P,it} = TL(X/X_P, Y, t) = TL(X^*, Y, t)$.

The input distance function is well-suited to measure technical efficiency. For empirical estimation of technical efficiency, we append a symmetric error term, v , to equation (3) and change the notation “ $-\ln D_{it}^I$ ” to “ u .” The resulting function (with the subscripts i suppressed for notational simplicity) is: $-\ln X_P = TL(X^*, Y, t) + v - u$, where the term $(-u)$ may be interpreted as inefficiency (as technical efficiency measures the distance from the frontier). This method is known as a stochastic frontier production function, where output of a firm is a function of a set of inputs, inefficiency $(-u)$ and a random error v (Aigner et al., 1977; Greene, 1995, 1997, 2000).

To estimate the function, we used Coelli’s FRONTIER program (Coelli, 1996), based on the error components model of Battese and Coelli (1992). Since $-u$ represents inefficiency, the technical efficiency scores are given by $\exp(-u) = D^I(X^*, Y, t)$. If a firm is not technically inefficient (the firm is on the frontier), u is equal to 0 and its technical efficiency score is 1.

In the absence of genuine panel data, repeated cross-sections of data across farm typologies are used to construct a pseudo-panel data set (see Deaton, 1985; Heshmati and Kumbhakar, 1992; Verbeek and Nijman, 1993). The pseudo-panels are created by grouping the individual observations into a number of homogeneous cohorts, demarcated on the basis of their common observable time-invariant characteristics, such as location and ERS farm typology. The subsequent economic analysis then uses the cohort means rather than the individual farm-level observations. ERS farm typology categories are summarized in Nehring et al. (2005). The resulting pseudo panel data set consists of 13 cohorts by State, for 1996-2000, measured as the weighted mean values of the variables to be analyzed. There are a total of 650 annual observations (130 per year), summarizing the activities of 1,934 farms in 1996, 3,890 in 1997, 2,311 in 1998, 3,201 in 1999, and 2,394 in 2000.

Economies of Scope

When a firm produces more than one output, there is a qualitative change in the production structure that makes the concept of economies of scale developed for a single output insufficient. For multiproduct firms, production economies may arise not only because the size of the firm is increased but also due to advantages derived from producing several outputs together rather than separately. Thus, more than one measure is necessary to capture the economies (or diseconomies) related to the scale of operation (volume of output) and the economies related to the scope of the operation (composition of output or product mix). The concepts of economies of scale and scope for multiproduct firms have been developed by Panzar and Willig (1977, 1981) and Baumol et al. (1982). They have been used in agriculture by Akridge and Hertel (1986) and Fernandez-Cornejo et al. (1992).

Economies of scope measure the cost savings due to simultaneous production relative to the cost of separate production. In general, scope economies occur when the cost of producing all products together is lower than producing them separately.

Formally, consider a partition of the output set N into two (disjoint) groups T and $N-T$. Let Y_T, Y_{N-T} be the output quantity (subvector) of each of the two groups and Y_N (or simply Y) the output vector, which consists of all the outputs. The respective cost functions $C(Y_T), C(Y_{N-T})$ give the minimum cost of producing the two output groups separately, and $C(Y_N)$ denotes the minimum cost of producing them together (Nehring et al., 2005).

The degree of economies of scope (SC) relative to the (output) set T is defined as:

$$(1) \quad SC = [C(Y_T) + C(Y_{N-T}) - C(Y_N)] / C(Y_N)$$

where SC will be positive if there are economies of scope and negative if there are diseconomies of scope. In our case, we consider the first subset of the partition to include the four conventional outputs (corn, soybeans, other crops, and livestock), $N=\{1,2,3,4\}$ and the second subset the non-conventional off-farm income-generating activities, $N-T=\{5\}$.

Farms that produce the two output groups separately are those that either produce conventional outputs with no off-farm activities or else those with off-farm work but no conventional outputs. While the sample includes farm households that produce conventional outputs and no off-farm activities, it technically does not include household with zero traditional outputs. However, the sample does include many farm households with very small revenues from traditional outputs because, for statistical purposes, a U.S. farm is currently defined as “any place from which \$1,000 or more of agricultural products were sold or normally would have been sold during the year under consideration.” (USDA, 2005).

The well-developed restricted cost function is used to estimate the scope economies. Consider n outputs, m variable inputs, and s fixed inputs and other exogenous factors such as location or weather proxies; $Y = (Y_1, \dots, Y_n)'$

denotes the vector of outputs, $X = (X_1, \dots, X_m)'$ denotes the vector of variable inputs, $Z = (Z_1, \dots, Z_s)'$ is the vector of non-negative quasi-fixed inputs and other (exogenous) factors, and $W = (W_1, \dots, W_m)'$ denotes the price vector of variable inputs. The restricted profit function is defined by:

$$(3) \quad C(W, Y, Z) = \text{Min} [W'X : \in T].$$

Under the usual assumptions on the technology (production possibilities set T), the restricted cost function is well defined and satisfies the usual regularity conditions.

Using a normalized quadratic variable cost function, which can be viewed as a second-order Taylor series approximation to the true cost function, we obtain:

$$(4) \quad C(W, Y, Z) = a_0 + (a' b' c') \begin{bmatrix} W \\ Y \\ Z \end{bmatrix} + 1/2(W' Y' Z') \begin{bmatrix} B & E & F \\ E' & C & G \\ F' & G' & D \end{bmatrix} \begin{bmatrix} W \\ Y \\ Z \end{bmatrix}$$

where W is a vector of normalized variable input prices, a_0 is a scalar parameter, and a , b , and c are vectors of constants of the same dimension as W , Y , and Z . The parameter matrices B , C , and H are symmetric and of the appropriate dimensions. Similarly, E , F , and G are matrices of unknown parameters.

Using Shephard's lemma, we obtain the demand functions for variable inputs which is estimated together with the cost function. We consider five outputs Y (corn, soybeans, other crops, livestock, and operator and spouse off-farm labor), five inputs X (hired labor, operator labor, spouse labor, miscellaneous inputs, and pesticides), and use the pesticides price as the *numeraire*. In addition the cost function is specified with two exogenous factors (Nehring et al., 2005).

The normalized quadratic variable cost function and the four cost-share equations are estimated in an iterated seemingly unrelated regression (ITSUR) framework using data for year 2000. The adjusted R^2 's were 0.99 for the quadratic cost function, 0.26 for the hired labor input, 0.21 for the operator labor equation, 0.30 for the spouse labor equation, and 0.60 for the miscellaneous inputs equation. However, 48 percent of coefficients for the joint estimates are significant at the 10 percent level.

The own-price effects for the inputs exhibit the expected negative signs. The own-price effect for hired labor is significant at the 10-percent level, while the own-price effects for operator labor and spouse labor are not significant in this cross-section. The own price elasticity of demand for hired labor is highly elastic, with a value of -2.62. In contrast, the own-price elasticities of demand for operator and spouse labor are highly inelastic, with values of -0.105 and -0.283. These results, however, are not directly comparable with cost function studies in the literature that do not include off-farm income-generating activities as an output.

Appendix 2—Incorporating Technology Adoption in the Farm Household Model

The Theoretical Framework

This model combines in a single framework the technology adoption and off-farm work decisions by the operator and spouse and follows the analysis developed by Fernandez-Cornejo et al. (2005). The model expands the farm household model offered by Huffman (1991) with several additions to allow for technology adoption. According to the agricultural household model, farm households maximize utility U subject to income, production technology, and time constraints. Household members receive utility from goods purchased for consumption G , leisure (including home time) $L = (L_o, L_s)$ for the operator and the spouse, and from factors exogenous to current household decisions, such as human capital $H = (H_o, H_s)$, and other factors Ψ (including household characteristics and weather). Thus:

$$(1) \quad \text{Max } U = U(G, L, H, \Psi)$$

Subject to the constraints:

$$(2) \quad P_g G = P_q Q - W_x X' + WM' + A \quad (\text{income constraint})$$

$$(3) \quad Q = Q[X(\Gamma), F(\Gamma), H, \Gamma, R], \quad \Gamma \geq 0 \quad (\text{technology constraint})$$

$$(4) \quad T = F(\Gamma) + M + L, \quad M \geq 0 \quad (\text{time constraint})$$

where P_g and G denote the price and quantity of goods purchased for consumption; P_q and Q represent the price and quantity of farm output; W_x and X are the price and quantity (row) vectors of farm inputs; $W = (W_o, W_s)$ represents off-farm wages paid to the operator and spouse; $M = (M_o, M_s)$ is the amount of time working off-farm by the operator and spouse; $F = (F_o, F_s)$ is the amount of time working on the farm by the operator and spouse; A is other income, including income (from interest, dividends, annuities, private pensions, and rents) and government transfers (such as Social Security, retirement, disability, and unemployment); R is a vector of exogenous factors that shift the production function, and $T = (T_o, T_s)$ denotes the (annual) time endowments for the operator and spouse. The production function is concave and has the usual regularity characteristics. Some technologies offer simplicity and flexibility that translate into reduced management time, freeing time for other uses. In these cases, the amount of time working on the farm by the operator and the spouse F (and possibly the use of other farm inputs X) is a function of Γ , the adoption intensity (extent of adoption) of the technology. A technology-constrained measure of (cash) household income is obtained by substituting (3) into (2) (Huffman, 1991):

$$(5) \quad P_g G = P_q Q[X(\Gamma), F(\Gamma), H, \Gamma, R] - W_x X(\Gamma)' + WM' + A$$

The first order conditions for optimality (Kuhn-Tucker conditions) are obtained by maximizing the Lagrangian expression \mathcal{L} over (G, L) and minimizing it over the Lagrange multipliers (λ, μ) , where $\mu = (\mu_o, \mu_s)$:

$$(6) \quad \mathcal{L} = U(G, L, H, \Psi) + \lambda \{ P_q Q[X(\Gamma), F(\Gamma), H, \Gamma, R] - W_x X(\Gamma)' + WM' + A - P_g G \} + \mu [T - F(\Gamma) - M - L]$$

The off-farm participation and adoption decisions may be obtained from the following Kuhn-Tucker conditions:

$$(7) \quad \partial \mathcal{L} / \partial X = \lambda (P_q \partial Q / \partial X - W_x) = 0$$

$$(8) \quad \partial \mathcal{L} / \partial F = \lambda P_q \partial Q / \partial F - \mu = 0$$

$$(9) \quad \partial \mathcal{L} / \partial \Gamma = \lambda \{ P_q [(\partial Q / \partial X)(dX/d\Gamma)' + (\partial Q / \partial F)(dF/d\Gamma)' + \partial Q / \partial \Gamma] - W_x (dX/d\Gamma)' \} - \mu (dF/d\Gamma)' \leq 0,$$

$$\Gamma \geq 0, \quad \Gamma \equiv \partial \mathcal{L} / \partial \Gamma = 0$$

$$(10) \quad \partial \mathcal{L} / \partial M = \lambda W - \mu \leq 0, \quad M \geq 0, \quad M(\lambda W - \mu) = 0$$

$$(11a, b) \quad \partial \mathcal{L} / \partial G = U_G - P_g \lambda = 0, \quad \partial \mathcal{L} / \partial L = U_L - \mu = 0$$

$$(12) \quad P_q Q[X(\Gamma), F(\Gamma), H, \Gamma, R] - W_x X(\Gamma)' + WM' + A - P_g G = 0$$

$$(13) \quad T - F(\Gamma) - M - L = 0$$

where U_L, U_G are the partial derivatives of the function U . Without loss of generality, both the operator and spouse are assumed to have positive optimal hours of leisure and farm work, i.e., equation (8) and (11b) are equalities.

The off-farm participation decision conditions for the operator and the spouse may be obtained from the optimality conditions for off-farm work, equation (10), together with equations (8) and (11b):

$$(14) \quad W \leq \mu / \lambda = P_q \partial Q / \partial F$$

where μ / λ is equal to the marginal rate of substitution between leisure and consumption goods (from equations 11a and 11b) and $P_q \partial Q / \partial F$ represents the value of the marginal product of farm labor for the operator and the spouse. Examining the components of (14), $W_i < \mu_i / \lambda$ (strict inequality) indicates that the total time endowment for the operator ($i = o$) or spouse ($i = s$) is allocated between farm work and leisure; optimal hours of off-farm work are zero (corner solution), i.e., $M_i^* = 0$. On the other hand, if $W_i = \mu_i / \lambda$, optimal hours of off-farm work may be positive ($M_i^* > 0$) and $W_i = \mu_i / \lambda = P_q \partial Q / \partial F_i$ (interior solution) (Lass et al., 1989; Huffman, 1991; Kimhi, 1994; Huffman and El-Osta, 1997). In this case, the value of the marginal product of farm labor is equal to the off-farm wage rate.²⁷

When an interior solution for M occurs, equations (7) and (8) can be solved together, independently of the rest of the Kuhn-Tucker conditions, to obtain the demand functions for onfarm labor, i.e., the optimal production and consumption decisions can be separated since the off-farm wage determines the value of the operator's and spouse's time ($W = \mu / \lambda$) (Huffman and Lange, 1989; Huffman, 1991).²⁸

²⁷The marginal value of time of the farm operator (or spouse) when all his/her time is allocated to farm work and leisure and none is allocated to off-farm work ($P_q \partial Q / \partial F_i |_{M_i=0}$) represents the shadow value of farm labor and is called the reservation wage for off-farm work for the operator ($i = o$) or spouse ($i = s$). In this context, the operator (or spouse) will work off-farm when his/her reservation wage is less than the anticipated off-farm wage rate and will not work off-farm otherwise. Assuming that both the operator and spouse face wages that are dependent on their marketable human capital characteristics ξ_i , local labor market conditions, and job characteristics Ω , but not on the amount of off-farm work (Huffman and Lange, 1989; Huffman, 1991; Tokle and Huffman, 1991), the off-farm market labor demand functions are $W_i = W_i(\xi_i, \Omega)$, ($i = o, s$).

²⁸Moreover, when an interior solution occurs, from (10), (11a), and (11b) we obtain $U_L / U_G = W / P_g$; that is, the marginal rate of substitution between consumption goods and leisure is equal to the ratio of the wage rate and the price of consumption goods.

The demand function for onfarm labor is then $F^* = F(W, W_x, P_q, H, \Gamma, R)$ and the demand for purchased farm inputs $X^* = X(W, W_x, P_q, H, \Gamma, R)$. These optimal input demand functions are substituted in the production function to obtain the supply of farm output $Q^* = S(W, W_x, P_q, H, \Gamma, R)$ and the maximum net household income may be expressed as:

$$(15) \quad NI^* = P_q S(W, W_x, P_q, H, \Gamma, R) - W_x X^* + WM' + A$$

Solving jointly equations (10), (11), and (15) we obtain the demand for leisure $L^* = L(W, P_g, NI^*, H, \Psi, T)$ and for consumption goods $G = G(W, P_g, NI^*, H, \Psi, \Gamma, T)$. The supply function for off-farm time is obtained by substitution of the optimal levels of leisure hours and farm work hours (Huffman, 1991):

$$(16) \quad M^* = T - F^* - L^* = M(W, W_x, P_q, P_g, NI^*, H, \Psi, \Gamma, \xi_i, \Omega, R, T)$$

Finally, a reduced-form expression of total household income is obtained by:

$$(17) \quad NI^* = NI(W_x, P_q, P_g, A, H, \Psi, \Gamma, R, T)$$

As Huffman (1991) notes, when optimal hours of off-farm work hours for the operator or the spouse are zero, the decision process is not recursive and production and consumption decisions must be made jointly. In this case, the arguments for the reduced-form expression of household income are the same as those in (17) but exclude the exogenous variables related to the job characteristics and labor marketability.

The technology adoption decision condition is obtained from the optimality conditions, equation (9) and equations (8) and (11b), noting that the expression in brackets in (9) is the total derivative $dQ/d\Gamma$. Thus, we obtain:

$$(18) \quad P_q dQ/d\Gamma - W_x (dX/d\Gamma)' - (\mu/\lambda)(dF/d\Gamma)' \leq 0$$

But from (11a) and (11b) $\mu/\lambda = P_g (U_L/U_G)$; then:

$$(19) \quad P_q dQ/d\Gamma - W_x (dX/d\Gamma)' - P_g (U_L/U_G)(dF/d\Gamma)' \leq 0$$

The left-hand-side of this expression may be interpreted as the marginal benefit of adoption $P_q dQ/d\Gamma$ minus the marginal cost of adoption, which includes the marginal cost of the production inputs $W_x (dX/d\Gamma)'$ and the marginal cost of the farm work $P_g (U_L/U_G)(dF/d\Gamma)'$ (of the operator and the spouse) brought about by adoption (could be negative if adoption saves managerial time), valued at the marginal rate of substitution between leisure and consumption goods (which, when off-farm work hours are positive, equals the off-farm wage rate). It will not be optimal to adopt if the inequality is strict (corner solution), wherein the marginal benefit of adoption falls short of the marginal cost of adoption. An interior solution for the optimal extent of adoption will occur when the equality is strict or when the value of the marginal benefit of adoption is equal to the marginal cost of adoption.

Given the cross-sectional nature of the data, one can use the implicit function theorem to derive expressions for off-farm labor supply for farm operator and spouse and technology adoption (which affects off-farm labor

supply of farm operators and spouses) that are functions of wages, prices, human capital, nonlabor income, and other exogenous factors. These factors are replaced in reduced-form representations of labor supply and adoption by observable farm, operator, and household characteristics, including human capital. The “ambient variables” (family size, access to urban areas), which might affect the productive capacity of the farm operator and the spouse, are also included. The following section outlines the empirical model and estimation method used to conduct the analysis.

Empirical Model

A two-stage econometric model is specified. The first stage, the decision model, examines the off-farm work participation and the technology adoption decisions. The second stage is used to estimate the impact of adoption on household income.

A simplified “reduced form” approach is followed (Goodwin and Holt, 2002; Goodwin and Mishra, 2004) to specify the empirical model, rather than explicitly estimating a structural model of labor supply. In this approach, the reduced form of the decision model is obtained by specifying the endogenous variables (M, F, Q, X) in terms of the exogenous variables, including $W_x, P_q, P_g, H, \Psi, \xi_i, \Omega, R, T$. Equation (14), implied by the Kuhn-Tucker conditions, is central to the off-farm work decision of the operator and the spouse and equation (19) is central to the adoption decision. Thus, considering a first-order approximation (linear terms) and adding the stochastic terms, the empirical representation of the decision model, which includes the off-farm participation of the operator (20a) and spouse (20b), and the technology adoption decision (20c), is:

$$(20a) \quad \beta_o Z_o' + \varepsilon_o \leq 0$$

$$(20b) \quad \beta_s Z_s' + \varepsilon_s \leq 0$$

$$(20c) \quad \beta_a Z_a' + \varepsilon_a \leq 0$$

where the (row) vectors $Z_o, Z_s,$ and Z_a include all the factors or attributes influencing linearly the off-farm participation (operator and spouse) and adoption decisions, and $\beta_o, \beta_s,$ and β_a are vectors of parameters. Assuming that the stochastic disturbances are normally distributed, each of these equations may be estimated by probit. However, because the disturbances ($\varepsilon_o, \varepsilon_s, \varepsilon_a$) are likely to be correlated, univariate probit equations are not appropriate.

Bivariate probit models have been used to model the off-farm employment decisions by the operator and spouse (Huffman and Lange, 1989; Lass et al., 1989; Tokle and Huffman, 1991). Since the decisions to work off farm and the technology adoption decision may be related, all three decisions are modeled together in a multivariate probit model (Greene, 1997). Formally, $[\varepsilon_o, \varepsilon_s, \varepsilon_a] \sim$ trivariate normal (TVN) $[0,0,0; 1,1,1; \rho_{12}, \rho_{13}, \rho_{23}]$, with variances ρ_{ij} ($i=j$) equal to 1 and correlations ρ_{ij} ($i \neq j$) where $i, j = 1, 2, 3$.

The joint estimation of three or more probit equations was computationally unfeasible until recently because of the difficulty in evaluating high-order multivariate normal integrals. Over the past decade, however, the estimation

has been made possible with Monte Carlo simulation techniques (Geweke et al., 1994; Greene, 1997).

The vector Z_i includes (i) farm factors, such as farm size and complexity of the operations; (ii) human capital (operator age/experience and education); (iii) household characteristics (such as the number of children); (iv) off-farm employment opportunities, which will depend on the farms' accessibility to urban areas and the change in the rate of unemployment in nearby urban areas; (v) farm typology; and (vi) government payments.²⁹ The factors or attributes influencing adoption, included in the vector Z_a , are farm factors, human capital, farm typology, a proxy for risk (risk-averse farmers are less likely to adopt agricultural innovations), and crop/seed prices.

The second stage, the income impact model, provides estimates of the impact of adoption on household income after controlling for other factors. The empirical representation of this model—based on equation (17), the reduced-form expression of household income—is $NI^* = NI(W_x, P_q, P_g, A, H, \Psi, \Gamma, R, T)$.

After linearizing this reduced form, separating out explicitly the adoption indicator variable, and appending a random disturbance \hat{a} , assumed to be normally distributed, we have:

$$(21) \quad NI^* = \theta V' + \alpha I + \varepsilon$$

where NI^* represents household income; V is a (row) vector of observable explanatory variables that may influence household income (other than technology adoption) such as prices, human capital, and “ambient variables” (family size, access to urban areas) that may affect the productive capacity of the farm operator and the spouse; I is an indicator variable for adoption ($I=1$ if adoption takes place and $I=0$ otherwise); and θ and α are appropriately dimensioned parameters. The impact of adoption on household income is measured by the estimate of the parameter α . However, as noted by Stefanides and Tauer (1999), if α is to measure the impact of adoption on income of a representative farm, farmers should be randomly assigned among adopter and nonadopter categories. This is not the case, since farmers make the adoption choices themselves. Therefore, adopters and nonadopters may be systematically different and these differences may manifest themselves in farm performance and could be confounded with differences due purely to adoption. This situation, called self-selection, may bias the statistical results unless corrected (Fernandez-Cornejo et al. 2002).

To correct for self-selection bias, we follow Maddala (1983) and Greene (1995) and obtain consistent estimates of the parameters θ and α by regarding self-selection and simultaneity (discussed earlier) as sources of endogeneity. Because the dummy variable I cannot be treated as exogenous, instrumental variable techniques are used to purge the dependence of I . The predicted probability of adoption, obtained from the decision model, is used as an instrument for I in equation (21).

Unlike the traditional selectivity model, in which the effects are calculated (separately) using the subsamples of adopters and nonadopters, the impact model uses all the observations and is known as a “treatment effects model,”

²⁹Following Goodwin and Holt (2002), some prices are not included in our empirical models since prices are approximately constant across households when data consist of cross-sectional observations taken at a point in time. We did include some prices, like the price of soybeans, but its coefficient was statistically insignificant.

used by Barnow et al. (1981). The treatment effects model consists of the regression $Y = \theta V' + \alpha I + \varepsilon$ where the observed indicator variable I ($I = 1$ if $I^* > 0$ and $I = 0$ if $I^* \leq 0$), indicates the presence or absence of some treatment (adoption of herbicide-tolerant crops in this case) and the unobserved or latent variable I^* is given by $I^* = \delta Z_a' + v$ (Greene, 1995).

Total household income (NI^*), as represented in (17), has two components: household income from farming ($FARMHHI$) and off-farm household income ($TOTOFI$). Household income from farming includes farm business household income, operator's paid farm income, household members' paid farm income, etc. (see detailed definitions in appendix table 1). Off-farm household income includes off-farm business income, income from operating other farm businesses, off-farm wages and salaries, etc.

The components of vector V include farm location and typology, operator age, education and experience, number of children, price of soybeans, a measure of specialization on soybean production, a measure of the extent of livestock operations, farm size, and proxies for local labor market conditions.

The data are obtained from the nationwide Agricultural Resource Management Survey (ARMS) developed by USDA (USDA, ERS, 2003). The ARMS survey is designed to link data on the resources used in agricultural production to data on use of technologies, other management techniques, chemical use, yields, and farm financial/economic conditions for selected field crops. The ARMS is a multiframe, probability-based survey in which sample farms are randomly selected from groups of farms stratified by attributes such as economic size, type of production, and land use.

The 2000 data set (used for the HT soybean and Bt corn case study) includes 17 soybean (corn) producing States: Arkansas, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Mississippi, Michigan, Minnesota, Missouri, Nebraska, North Carolina, Ohio, South Dakota, Tennessee, and Wisconsin. After selecting those farms that planted soybeans (corn) in 2000 and eliminating those observations with missing data, there were 2,258 observations available for the soybean analysis and 2513 observations for corn.

The 2001 corn data set (used for the yield monitor and conservation tillage case studies) includes observations of 17 corn-producing States. After eliminating observations with missing data, there were 1,763 observations available for analysis.

Because of the complexity of the survey design, a weighted least-squares technique is used to estimate the parameters using full-sample weights developed by the USDA's National Agricultural Statistics Service. Standard errors are estimated using a delete-a-group jackknife method (Kott, 1998; Kott and Stukel, 1997) where a group of observations is deleted in each replication. The sample is partitioned into r groups of observations ($r = 15$) and resampled, thus forming 15 replicates and deleting one group of observations in each replicate.

Appendix table 2 shows the parameter estimates α (equation 21) along with standard errors. These parameters may be interpreted as the derivatives of household income with respect to the probability of adoption and are used to obtain the elasticities shown in table 7.

Household (HH) income variable definitions

1. **Household income from farming (FARMHHI)** = Farm Business Income HH Share
 + Operator Paid on Farm
 + Household Members Paid on Farm
 + Net Income from Rented Land

Where:

$$\text{Farm Business Income HH Share} = \text{Net Cash Farm Business Income}$$

- Depreciation
- Gross Income from Rented Land
- Operator Paid Onfarm
- Income Due to Other Households

$$\text{Net Cash Farm Income} = \text{Gross Cash Farm Income} - \text{Cash Operating Expenses}$$

Gross Cash Farm Income = Crop and livestock income including CC loans + Other farm income (includes government payments, income from custom work and machine hire, income from livestock grazing, other farm-related income, income from farm land rented to others, fee income from crops removed under production contract, fee income from livestock removed under production contract).

Total Cash Operating Expenses (hired labor, contract labor, seed, fertilizer, chemicals, fuel, supplies, tractor and other equipment leasing, repairs, custom work, general business, real estate and property taxes, insurance, interest, purchased feed, purchased livestock).

2. **Off-Farm Household Income (TOTOFI)** = Off-farm business income
 + Income from operating other farm businesses
 + Off-farm wages and salaries
 + Interest and dividend income
 + Other off-farm income
 + Rental income
3. **Total Household Income (TOTHHI)** = Household Income from Farming (FARMHHI)
 + Off-Farm Household Income (TOTOFI)

Parameter estimates of probability of adoption term of the household income equation for technologies of varying managerial intensity

	Yield monitors			Bt corn			Conservation tillage			Herbicide-tolerant soybean		
	Estimate	std. err.	t-value	Estimate	std. err.	t-value	Estimate	std. err.	t-value	Estimate	std. err.	t-value
Onfarm household annual income	25.1	63.8	(0.39)	-13.9	10.9	(-1.29)	6.4	49.5	(0.13)	-30.4	29.8	(-1.02)
Off-farm household annual income	-124.9	35.3	(-3.54)	-36.7	36.2	(-1.07)	87.3	30.3	(2.88)	133.4	67.0	(1.99)
Total household annual income	-100.8	68.7	(-1.47)	-50.6	36.5	(-1.39)	93.9	51.3	(1.83)	104.1	59.0	(1.76)

Note. Standard errors calculated using the delete-a-group jackknife method.