The Impacts of Change in Local Industrial Composition on Off-Farm Labor Supply

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Abstract

Most U.S. farm households have either the operator or spouse working off-farm for wages and salaries or proprietorships. Additionally, off-farm income continues to grow as a share of total household income. Little is known about how changes in local industrial composition impact off-farm labor decisions. Using a household utility maximization framework, this analysis employs a two-stage process to 1) predict joint off-farm labor participation of operators and spouses, and 2) measure the impact of farm and household characteristics, and changes in county-level industry on levels of off-farm labor supply. Results show that labor participation decisions are jointly determined. Human capital is among the most significant individual characteristics impacting labor supply. The most important factors are the industrial sector of the off-farm job, and whether that sector is growing or in decline. Growth in retail trade and service employment is associated with increases in labor supply for the operator and spouse.

Key words: farm household, labor supply, bivariate logit
JEL Codes: Q12, J22, R23

1. Introduction

The importance of off-farm income to farm households has steadily grown in the U.S. In 1960, 42 percent of household income was from off-farm. By the early 1980s the amount had grown to 72 percent (USDA, 1984). Data from the 2008 Agricultural Resource Management Survey (ARMS) show that off-farm income in the U.S. was just under 89 percent of total farm household income. Off-farm labor income alone represented 55 percent of total farm household income (71% for rural residence, 48% for intermediate, and 12% for commercial farm households). Given the increasing share of off-farm income one consequence is the increasing importance that local economic opportunities may have on farm household income via off-farm labor participation decisions. Local labor market conditions and characteristics are theoretically relevant to the determination of off-farm labor supply and off-farm labor earnings. However, previous attempts at analyzing the importance of local market conditions have shown weak or insignificant correlation with off-farm labor decisions and off-farm income from labor earnings.

Moreover, less is known about how changes in employment opportunities off the farm impact labor decisions of farm households and off-farm income. These impacts are likely to depend upon the size and type of farm household, kind of occupation, place of work, opportunity cost of off-farm employment, and local labor market. As off-farm employment opportunities change via changes in local industrial composition, farm households may have to drive longer distances, switch to working in other sectors, or make the decision to work more on-farm. This is particularly relevant depending on the relative difference between on-farm and off-farm wages.

2. Background

Previous analysis has used neoclassical labor supply theory to explain off-farm participation (Huffman, 1980; Sumner, 1982; Johnson, 1985; Gunter and McNamara, 1990; Mishra and Goodwin, 1997) while others have used the theory of time allocation (El-Osta et al., 2004; Ahearn et al., 2006). An additional theoretical link to off-farm labor participation is directly related to the opportunities available to households determined in part by local market conditions (Gunter and McNamara, 1990). These off-farm labor opportunities vary geographically because economic activity is not evenly or homogenously distributed across space. Similar households located in different regions may face different off-farm labor opportunities due to differences in concentration of activity, commuting costs, and commuting time. Local labor market characteristics that impact off-farm labor decisions and earnings also impact the relative marginal utility of time spent working on and off the farm.

One of the limitations of previous studies has been limited empirical modeling of factors impacting the spatial distribution of economic activity. This has been reflected in the simplistic measures of local conditions, i.e. broad categorical variables. Another limitation in some cases has been the measurement of farm households and household activity based upon aggregate data. A third limitation of previous studies is the static nature of local factors used in modeling household behavior. Changes in local conditions are likely to impact off-farm labor decisions and earnings of households.

Off-Farm Labor Supply and Changes in Local Industrial Composition

Previous research has documented that about 70% of married farm-couple households have either the operator, spouse, or both working off-farm (El-Osta et al. 2008). Decisions to work off-farm are hypothesized to be affected by the industrial composition and industrial growth in the commuting area of the farm household. Table 1 shows shares of wage earnings by sector in metro and non-metro areas of the U.S. using 2008 data from the Bureau of Economic Analysis, REIS. Manufacturing represents 13.5% in metro versus 24% of earnings in non-metro areas. Likewise, professional and scientific services account for around 11% versus 4% of earnings in metro and non-metro areas, respectively. Given that manufacturing makes up the largest share of non-metro private earnings in the U.S., it is pertinent to consider how structural changes in that sector due to increases in labor productivity affect off-farm labor supply. If several manufacturing plants close down in an area where farm operators or their spouses work, how does the household respond? Will they take jobs in lower paying sectors, drive farther distances to a similar manufacturing job, or reallocate more resources back to the farm? The purpose of this paper is to model these issues from a farm household perspective. The contribution from the present analysis to the literature is twofold-- a more rigorous conceptual treatment of local labor market conditions, using micro-level data on farm households and unsuppressed data on local industrial activity.

<< Insert Table 1 around here >>

3. Household Model

Under a utility maximization framework of the household, the purpose of this study is to measure the impact of changes in local industrial composition on off-farm labor decisions, while controlling for personal characteristics, farm structure, and family characteristics. Following Ahearn et al. (2006) and El-Osta et al. (2008), the optimization problem the household faces is:

(1) Maximize $U = U(Y, L_o, L_s)$,

subject to:

(2) $T_o = L_o + J_o + F_o$

(3) $T_s = L_s + J_s + F_s$

(4) $P_y Y = w_o J_o + w_s J_s + p_f Q_f - w_f X_f + M$

(5) $Q_f = f(F_o, F_s, X_f, C_o, C_s)$

(6) $J_o = f(C_o, H, Z)$

(7) $J_s = f(C_s, H, Z)$

where Y denotes consumption goods; L_o is leisure of the farm operator, O, and L_s is leisure for the spouse of the farm operator, S; T is the total time endowment, L is the time allocated to leisure, J is time allocated to an off-farm job, F is time allocated to farm work; P_y denotes the price of consumption bundle good Y, w is the off-farm wage rate; p_f are farm output prices (goods and services), Q_f are farm output quantities (goods and services); w_f are farm input prices, X_f are farm input quantities, M signifies other household non-labor income, C is human capital, H contains household specific attributes, and Z describes location specific characteristics (e.g., industrial composition). Equations (4) and (5) are budget and production technology constraints, respectively. Equations (6) and (7) are off-farm labor supply, which are assumed to be functions of human capital, household characteristics, and location specific factors for the operator and spouse, respectively. Substituting (5-7) into (4) yields the budget constraint written as:

$$(8) \qquad P_y Y = w_o\, f\,(C_o, H, Z) + w_s\, f\,(C_s, H, Z) + p_f\, f\,(F_o, F_s, X_f, C_o, C_s) - w_f\, X_f + M.$$

The functional forms of utility and production functions are assumed to be concave, continuous, and twice differentiable, such that the first-order conditions from the model generate the optimality conditions for time allocation across farm and off-farm activities. Additionally, the operator and spouse are assumed to be risk neutral.

4. Data & Empirical Model

Data Description

This analysis utilizes micro level data of farm households from the 2008 Cost and Returns Report of the Agricultural Resource Management Survey (ARMS) (USDA, ERS, 2009) to model household labor supply and industrial activity from the 2001 and 2008 unsuppressed Quarterly Census of Employment and Wages (BLS). These data have not previously been jointly used to measure the impact of local labor market characteristics on off-farm labor decisions. For this analysis, the 2008 ARMS sample is restricted to family-owned, married couple, farm households. The resulting sample is 4,377 households, which represent about 1.47 million farm households nation-wide based on full-sample weights. The ARMS contains the county FIPS code where the household is located. However, not all U.S. counties are represented in the sample. From the sample of households, 1,910 counties are represented. Moreover, multiple households can be from the same county in the sample. This list of counties is used to pull data from the unsuppressed files of the QCEW of BLS. The matching allows county-level industrial data to be appended to the corresponding household in ARMS.

Table 2 reports the weighted means of the data used from the 2008 ARMS. The table is organized to show variables that are specific to operator or spouse versus those that measure aspects of the household or the location of the household. Given that ARMS has a complex survey design, it is necessary to take into account that each household in the sample represents a weighted number of households like it in the entire population. NASS provides 30 replicate weights from a resampling process of the original sample of surveyed farms. These 30 replicates and the full sample weights are used in a delete-a-group jackknife procedure to report sample means in the software *R* using the *survey* package (Lumley, 2011).

<< Insert Table 2 about here >>

In this analysis, off-farm work participation is based on a positive response on the ARMS questionnaire of operators and spouses who work off-farm for wages and salaries or at an off-farm business that they own. Figure 1 shows that of family farms with married couples, 55% of households in the sample have at least the operator, spouse, or both working off-farm. What is of special interest is the industrial sector of their off-farm job. Figures 2 and 3 show sector shares of off-farm jobs for the operator and spouse, respectively. Due to survey design and size constraints, some sectors are necessarily grouped for a total of ten. Those grouped together include: agriculture, forestry, fishing, hunting, and mining; education and health services; wholesale, warehouse, utilities, and transportation; finance, insurance real estate, professional and technical services; recreation and tourism; and retail and personal services.[2] Operators mostly work in AFFH & Mining (17%), Construction (17%), and Manufacturing (15%). Spouses mostly participate in Educ. & Health (36%), FIRE & Prof. (12%), and Retail & Personal Serv. (12%). These differences can largely be explained by traditional gender roles and gender participation in employment, i.e. male operators working as construction workers off-farm. Although ARMS has collected information on sector participation in the past, this is the first analysis to use them to model off-farm labor supply.

<< Insert Figure 1 about here >>

<< Insert Figure 2 about here >>

Another unique data source used in this analysis is the non-public use files of the QCEW from BLS. These data are utilized to construct changes in county-level measures of industrial composition. QCEW contains data on employment, establishment count, and wages by NAICS. While these data are available in the County Business Patterns data of the U.S. Census, they are suppressed when the number of establishments or employment is too low for a particular sector in each county. The measure constructed to capture changes in industrial composition is the growth of employment (from 2001 to 2008) per establishment (in 2001) in a sector. Employment per establishment captures the size of employment as well as the investment in establishments for a particular sector. This measure also captures county-level increasing returns to scale from

[2] Beginning with 2009 ARMS education and health services are broken into separate categories.

establishments that employee large amounts of workers. Table 3 reports statistics of 19 two-digit NAICS sectors for the sample of counties in the ARMS sample used in this analysis. The largest changes occurred in management of companies and enterprises (MCEGR) with 56% average growth in the number of employees per establishment from 2001 to 2008. The largest decline occurred in manufacturing (MANFGR) and finance and insurance (FIGR), both at -4.2% from 2001 to 2008. These measures will be used in the second stage of a two-stage approach to modeling off-farm labor supply of operators and spouses.

<< Table 3 about here >>

Jointness of Off-Farm Labor Decisions

Let w_r be the reservation wages that individuals face for farm and leisure time. If the wage they receive at an off-farm job exceeds their reservation wage, rational individuals will be willing to work off-farm. Individuals will adjust their time allocation until the marginal value of allocating their time across activities is equal. Previous studies of off-farm labor participation have used bivariate probit models to estimate the joint labor decision between operater and spouse (Huffman and Lange, 1989; Ahearn et al. 2006). An alternative to that is the bivariate logit model (Gumbel, 1961), which relaxes the restriction of normality in the error terms, which rarely holds in practice. The bivariate logit model is used to model off-farm work participation decisions by:

$$(9)\quad y_o^* = \gamma_o' X_o + \mu_o, \quad y_o = 1 \text{ if } w_o^r < w_o, 0 \text{ otherwise,}$$
$$y_s^* = \gamma_s' X_s + \mu_s, \quad y_s = 1 \text{ if } w_s^r < w_s, 0 \text{ otherwise,}$$

where X_o and X_s are vectors of exogenous covariates, γ_o and γ_s are vectors of parameters, μ_o and μ_s, and o and s index the operator and spouse.[3] Each pair of dependent variables (y_o; y_s) has four potential outcomes, (y_o= 1; y_s = 1), (y_o= 1; y_s = 0), (y_o= 0; y_s = 1), and (y_o= 0; y_s = 0). The corresponding probability is:

$$(10)\quad \pi_i = \frac{1}{1+\exp(-\gamma_i' X_i)} \qquad \text{for } i = o, s,$$

where the joint probability is $\pi_{os} = \Pr(y_o = 1 \text{ and } y_s = 1)$, and $\pi_{00} = 1 - \pi_{11} - \pi_{10} - \pi_{01}$. The systemic components model the marginal probabilities as well as the odds ratio, $\psi = \pi_{00}\, \pi_{01} / \pi_{10}\, \pi_{11}$, which describes the dependence of one marginal on the other. The predicted joint probabilities are given by:

$$(11)\quad \begin{aligned} \pi_{11} &= \begin{Bmatrix} \frac{1}{2}(\psi-1)^{-1} - a - \sqrt{a^2+b} \\ \pi_o \pi_s \end{Bmatrix} \begin{matrix} \text{for } \psi = 1 \\ \text{for } \psi \neq 1 \end{matrix} \\ \pi_{10} &= \pi_o - \pi_{11}, \\ \pi_{01} &= \pi_s - \pi_{11}, \\ \pi_{00} &= 1 - \pi_{10} - \pi_{01} - \pi_{11}, \end{aligned}$$

where $a = 1 + (\pi_o + \pi_s)(\psi - 1)$, $b = -4\psi(\psi - 1)\pi_o\pi_s$, and joint probabilities must sum to one. If the odds ratio coefficient is significant the labor participation decisions are jointly determined.

Factors that are hypothesized to affect labor participation decisions are also likely to impact the level of labor supplied. Given that it is desired to estimate labor supply, it is

[3] The bivariate logit was estimated in R version 2.11.0 using the package *Zelig* (Imai et al. 2007, 2008).

necessary to account for the potential correlation between labor participation and levels of labor supplied by utilizing Lee's generalized inverse Mills ratios (Lee, 1982; 1983) following the estimation equations (9). Lee's generalized inverse Mills ratios are given by:

$$(12)\quad \varphi_i = (1-P_i)\frac{\Phi\left(\pi\cdot\exp\left(-0.5\cdot\left(\frac{\exp(\gamma_i' X_i)}{1+\exp(\gamma_i' X_i)}\right)^2\right)\right)}{1-\frac{\exp(\gamma_i' X_i)}{1+\exp(\gamma_i' X_i)}} - P_i\frac{\Phi\left(\pi\cdot\exp\left(-0.5\cdot\left(\frac{\exp(\gamma_i' X_i)}{1+\exp(\gamma_i' X_i)}\right)^2\right)\right)}{\frac{\exp(\gamma_i' X_i)}{1+\exp(\gamma_i' X_i)}},$$

where Φ is the standard normal of the probability density function of the logit model, π is the mathematical Pi, i indexes operator or spouse and $P_i = 1$, when the operator or spouse works off-farm. If P =1, the first expression goes to zero and only the second term is used in calculating the inverse Mills ratio. Likewise, if $P = 0$, only the first expression is evaluated in the expression. Using equation (12) allows for the full sample to be used in estimating the level of labor supply, which is discussed next. Restricting the sample in the second stage to only those who work off-farm is difficult when there are several possible combinations of only the operator or spouse working off-farm in the household. As a result, it is non-trivial to use the full sample in the second stage model when labor decisions between the operator and spouse are jointly determined.

Estimation of Two-Stage Model

Labor supply (*LS*) of the operator and spouse are estimated in a linear system of equations using seemingly unrelated regressions (SUR). The inverse Mills ratios for both the operator and spouse are included in each labor supply equation, which accounts for the cross-equation correlation between the operator and spouses labor participation equations as well as the potential correlation between unobserved factors impacting labor participation and labor supply. The system of equations are expressed as:

$$(13) \quad \begin{aligned} LS_{\mathrm{o}} &= \alpha_{\mathrm{o}} + \beta_{\mathrm{o}}' X_{\mathrm{o}} + \lambda_{\mathrm{o}}' Z + \rho_{\mathrm{o}}\varphi_{\mathrm{o}} + \sigma_{\mathrm{o}}\varphi_{\mathrm{s}} + \varepsilon_{\mathrm{o}}, \\ LS_{\mathrm{s}} &= \alpha_{\mathrm{s}} + \beta_{\mathrm{s}}' X_{\mathrm{s}} + \lambda_{\mathrm{s}}' Z + \rho_{\mathrm{s}}\varphi_{\mathrm{o}} + \sigma_{\mathrm{s}}\varphi_{\mathrm{s}} + \varepsilon_{\mathrm{s}}, \end{aligned}$$

where *o* and *s* index the operator and spouse, *X* is a vector of exogenous regressors that contain information on the operator/spouse, household, and farm operation, *Z* contains exogenous information on county-level changes in industrial composition, φ_{o} and φ_{s} are the inverse Mills ratios calculated from the bivariate logit model of labor participation, ε is a vector of residuals, α is an intercept term, β and λ are vectors of parameters, and ρ and σ are parameters of the operator and spouse inverse Mills ratios.

5. Results

Off-Farm Labor Participation Decision

Results from the off-farm labor participation model are shown in Figure 4 and Table 4. Normality tests using a Kolmogorov-Smirnov procedure rejected normality in the residuals of both operator and spouse equations estimated via a bivariate probit model.[4] As a result a bivariate logit model was used to model the off-farm labor participation. The coefficient on the log odds ratio (ψ) is positive and statistically significant indicating that the off-farm labor decisions of operators and spouses in the sample are jointly determined. Figure 4 shows the

[4] The K-S tests statistics were statistically significant at the 95% confidence interval with values of 0.26 and 0.22 for the operator and spouse equation residuals, respectively.

predicted probabilities across possible labor participation decisions of household. Of the households that have a member working off-farm, highest probability is for spouse-only off-farm labor at 0.279. The predicted probability of both the operator and spouse working off-farm is 0.197 versus 0.448 for neither of them working off-farm.

<< Insert Figure 4 around here >>

Two measures, off-farm income in the previous year ($OFFINC_{t-1}$) and gross farm sales in the previous year ($SALES_{t-1}$) are used to account for prior household and farm characteristics that are expected to be correlated with current labor participation decisions. The bivariate logit results show that $OFFINC_{t-1}$ has the expected positive and significant relationship with off-farm labor participation for both the operator and spouse. Wages and salaries from off-farm work account for about 55% of total off-farm income in the current sample. As a result, a household with high levels of off-farm income is expected to utilize those income sources in the future, given the opportunity. Likewise, $SALES_{t-1}$ is negatively correlated with the labor participation decision, which indicates that as farm sales increase, the probability off-farm labor participation decreases. Operators are also more likely to work off-farm for small (SFARM) and medium sized farms (MFARM) relative to large farms.[5] Spousal off-farm labor participation decisions are not significantly impacted by farm size, ceteris paribus. Combined these results are theoretically consistent with the operator playing a larger role in farm operations and thus being more time constrained as farm size increases.

<< Insert Table 4 around here >>

[5] Large farms (sales greater than $250,000) serve as the reference group.

Farm specialization is also expected to impact off-farm labor participation. Some operations are expected to require more time on the farm and as a result be more of a binding constraint for the operator versus the spouse. In general, the results are consistent with previous findings in Ahearn et al. (2006). Table 4 shows that operators and spouses of cash grain farms (CGFARM) have positive and significant coefficients.[6] Poultry farms (PFARM) has a positive and significant coefficient for operators, which is consistent with the historical structuring of poultry farms being part-time operations (MacDonald, 2008). Other significant results in explaining spouse off-farm labor participation include hog operations (HFARM) and general livestock farms (GLFARM). Both were positively correlated with spousal off-farm work. On the other hand, high value crop farms (HVCFARM), e.g. fruit and nuts, were negatively associated with spouse off-farm labor participation. This reflects that the opportunity cost of off-farm alternatives is sufficiently highly for spouses to work on-farm when specializing in high value crops. Industrial specialization at the county-level is expected to impact off-farm labor opportunities and as a result, labor participation decisions. County typologies based upon economic specialization were constructed by ERS (2005). The underlying data are from the year 2000 and prior. As such, these measures control for the "historical" industrial base of the counties where farm households in the sample are located. Counties that are not dependent on a particular sector serve as the reference group. Only farm dependent counties (FARMD) were significant in explaining off-farm labor participation of operators. The negative coefficient suggests that farm dependent counties have fewer alternatives for off-farm labor, which is consistent with expectations.

[6] Dairy farm is the reference group.

Off-Farm Labor Supply

The analysis in this section uses the inverse Mills ratios (IMRs) from the labor participation equations as additional explanatory variables in the off-farm labor supply equations for operators and spouses. Including the IMRs allows for self-selection to work off-farm as well as the jointness in labor supply decisions between operators and spouses in the same household. Full-sample weights were used in the estimation since the number of covariates in the model exceeds the number of replicate weights that are available to be used in a jackknife procedure (National Research Council, 2007, p. 131). Table 5 shows the SUR results for operator and spouse off-farm labor supply. The weighted system R^2 is 0.785. The inverse Mills ratios (OPERATOR IMR and SPOUSE IMR) are statistically significant in both equations, with the exception of SPOUSE IMR in the operators equation. This suggests correlation between unobservables in the labor participation and labor supply equations.

<< Insert Table 5 around here >>

Household off-farm net worth (OFFNETW), which measures the net worth of a household excluding farm assets, was positive and statistically significant. However, the marginal effects were small per $1,000 for the operator (0.185) and spouse (0.079) labor supply. This suggests that wealth does not have an economically significant impact on off-farm labor supply. Net farm income (NFI), off-farm dividend (DIVD) and interest income (INTERST), have the expected negative sign on the coefficients. As income levels increase in these categories, labor supply of operators and spouses fall. However, these impacts are small with a $1000 increase in dividend income translating into a reduction of three hours for operators and

1.5 hours for spouses. Recall that the average household in the sample has $1,390 in dividend income.

Operator and spouse age (AGE) have the expected negative signs, with a one year increase in age translating into a nine and five hour labor supply reduction in annual hours, respectively. Related to age, the number of children is separated into the count under the age of six (CHILD<6) and the count between six and 17 years of age (CHILD > 6 ≤ 17). Each CHILD<6 corresponds to a 66 hour reduction for operators, but is not significant for spouse labor supply. However, the effect seems to be reversed with older children. The marginal impact of an additional CHILD > 6 ≤ 17 corresponds with a 23 hour reduction in the spouse's labor supply, but has no significant impact on the operator's labor supply.

Human capital of operators and spouses is measured by categorical variables for a high school diploma (HSDEGREE), some college (SCOLLEGE), and college degree (CDEGREE). Less than a high school diploma serves as the reference category. The results suggest that human capital impacts spouses' off-farm labor supply differently than the operators'. SCOLLEGE and CDEGREE are significant for operators compared with the reference category with 107 and 90 increased hours, respectively. Only CDEGREE was significant for spouses with a 165 hour increase compared with less than a high school diploma. The difference is expected to be from differences in opportunity costs. For example, more job opportunities for operators at an intermediate skill level versus spouses working off-farm at higher skilled jobs could reflect these differences. Further support of this claim is found in the present sample where, 36% of spouse off-farm jobs are in the education and health services sectors, where skill levels are presumed to be higher.

All of the coefficients for jobs by sector are significant in explaining operator and spouse labor supply and range in size for operators and spouses from 936 to 1,327 and 772 to 1,125. Operators and spouses who have manufacturing jobs (MANFJOB) supply the most off farm annual labor at 1,327 and 1,148 hours, respectively. This indicates that the manufacturing sector remains important to farm household labor supply despite the sector's decline since 2001. Non government services (NGSJOB) has the second largest labor supply coefficient (1,289) for operators, while recreation and tourism (REJOB) has for spouses (1,125). Distance traveled to off-farm jobs (JOBDIST) was statistically positive and significant. Normally labor supply would decrease as travel distance increased. The positive coefficient can be explained by possible differences between part-time and full-time employment. Labor supply would be correlated with distance if operators and spouses have to drive longer to jobs where they work more hours. Negative and significant coefficients on the distance from the farm household to the nearest city of at least 10,000 people (DIST10K) suggest that there is a reduction in labor supply as a result of distance to a population center where agglomeration is likely to occur, albeit small.

Changes in county-level industrial composition by in large are not significant in explaining off-farm labor supply in the specification presented in Table 5. A few exceptions are found with retail trade (RETGR), where a one percent increase in the number of employees per establishment translates into a 162 and 79 labor hour increase for operators and spouses, respectively. Real estate, rental, and leasing (RERLGR) coefficient was negative and significant in the spouse equation most likely due to the housing bubble in 2008. Growth in non government services was positive and significant in operator labor hours suggesting that a one percent increase in service employees per establishment would result in a 23 hour increase in operators' annual labor supply.

The sector results could be susceptible to spurious correlation. To control for that, a second specification was used where the changes in industrial composition were interacted with the off-farm jobs within the same sector. The remainder of the specification was not changed. As an example, this would help isolate the impact on off-farm labor supply that a decline in manufacturing has on an operator or spouse with an off-farm job in manufacturing. The results are reported in Table 6. The weighted system R^2 was 0.788. Since ARMS collapses some of the sectors when it asks about off-farm jobs, it is necessary in some cases to interact the job category with multiple measures of change in industrial composition. For instance, agriculture, forestry, fishing, hunting, and mining (AFFHMJOB) are one category, so it is interacted with AGGR and MINGR, which correspond to the growth in employment per establishment for the agricultural, forestry, fishing, and hunting and mining sectors.

The results in Table 6 are very similar to those presented in Table 5. Most coefficients only slightly differ in size and maintain the same level of statistical and economic significance. The exceptions are the coefficients on the off-farm job and industry interactions. A one percent decline in utilities (UTILGR) significantly decreases operator labor supply whose off-farm job is WWUTJOB by 248 hours. Likewise, a one percent decline in manufacturing (MANFGR) significantly decreases spouse labor supply whose off-farm job is MANFJOB by 288 hours. The largest positive changes for operators occur in retail trade (1,070 hours) and accommodation and food services (2,323 hours) from a one percent increase in employment per establishment for the respective sectors. The coefficients on WWUTJOB × TWGR and RPSJOB × AERGR indicate that spouses experience respective increases of 265 and 686 annual hours from a one percent increase in the transportation and arts, entertainment, and recreation sectors. The results also show that a decline in professional services (PSTGR) decreases operators and spouses labor supply whom work in FIRPJOB by a corresponding 430 and 142 annual hours.

The overall results indicate that farm household labor supply is responding to sector growth in retail trade, accommodation and food service sectors. Operators and spouses are potentially experiencing reductions in labor supply if their jobs are in finance, real estate, insurance, or professional and technical services. However, operators and spouses are impacted differently by changes in non-government services. One explanation is that operators are disproportionally in a part of the sector that is growing versus spouses in a part that is declining.

6. Conclusions

This analysis utilizes micro level data of farm households from the 2008 ARMS (USDA) and industrial activity in 2001 and 2008 from the non-public Quarterly Census of Employment and Wages (BLS) to measure how county-level changes in industrial composition impact off-farm labor decisions. The contribution from the present analysis to the literature is twofold: (1) a more rigorous conceptual treatment of local labor market conditions is developed, (2) using micro-level data on farm households and unsuppressed data on local industrial activity is used for the first time. A two-stage model is used to model 1) the joint labor participation decisions of farm operators and spouses by estimating a bivariate logit model and 2) the level of annual labor hours supplied by estimating a system of equations for the operator and spouse. Results indicate that labor participation decisions are jointly determined and are highly correlated with the size of the farm, with smaller farms being more likely to work off the farm. Labor supply is mostly impacted by the type of job and educational attainment. Growth in retail trade and service employment is associated with increases in labor supply for the operator and spouse.

One limitation of this study is information on previous off-farm labor decisions made by households. ARMS does not currently ask questions about previous labor decisions. Year to year the farm operations that are sampled change, making panel analysis difficult. Another limitation is related to industrial activity measures. There are at present no county level measures of output by sector. Sectors, such as manufacturing, could be increasing in real value of output per employee. It may be possible to construct these measures at the state level, but doing so would reduce the amount of variation in the sample once that industrial data where matched with the ARMS sample. Future analysis should take these issues into consideration.

References

Ahearn, M.C., H. El-Osta, and J. Dewbre. 2006."The Impact of Coupled and Decoupled Government Subsidies on Off-Farm Labor Participation of U.S. Farm Operators. *American Journal of Agricultural Economics* 88(2): 393-408.

El-Osta, H.S., A.K. Mishra, and M.C. Ahearn. 2004. "Labor Supply by Farm Operators Under 'Decoupled' Farm Program Payments." *Review of Economics of the Household* 2: 367-385.

El-Osta, H.S., A.K. Mishra, and M.J. Morehart. 2008. "Off-Farm Labor Participation Decisions of Married Farm Couples and the Role of Government Payments." *Review of Agricultural Economics* 30(2): 331-332.

Gumbel, E.J. 1961. "Bivariate Logistic Distributions." *Journal of the American Statistical Association* 56(4): 335-349.

Gunter, L. and K.T. McNamara. 1990. "The Impact of Local Labor Market Conditions on the Off-Farm Earnings of Farm Operators." *Southern Journal of Agricultural Economics* 22(1): 155-165.

Huffman, W.E. 1980. "Farm and Off-Farm Work Decisions: The Role of Human Capital." *The Review of Economics and Statistics* 62: 14-23.

Huffman, W.E. and M.D. Lange. 1989. "Off-Farm Work Decisions of Husbands and Wives: Joint Decision Making." *The Review of Economics and Statistics* 71(3): 471-480.

Imai, K., G. King, and O. Lau. 2007. *Zelig: Everyone's Statistical Software*. Available at http://gking.harvard.edu/zelig.

Imai, K., G. King, and O. Lau. 2008. "Toward A Common Framework for Statistical Analysis and Development." *Journal of Computational and Graphical Statistics* 17(4): 892-913.

Johnson, T.G. "Off-Farm Employment of Small-Farm Operators: A Strategy for Survival." *Strategy for Survival of Small Farmers: International Implications*. Thomas T. Williams, ed., Human Resources Development Center, Tuskegee Institute, 1985.

Lee, L.F. 1982. "Some Approaches to the Correction of Selectivity Bias." *The Review of Economic Studies* 49(3): 355-372.

Lee, L.F. 1983. "Generalized Econometric Models with Selectivity." *Econometrica* 51(2): 507-512.

Lumley, T. 2011. *Survey analysis in R*. Available at http://faculty.washington.edu/tlumley/survey/.

MacDonald, J. 2008. “The Economic Organization of U.S. Broiler Production.” U.S. Department of Agriculture, Economic Research Service. Economic Information Bulletin No. 38.

Mishra, A.K. and B.K. Goodwin. “Farm Income Variability and the Supply of Off-Farm Labor.” *Amer. J. Agr. Econ.*, 79(August 1997): 880-887.

National Research Council. 2007. “Understanding American Agriculture: Challenges for the Agricultural Resource Management Survey.” Committee on National Statistics. The National Academic Press. Available at http://www.nap.edu/catalog/11990.html.

Sumner, D.A. “The Off-Farm Labor Supply of Farmers.” *Amer. J. Agr. Econ.*, 64(3) (1982): 499-509.

U.S. Department of Agriculture, Economic Research Service, National Economic Branch. “Economic Indicators of the Farm Sector: Income and Balance Sheet Statistics, 1983.” December, 1984.

U.S. Department of Agriculture, Economic Research Service. 2005. *Measuring Rurality: 2004 County Typology Codes*. Available at http://www.ers.usda.gov/Briefing/Rurality/Typology/Methods/

U.S. Department of Agriculture, Economic Research Service. 2009. *Agricultural Resource Management Survey Briefing Room.* Washington DC. Available at http://www.ers.usda.gov/Briefing/ARMS/

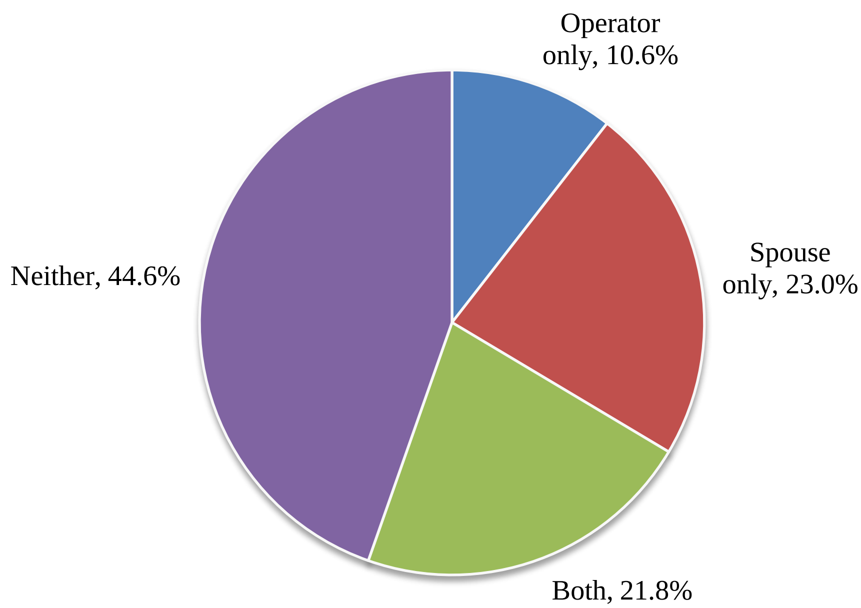

Figure 1. Household Off-Farm Labor Participation
Source: 2008 ARMS Costs and Returns Report

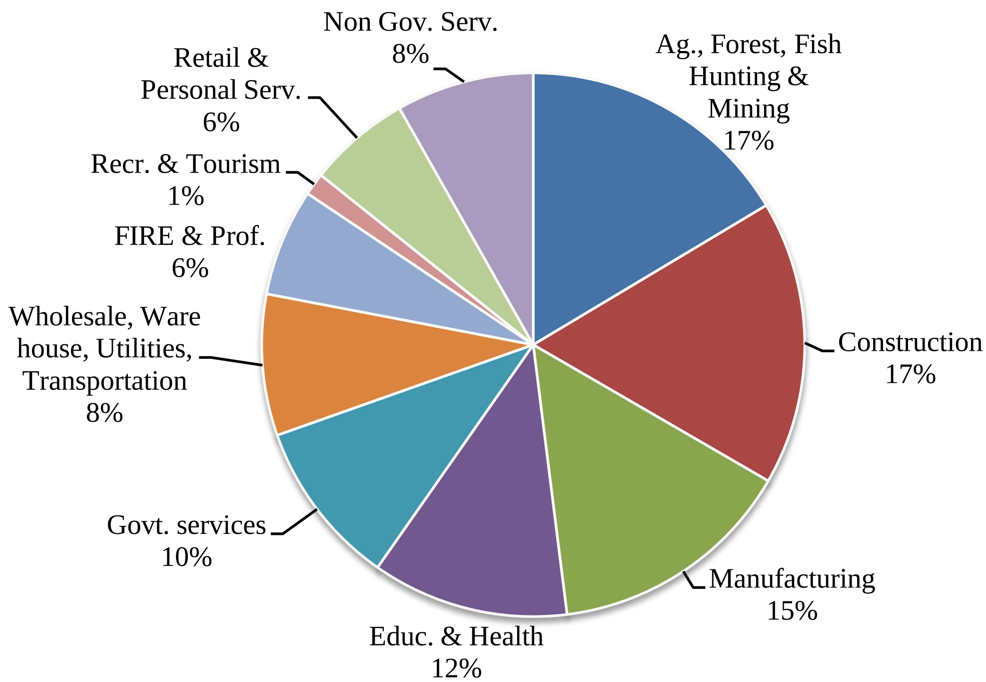

Figure 2. Industrial Sector of Operator Off-Farm Jobs
Source: 2008 ARMS Costs and Returns Report

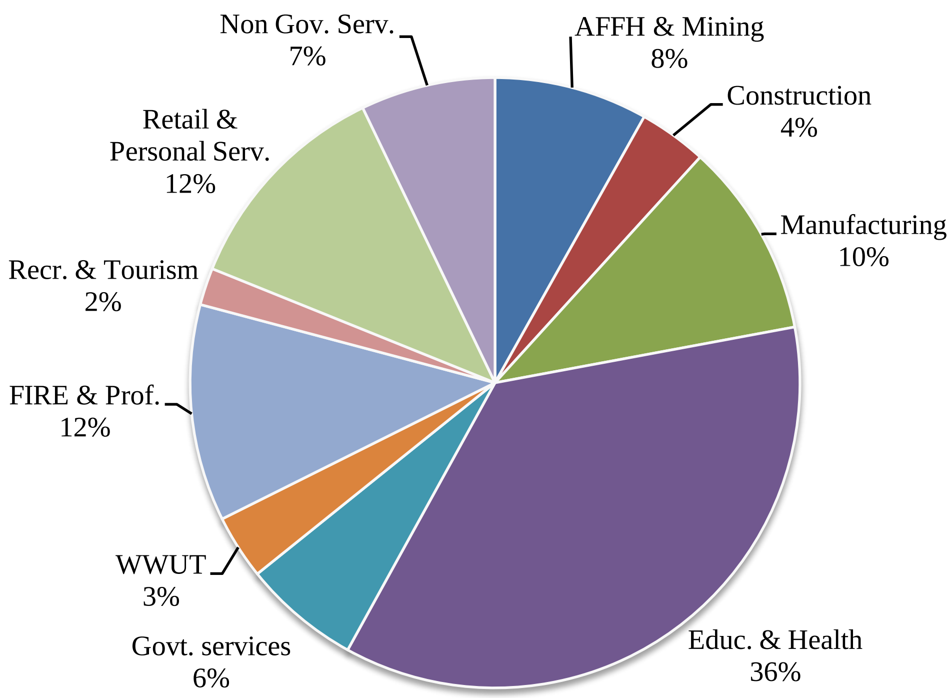

Figure 3. Industrial Sector of Spouse Off-Farm Jobs
Source: 2008 ARMS Costs and Returns Report

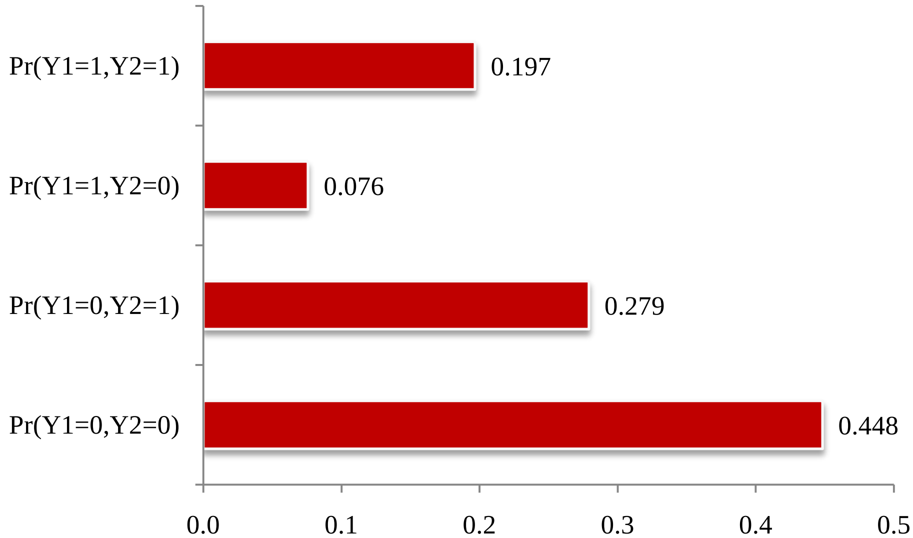

Figure 4. Predicted Probabilities of Off-Farm Work Participation

Table 1. 2008 Sector Shares of U.S. Private Earnings

	2008 Private Earnings	
Sector	Metro %	Non-Metro %
Agriculture, forestry, fishing, and hunting[1]	0.44%	2.54%
Mining	0.82%	3.93%
Utilities	0.91%	1.83%
Construction	6.70%	7.35%
Manufacturing	13.52%	23.91%
Wholesale trade	6.94%	4.95%
Retail trade	7.52%	10.30%
Transportation and warehousing	3.88%	4.91%
Information	4.26%	1.61%
Finance and insurance	10.02%	4.07%
Real estate and rental and leasing	1.78%	1.00%
Professional and technical services	11.32%	3.96%
Management of companies and enterprises	3.61%	1.37%
Administrative and waste services	4.97%	3.07%
Educational services	2.07%	1.31%
Health care and social assistance	12.50%	13.94%
Arts, entertainment, and recreation	1.30%	0.91%
Accommodation and food services	3.83%	4.65%
Other services, except public admin.	3.63%	4.37%

[1] Farm compensation was included. Source: Bureau of Economic Analysis, REIS.

Table 2. Weighted Means of ARMS Data

Variables	Definition	Operator	Spouse	Household
LFP	labor force participation (1/0)	0.49	0.51	
LSUPPLY	labor supply (annual hours)	982.30	985.46	
AGE	age	57.66	55.24	
HSDEGREE	high school degree (1/0)	0.36	0.37	
SCOLLEGE	some college (1/0)	0.29	0.27	
CDEGREE	college degree (1/0)	0.24	0.29	
JOBDIST	distance to off-farm job (miles)	9.74	7.94	
AFFHMJOB	agriculture, forestry, fishing, hunting, or mining job (1/0)	0.08	0.04	
CONSJOB	construction job (1/0)	0.07	0.02	
MANFJOB	manufacturing job (1/0)	0.06	0.05	
EHSJOB	education or health services job (1/0)	0.05	0.19	
GOVJOB	government services job (1/0)	0.04	0.04	
WWUTJOB	wholesale, warehouse, utilities, or transportation job (1/0)	0.03	0.02	
FIRPJOB	finance, insurance, real estate, or professional services job (1/0)	0.03	0.05	
RECJOB	recreation or tourism job (1/0)	0.005	0.01	
RPSJOB	retail or personal services job (1/0)	0.03	0.06	
NGSJOB	non-government services job (1/0)	0.05	0.03	
OFFNETW	off-farm net worth ($ thous)			239.06
NETFINC	net farm income ($ thous)			27.18
$OFFINC_{t-1}$	previous year's off-farm income ($ thous)			51.43
$SALES_{t-1}$	previous year's farm sales ($ thous)			83.28
DIVD	off-farm dividend income ($ thous)			1.39
INTERST	off-farm interest income ($ thous)			2.28
CHILD < 6	number of children under 6 yrs. old			0.14
CHILD > 6 ≤ 17	number of children between 6 to 17 yrs. old			0.43
CGFARM	cash grain farm (1/0)			0.15
HVCFARM	high value crop farm (1/0)			0.06
BCFARM	beef cattle farm (1/0)			0.35
HFARM	hog farm (1/0)			0.01
PFARM	poultry farm (1/0)			0.02
GLFARM	general livestock farm (1/0)			0.15
SFARM	small farm, sales < $15,000 (1/0)			0.57
MFARM	medium farm, $15,000 ≤ sales < $250,000 (1/0)			0.32
DIST10K	distance to nearest city of 10,000 people or more (miles)			22.40
FARMD	farming dependent county (1/0)			0.10
MINED	mining dependent county (1/0)			0.02
MANFD	manufacturing dependent county (1/0)			0.34
GOVTD	government dependent county (1/0)			0.10
SERVD	services dependent county (1/0)			0.09

Source: 2008 ARMS CRR; Calculated using delete-a-group jackknife procedure with 30 replicate weights. Sample size = 4,377; Population = 1,472,652

Table 3. Sample Means of County Industrial Data from QCEW

Label	Definition	Mean	Std Dev
AGGR	Growth in employees per establishment in ag., forestry, fishing, and hunting	0.214	6.251
MINGR	" mining	0.189	1.262
UTILGR	" utilities	0.074	0.746
CONSTGR	" construction	0.069	0.527
MANFGR	" manufacturing	-0.042	0.409
WTGR	" wholesale trade	0.053	0.427
RETGR	" retail trade	0.066	0.170
TWGR	" transportation and warehousing	0.231	1.474
INFGR	" information	-0.031	0.513
FIGR	" finance and insurance	-0.042	0.281
RERLGR	" real estate and rental and leasing	0.014	0.550
PSTGR	" professional, scientific, and technical services	0.111	1.047
MCEGR	" management of companies and enterprises	0.560	4.651
ASWRGR	" administrative and support and waste mgmt. and remediation services	0.256	1.650
EDUCGR	" educational services	0.172	1.267
HCSAGR	" health care and social assistance	0.004	0.277
AERGR	" arts, entertainment, and recreation	0.106	1.208
AFSGR	" accommodation and food services	0.038	0.257
ONGSGR	" other non-government services	0.074	0.523

Source: Quarterly Census of Employment and Wages, Bureau of Labor Statistics; N = 1,910 counties matched from the ARMS sample used in the present analysis.

Table 4. Bivariate Logistic Results of Labor Participation Decisions

	Operator Participation		Spouse Participation	
Variable	Beta	Std. Err	Beta	Std. Err
CONSTANT	-1.713***	0.159	-0.414***	0.124
$OFFINC_{t-1}$	0.012***	0.001	0.006***	0.001
$SALES_{t-1}$	-0.001***	0.0001	-0.0005***	0.0001
SFARM	1.413***	0.149	0.165	0.123
MFARM	0.702***	0.132	0.053	0.107
CGFARM	0.329***	0.122	0.432***	0.098
HVCFARM	-0.055	0.147	-0.441***	0.123
BCFARM	0.062	0.106	0.007	0.093
HFARM	0.208	0.265	0.396*	0.205
PFARM	0.464***	0.163	0.107	0.135
GLFARM	0.171	0.143	0.328**	0.130
FARMD	-0.232*	0.119	0.012	0.098
MINED	-0.298	0.251	-0.233	0.216
MANFD	-0.036	0.091	-0.007	0.079
GOVTD	-0.193	0.134	0.006	0.114
SERVD	0.048	0.139	-0.022	0.122
ψ	1.171***	0.077		
Pseudo R^2	0.099			
Log Likelihood	-4954.283			

N = 4,377; Estimates use full sample weights from ARMS. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively.

Table 5. Second Stage SUR Estimation of Labor Supply

	Operator Labor Hours		Spouse Labor Hours	
Variable	Beta	Std. Err	Beta	Std. Err
CONSTANT	915.778***	68.580	757.011***	59.479
OFFNETW	0.185***	0.021	0.079***	0.017
NETFINC	-0.221***	0.037	-0.086***	0.029
DIVD	-3.216***	0.956	-1.564**	0.765
INTERST	-1.386	0.952	-0.968	0.761
AGE	-9.105***	0.915	-5.331***	0.756
CHILD < 6	-69.386***	18.856	-0.305	15.189
CHILD > 6 ≤ 17	10.856	10.094	-23.609***	8.144
HSDEGREE	37.124	30.703	38.439	29.703
SCOLLEGE	107.534***	31.986	46.977	30.623
CDEGREE	90.504***	33.332	165.460***	30.930
AFFHMJOB	936.720***	38.308	868.064***	46.160
CONSJOB	1103.890***	41.217	1072.474***	61.997
MANFJOB	1327.940***	40.852	1148.820***	43.580
EHSJOB	1095.222***	46.198	830.744***	35.787
GOVJOB	1068.624***	47.024	947.805***	46.613
WWUTJOB	1269.596***	51.687	781.852***	61.354
FIRPJOB	1083.740***	52.568	1090.663***	43.209
RECJOB	1028.240***	121.246	1125.704***	72.279
RPSJOB	1140.908***	55.426	772.100***	42.984
NGSJOB	1289.099***	45.609	951.046***	49.994
JOBDIST	0.768***	0.193	0.457***	0.075
DIST10K	-1.830***	0.400	-0.519***	0.319
AGGR	-0.179	0.906	0.117	0.724
MINGR	-1.142	6.449	-4.970	5.176
UTILGR	-9.452	15.008	15.377	11.992
CONSTGR	23.667	18.000	-12.863	14.417
MANFGR	7.230	23.838	24.545	19.078
WTGR	36.714	23.313	0.251	18.646
RETGR	162.843***	55.345	79.243*	44.341
TWGR	4.233	6.172	5.289	4.940
INFGR	-9.840	18.180	12.316	14.586
FIGR	-37.357	33.605	10.478	26.765
RERLGR	-14.344	17.013	-34.210**	13.558
PSTGR	1.475	12.246	-15.061	9.763
MCEGR	3.745***	1.701	0.710	1.356
ASWRGR	5.287	3.942	-17.718***	3.133
EDUCGR	-3.239	6.286	-3.784	5.022
HCSAGR	57.818	34.028	-17.192	27.126
AERGR	-6.349	9.778	-7.137	7.798
AFSGR	40.270	39.142	43.133	31.331
NGSGR	23.733***	13.748	-5.022	10.975
OPERATOR IMR	-488.137***	18.225	19.334*	10.300
SPOUSE IMR	5.054	12.103	-598.060***	20.988

N = 4,777 ; System R^2 = 0.785; Estimates use full sample weights from ARMS. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively.

Table 6. Second Stage SUR Estimation of Job-Industry Impacts on Labor Supply

	Operator Labor Hours		Spouse Labor Hours	
Variable	Beta	Std. Err	Beta	Std. Err
CONSTANT	949.867***	67.793	766.397***	58.991
OFFNETW	0.194***	0.021	0.072***	0.017
NETFINC	-0.223***	0.036	-0.086***	0.029
DIVD	-3.047***	0.949	-1.502**	0.759
INTERST	-1.281	0.946	-1.265*	0.754
AGE	-9.360***	0.905	-5.482***	0.753
CHILD < 6	-66.715***	18.674	-2.536	15.065
CHILD > 6 ≤ 17	9.030	9.994	-23.067***	8.065
HSDEGREE	39.700	30.455	30.607	29.462
SCOLLEGE	104.085***	31.659	42.253	30.437
CDEGREE	81.793**	32.998	161.484***	30.709
AFFHMJOB	930.716***	38.039	890.815***	46.423
CONSJOB	1088.880***	40.994	1066.628***	62.654
MANFJOB	1326.645***	41.093	1132.841***	44.269
EHSJOB	1089.983***	46.609	840.399***	35.656
GOVJOB	1060.873***	46.582	951.686***	46.285
WWUTJOB	1281.030***	53.338	701.301***	72.173
FIRPJOB	1110.281***	521.720	1087.005***	43.808
RECJOB	1009.744***	120.673	1203.869***	74.313
RPSJOB	1092.290***	55.993	794.350***	44.563
NGSJOB	1189.734***	48.774	984.043***	52.211
JOBDIST	0.800***	0.191	0.456***	0.074
DIST10K	-1.651***	0.388	-0.498	0.310
AFFHMJOB × AGGR	-7.734	27.957	-0.774	23.529
AFFHMJOB × MINGR	13.008	16.834	152.436***	58.808
WWUTJOB × UTILGR	-248.059***	92.383	-14.845	170.777
CONSJOB × CONSTGR	47.769	45.327	60.155	41.860
MANFJOB × MANFGR	192.741	142.032	-288.821**	145.015
WWUTJOB × WTGR	-107.461	97.399	247.378	226.925
RPSJOB × RETGR	1070.927***	321.294	-268.923	227.784
WWUTJOB × TWGR	116.084	102.394	265.307***	98.345
NGSJOB × INFGR	-207.786***	52.625	-50.086	41.064
FIRPJOB × FIGR	153.068	195.830	-170.385	131.948
FIRPJOB × RERLGR	-119.667	88.734	-42.676	91.360
FIRPJOB × PSTGR	-430.202***	140.032	-142.404**	67.853
NGSJOB × ASWRGR	56.078	36.666	73.665**	34.898
EHSJOB × EDUCGR	-25.531	57.684	-2.234	8.764
EHSJOB × HCSAGR	-194.470	138.927	-49.778	61.353
RPSJOB × AERGR	308.156	280.957	686.384***	142.614
RPSJOB × AFSGR	2323.018***	690.554	395.247	385.067
NGSJOB × NGSGR	912.453***	160.337	-683.766***	97.882
OPERATOR IMR	-491.787***	18.019	18.844*	10.260
SPOUSE IMR	0.613	12.007	-594.877***	20.925

N = 4,777 ; System R^2 = 0.788; Estimates use full sample weights from ARMS. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively.