THE IMPACT OF AGING AND UNDEREMPLOYMENT ON INCOME DISPARITY AND PROFESSIONAL NETWORKS AND TECHNOLOGY ADOPTION

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
December, 2022

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UNDEREMPLOYMENT ON INCOME DISPARITY

AND PROFESSIONAL NETWORKS AND

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Date of Degree: DECEMBER, 2022

Title of Study: THE IMPACT OF AGING AND UNDEREMPLOYMENT ON INCOME DISPARITY AND PROFESSIONAL NETWORKS AND TECHNOLOGY ADOPTION

Major Field: AGRICULTURAL ECONOMICS

Abstract: The first paper examines how aging and underemployment affect household income and household income disparity between agricultural and non-agricultural sectors. A three-step regression analysis was conducted to estimate the aging and underemployment effects on household income and the income disparity between agricultural and non-agricultural households. First, we estimate aging and underemployment effects on household income from all households using a year fixed-effect longitudinal model. Second, our study investigates whether the marginal effect of aging and underemployment on household income differs between agricultural and non-agricultural sectors. Finally, we simulate using the estimated model to illustrate how government policies could help reduce the income disparity. Results from policy simulations suggest that the implementation of proper government policies to address aging and underemployment problems in agricultural households could significantly reduce the income disparity between agricultural and non-agricultural sectors.

The second paper examines the effect of information-intensive social networking on technology adoption decisions using 231 turfgrass professionals' Twitter accounts data. To address the reflection problem in social networking analysis, we account for the networking heterogeneity that confounds in social networking process. The confounding effects are decomposed into individual- and group-level similarities, herd behavior, and clustering effects. To account for network structure-based heterogeneities (herd behavior and clustering effects), we employ the spatial autoregressive probit model that directly incorporates network structures into the model as a matrix system (i.e., adjacency matrix). A Bayesian estimation method is applied in our study to address the convergence problem that arises due to the complexity of model specifications. Empirical results show positive and significant information-intensive networking effect, observation-based networking effect (herd behavior) effect, and group-level similarity effects on turfgrass professionals' decision-making process. The results also indicate that the information-intensive networking effect is larger than the observation-based networking effect. The interaction term between group-specific effects and observation-based networking effects explains the networking effect could significantly differ by each professional group. These results suggest policy and marketing strategy for new technology adoption should target to promote new technologies to individuals who are actively exchanging information through networking, while considering the networking behavior by groups to which the individuals belong.

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CHAPTER I

IMPACT OF AGING AND UNDEREMPLOYMENT ON INCOME DISPARITY BETWEEN AGRICULTURAL AND NON-AGRICULTURAL HOUSEHOLDS

Abstract

This paper examines how aging and underemployment affect household income and income disparity between agricultural and non-agricultural sectors. Our study uses household panel data from South Korea for the period 2009–2016, which includes, on average, 6721 representative households each year. A three-step regression analysis was conducted to estimate the aging and underemployment effects on household income and the income disparity between agricultural and non-agricultural households. First, we estimate aging and underemployment effects on household income from all households using a year fixed-effect longitudinal model. Second, our study investigates whether the marginal effect of aging and underemployment on household income differs between agricultural and non-agricultural sectors. Finally, we simulate using the estimated model to illustrate how government policies could help reduce the income disparity. Our results show that aging and underemployment affect household income negatively overall. The negative marginal effect of the two factors was greater in the agricultural sector than in the non-agricultural sector. Results from policy simulations suggest that the implementation of proper government policies to address aging and underemployment problems in agricultural households could significantly reduce the income disparity between agricultural and non-agricultural sectors.

Keywords: income disparity; agricultural and non-agricultural households; underemployment; aging

1. Introduction

The income disparity between agricultural and non-agricultural households has been increasing in many countries. The extreme income gap between these two sectors can increase social costs in the long-run, such as rising poverty rates, deteriorating labor quality in low-income sectors, and impeding economic growth. (Stiglitz 2012; Dabla-Norris et al. 2015; Yao and Jiang 2021). Studies in the labor economics literature often link population aging and underemployment to low labor participation and productivity, fewer savings, and greater financial pressure on households (Bloom et al. 2010). Population aging in agricultural households becomes more prevalent than in non-agricultural households as better-educated, wealthier, and younger-generation workers tend to shun low-paying manual jobs in agriculture (Kim 2009; Constant 2014). Underemployment, which was considered an urban-specific issue in the past, is also a serious problem among agricultural households because of surplus labor, particularly in developing countries (Golub and Hayat 2015). Underemployment is the condition where workers' working hours are less than full-time or positions are inadequate concerning workers' training or economic needs (Friedland and Price 2003). Therefore, the term underemployed workers refers to relatively less productive workers. Even in many developed countries, new technology adoption and structural change result in a greater extent of underemployment in the agricultural labor market (e.g., due to the adoption of newly developed farm equipment, farmers need fewer workers to operate their farms; yet all family workers are still classified as employed farm workers) (Errington 1988). The underemployed agricultural household members (who are likely less productive family workers) decrease overall household productivity and per capita household income.

Many studies in labor economics point out that aging and underemployment are major factors in determining the wage, well-being, and productivity level of workers (e.g., Friedland and Price 2003; Bell and Blanchflower 2018b; Seok et al. 2018; Du et al. 2019). A few studies specifically argue that aging and underemployment become more prevalent and problematic in the agricultural sector than non-agricultural sectors, which could be two major factors affecting the income disparity between agricultural and non-agricultural households. For example, Lee et al. (2013) show that the Korea Gini index increased from 0.330 to 0.342 between 2006 and 2011 and that population aging has a significant effect on the inequality index. Bell and Blanchflower (2018b, 2018a) find that for the post-Great Depression period in the U.K. and U.S., underemployment had a more significant role in wages than unemployment for all industries. In addition, Loughrey and Hennessy (2014) show that the underemployment rate increased by 10% from 2002 to 2010 in the Irish agricultural sector and that the change in the underemployment rate was significantly correlated with a change in agricultural household income. Previous studies provide ample evidence that aging and underemployment play a significant role in the economic condition of agricultural and non-agricultural households (e.g., Friedland and Price 2003; Loughrey and Hennessy 2014; Golub and Hayat 2015; Guo et al. 2015; Bell and Blanchflower 2018a; Seok et al. 2018; Du et al. 2019). However, little has been done in the literature to empirically examine the effects of aging and underemployment on household income and income disparity between agricultural and non-agricultural sectors.

The important question we seek to answer in this study is: are aging and underemployment major factors of household income and income disparity between agricultural and non-agricultural households? If they are, what would be the appropriate policy direction to address this problem? Although earlier studies in the literature provide ample evidence that aging and underemployment play a significant role in the economic condition of agricultural and non-agricultural households, it has done little to empirically answer the aforementioned question. To answer the question, we first estimate three longitudinal models for all households, agricultural households, and non-agricultural households. Then, to examine the relative importance of aging and underemployment in determining household income and income disparity between the two sectors, the marginal effects of aging and underemployment on household income are calculated in elasticity form using estimates from the three longitudinal regressions. Third, income disparity is estimated using both longitudinal and cross-sectional models. Finally, the estimated disparity is simulated under five scenarios of reduced aging and underemployment to see if government policies to reduce aging and the underemployment problem in agriculture could mitigate the current income disparity between agricultural and non-agricultural households. Previous studies also report that aging and employment status, including underemployment, are likely endogenous (Ham 1982; Jäckle and Himmler 2010; Aiyar and Ebeke 2016). Therefore, we use a fixed-effect longitudinal model with a Gaussian copula correction procedure to control the endogeneity and unobservable effects (e.g., change in government policy).

Our results show that aging and underemployment negatively affect household income overall. The negative marginal effect of the two factors was greater in the agricultural sector than in the non-agricultural sector, particularly when the endogeneity of aging and employment status variables are controlled. Simulation results suggest that decreasing aging and underemployment from the agricultural sector would significantly reduce the income gap between the two sectors. Our findings could be applicable to various agricultural policies to mitigate income disparity between agricultural and non-agricultural households in many countries undergoing aging and underemployment problems.

2. Literature Review

In the past, agriculture was considered the backbone of the overall economy in many countries. However, structural changes due to technological advancements, globalization, and environmental constraints have led to a deterioration of the social and economic status of agriculture (Byerlee et al.

2009). One important issue caused by the structural changes is the increased income disparity between the agricultural and non-agricultural sectors. Increased income disparity has generated both economic and social problems regardless of countries' level of economic development such as a decrease in quality of economic growth factors (e.g., labor) (Byerlee et al. 2009; Ravallion and Chen 2007). Previous studies claim that the "urban bias" caused by the rapid labor transfer from agriculture to non-agriculture has resulted in negative effects of structural changes such as an increasingly aging population and a high underemployment rate in the agricultural sector (Staatz and Eicher 1998).

Aging refers to the increasing ratio of older adults (typically aged over 65) among the population. Clark et al. (Clark et al. 1978) and Pammolli et al. (2012) argue that population aging could burden the whole economy by increasing support costs for older adults (e.g., pension and medical expenses). Furthermore, the increased social expenditure required by an aging population may increase income inequality at the country (Lee et al. 2013) or regional (Zhong 2011) level.

Cymbranowicz (2016) points out that underemployment, which is also considered "incomplete employment," has become one of the biggest problems in the labor market since the great recession drastically increased the underemployment rate in most countries. In the U.K., for example, the underemployment rate exceeded the unemployment rate during the great recession (Heyes et al. 2017) and now, underemployment has a greater influence on wage income than unemployment (Bell and Blanchflower 2018b). Underemployment generally refers to the situation where job openings are filled (or the employed workers are replaced) with workers who (1) earn a lower wage than the average wage of half of the population, (2) are underutilized, or (3) work less regardless of their willingness or capability to work. This "incomplete employment" can cause a decrease in overall wage income.

Many earlier studies find that income is highly correlated with aging and underemployment rate. In these studies, factors affecting agricultural household income include household economic conditions, conditions of farmland, regional economic environments, and farm policies (Yang 1999; Dagum and Slottje 2000; Benayas et al. 2007; Sicular et al. 2007; Qian and Smyth 2008; Fisher et al. 2010; Imai and Malaeb 2016; Zhang and Posso 2019). However, only a few studies discuss the potential impact of aging and underemployment on agricultural households. Some studies consider the age of farm operators or the number of laborers (Zhang et al. 2014; Su et al. 2018) as important factors of agricultural household productivity. Nonetheless, household-level aging or employment status (e.g., underemployment) has rarely been examined to study agricultural income and income disparity in the literature.

Seok et al. (2018) and Boockmann et al. (2012) claim that the aging agricultural workforce is likely to decrease the productivity level and labor participation rate in the agricultural sector. Spěšná et al. (2009) also find that low wages in the agricultural sector serve as a barrier for young people to participate in the agricultural workforce and as a result, increase the proportion of aged workers in agriculture over time. The increased population of aged workers in agriculture could be closely related to the situation where most of the elderly agricultural workforce lives below the poverty line in some countries (Masud and Haron 2014).

A few studies argue that household income is harmed by underemployment if workers unintentionally work less (Wilkins 2007), if a lack of infrastructure exists (Slack et al. 2018), or if workers are underemployed due to the economic crisis such as the great recession (Bell and Blanchflower 2018b). As these problems become severe in the agricultural sector, underemployment is considered one of the determining factors of the low-income problem in agriculture (Amuedo-Dorantes 2000; Dethier and Effenberger 2012; Whelan et al. 2016).

Although many studies point out that aging and underemployment are important factors to determine income, the effect of aging and underemployment on agricultural income has been rarely studied in the literature. A primary reason for the lack of studies on the underemployment effect on agricultural incomes may be due to the fact that underemployment is mostly hidden or neglected in the agricultural sector. In many countries, agricultural labor data are collected mostly through self-reported surveys, and many farm household individuals tend to report themselves as either farm or family workers whether or not they contribute to farm production. Besides, unlike the non-agricultural sector, the agricultural sector lacks information about workers' productivity (e.g., annual performance evaluation), particularly about family workers' contribution to farm productivity. It is not likely that the head of the agricultural household (likely the farm operator) provides an objective evaluation of family workers' contributions to farm production. Therefore, underemployment is less detectable in the agricultural sector than in the non-agricultural sector. The hidden underemployment problem may have been gradually increased and may have affected household income negatively in the agricultural sector (Glauber 2013; Loughrey and Hennessy 2013, 2014). To address the problem, previous studies generally use three underemployment criteria such as working hours, income level, and skill level-based measures (Friedland and Price 2003; Heyes et al. 2017; Hussmanns 2007).

3. Methodology

Our study estimates a household income model to examine the effect of aging and underemployment on household income. The household income model is estimated over an individual income model because the household model is able to account for interrelationships of aging and underemployment effects of individuals in the same household. For example, for a household with an employed husband and an underemployed wife, the husband's employment status could be affected by his wife's employment status (e.g., the husband may work more hours to cover the decreased household income due to his wife's underemployment or unemployment). A cross-sectional approach is common in income inequality studies at the country or regional level (Ross et al. 2005). However, a cross-sectional analysis could lead to biased estimates unless the data is collected under a specific experimental design to account for the household or year-specific effects (Du et al. 2019). Therefore, a longitudinal model is used with year-specific fixed-effect terms for our study. The longitudinal model allows for more variability and efficiency than the time-series or cross-sectional model (Greene 2011). The fixed-effect model accounts for the heterogeneity caused by unobservable household-specific or time-specific factors (Greene 2011). For example, household income distribution could hinge on government policy (Sicular et al. 2017), and the policy effect may differ by each unit in the model (Clarke et al. 2015). The fixed-effect model accounts for the unobservable and non-random policy effects over time with year-specific effect terms (Wooldridge 2016).

Consider the following longitudinal regression model,

$$y_{it} = \alpha_t + v_i + x_{it}\beta + e_{it}, \tag{1}$$

where y_{it} is the per capita income of household i in year t, α_t is a year-specific effect, v_i is a household effect, x_{it} represents covariates, and e_{it} is an error term. In Equation (1), the parameter vector, β, represents covariates' marginal effect on household i's income. The covariates, x_{it}, include the ratio of aged individuals (aged over 65) for each household, unemployment ratio, underemployment ratio, out of the labor force ratio, financial asset value, real estate value, and household head's education level.

Equation (1) can be estimated by either a random effect or fixed-effect model. The random-effect model would be better if any correlation between unobservable individual effects and covariates can be avoided (Clarke et al. 2015; Wooldridge 2016). If the individual random-effect term and covariates are correlated, the estimator would be inconsistent with the random-effect model (Greene 2011; Wooldridge 2016). However, unobserved individual characteristics such as unobserved time-invariant heterogeneity (e.g., innate intelligence and other genetic traits) could be potentially correlated with covariates such as observed individuals' socioeconomic status variables (e.g., employment status, education, aging, asset values) (Kamar et al. 2019). The Hausman test rejects the random effect model in favor of a fixed-effect model in our study at the 1% level (Chi-square (χ^2) statistic = 682.92, df = 12, p-value < 0.001). Therefore, the fixed-effect model is estimated with a year-specific term for Equation (1). The year-specific term, α_t (i.e., year dummies), represents unobserved annual variations on per capita household income caused by, for example, macroeconomic policies over time (Gösser and Moshgbar 2020).

To measure the aging effect at the household level, we use the ratio of household members aged 65 years or over to the total household members (Sicular et al. 2007). If the ratio is the same or greater than 0.5, the household is considered aged (OECD 2017). Previous studies claim that labor statistics reported in the literature tend to under-measure unemployment, and alternative measures need to be developed (Bardhan 1978; Poterba and Summers 1984). Feng and Hu (2013) argue that frequently reported unemployment statistics (individuals who are unemployed and actively seeking employment) could have been under-measured due to the unemployed who are barely willing to find work (Carrillo-Tudela et al. 2021). For instance, discouraged workers (individuals who are unemployed and willing to be employed but not actively seeking employment) are neither unemployed nor out of the labor force by the bureau of labor statistics' criteria (Bureau of Labor Statistics 2021). However, the discouraged workers may have the same impact on household income level as unemployed workers do. Feng et al. (2018) suggest that the unemployment measure, the U-6 measure (that includes conventional unemployment, discouraged workers, and workers who work less than 36 h per week) from the United States Bureau of Labor Statistics (2021) is more robust than conventional unemployment because it includes fewer measurement errors. Therefore, we use the U-6 measure as unemployment in our study. As stated earlier, three types of underemployment have been considered in the literature: working hour-, income-, and skill-based underemployment (Friedland and Price 2003; Loughrey and Hennessy 2014; Hussmanns 2007). However, a few studies suggest that people who work less than their desired working hours (less than 36 h per week) need be a part of unemployment (Mitchell and Carlson 2000; Haugen 2009). Moreover, the studies indicate that economic consequences between unemployment and underemployment differ significantly (Wilkins 2007). Therefore, we consider income- and skill-based underemployment measures in this study. Each household member is classified as "income-based underemployed" if the household income is less than 50% of the median population income (Friedland and Price 2003). If a household member finds the task (or position) not suited to her skill or education level and is not classified as "income-based underemployment," the member is considered "skill-based underemployment." If a household member meets at least one of these two definitions, this person is considered underemployed. Out of the labor force may seem indifferent to unemployment in terms of financial contribution to households. However, Flinn and Heckman (1983) show that unemployment and out of the labor force are strictly distinguishable in terms of economic behavior. Asset values also contribute to household income, especially when considering the income disparity between sectors at the household level (Sicular et al. 2017). Education level has been also correlated to an individual's income level and income inequality in the economics literature due to its impact on human capital and economic outcomes (Gallie et al. 2003; Zeng and Wang 2014; Burgess 2016).

Many studies suggest that population aging has been a growing tendency that greatly affects the employment status of aged individuals (Johnson 2012). Under this environment, aged workers are more likely to be at risk of underemployment, especially in developed countries (Virick 2011). Findings from these studies suggest a high correlation between aging and underemployment. To incorporate these findings in our analysis, interaction terms between aging and the variables representing employment status (i.e., unemployment, underemployment, and out of labor force) as a part of the covariates x_{it} in equation (1).

Equation (1) is estimated with three samples: all households, agricultural households, and non-agricultural households. The conventional definition of an agricultural household is a household in which all members make a living through farming. Nonetheless, since some farmers can work for management positions in agricultural firms rather than for farm production, the number of agricultural households in the traditional sense has been declining (Kim 1993). Therefore, a new definition of agricultural households has been developed in narrow and broad senses (Karlsson and Berkeley 2005). The narrow meaning of agricultural household is the household in which the main income source is farming (Briggeman et al. 2007). The broad meaning of an agricultural household is the household that the household head (OECD 2020) or any household member (OECD 2001) participates in the agricultural activity to generate income. The broad definition of an agricultural household is used in this study.

Using estimates from Equation (1), the income disparity between agricultural and non-agricultural sectors, $\Delta\hat{y}$, is calculated as:

$$\Delta\hat{y} = \hat{y}_{it}^{NAC} - \hat{y}_{it}^{AC}, \tag{2}$$

where $\hat{y}_{it}^{NAC}$ and $\hat{y}_{it}^{AC}$ are the predicted household per capita income for non-agricultural and agricultural households, respectively. Then, Equation (2) is simulated with different scenarios of government policy on aging and underemployment. The purpose of the simulation is to show the effect of government policies, effectively lowering the extent of aging and underemployment in the agricultural sector, on income disparity. The simulated income disparity between sectors is represented by:

$$\Delta\hat{y}_s = E(y_{it}^{NAC}) - \left(E(y_{it}^{AC}) \middle| C_{it}^{AC} * \left(1 - \frac{\theta_s}{100}\right)\right), \tag{3}$$

where $\Delta\hat{y}_s$ is the income disparity between sectors estimated with a range of scenarios of aging and underemployment levels, $E(y_{it}^{NAC})$ and $E(y_{it}^{AC})$ refer to non-agricultural and agricultural sector's expected income, respectively, C_{it}^{AC} represents the target covariate vector (i.e., aging and underemployment variables) for simulation, and θ_s is the shock (i.e., reduction rate of aging and underemployment ratio in the agricultural sector by policy) on target covariates in scenario *s*.

Each year, five percent of our household panel was replaced to maintain the sample representativeness and avoid attrition (Hausman and Wise 1979). As a result, like many other micro panel datasets in general, our panel data is unbalanced. In this case, the degree of freedom to compute variance estimates is no longer the number of regressors multiplied by the number of observations because of missing observations. Hence, with the conventional approach, the variance estimate would be biased with an unbalanced panel dataset. A few studies suggest ways to address this issue (Fuller and Batteses (1974); Wansbeek and Kapteyn (1989)). Our study uses Wansbeek and Kapteyn (1989)'s method because it allows year fixed-effect terms to account for unobservable policy effects, but no dynamics nor simultaneity need to be considered to generalize the variance matrix.

Previous studies point out that aging and employment status could cause endogeneity problems, especially for measures from self-reported surveys. For instance, aging could affect household member's work performance and therefore the employment status of each household member (Garibaldi and Wasmer 2005; Lindeboom and Kerkhofs 2009). Therefore, the aging could be a main determinant of each employment status (underemployment, unemployment, and out of labor force), which suggests the potential endogeneity issue in Equation (1). Results from the Hausman specification test show that all aging and employment variables (age over 65 ratio, underemployment ratio, unemployment ratio, and out of the labor force ratio) in our study fail to reject the null of consistent estimators with no endogeneity. To address the endogeneity problem of these variables, we use the Gaussian copula correction procedure (Park and Gupta 2012). The Gaussian copula correction approach simultaneously accounts for all correlations between the endogenous variables and error terms through the Gaussian copula, assuming a joint normal distribution between these correlated variables.

4. Data

Our study uses household panel data collected by the Korea Labor Institute (KLI) in Korea from 2009 to 2016. Each year, KLI surveys, on average, 6721 representative households living in rural and urban areas. The KLI panel data include socioeconomic characteristics such as age, education, occupation, employment status, asset value, and income level. The KLI survey classifies households as agricultural households if they meet one or more of the following conditions: (a) a total annual agricultural or forestry turnover of $900 or more, (b) a total livestock value on a farm of over $500, (c) total farmland used for farm production over 0.245 acres, (d) a household owns at least 300 acres for a forestry business in the last five years, and/or (e) a household has been in the agriculture or forestry business for more than one year (Kim et al. 2017). The KLI classification is consistent with the broad definition of the agricultural household discussed in the previous section.

The KLI data are well suited for our research objectives due to the following three reasons. First, aging and underemployment became significant factors affecting people's quality of life and economic conditions in Korea since the financial crisis in 1997 (Kim and Park 2006; Roh et al. 2014; Yoo et al. 2016). Second, findings from Korea could be equally applied to other countries, particularly those that are in the early stage of becoming developed countries and undergo similar aging and underemployment problems. Finally, unlike other countries, the underemployment problem has not been aggressively addressed by the Korean government[1], which implies we have relatively few externalities to consider in assessing the causal effect between income and underemployment.

Unlike many earlier studies, we do not include race, ethnicity, region, occupation, and industry type in our household income per capita equation. Race and ethnicity are not considered because the Korean population is highly homogeneous, with less than 5% of non-Korean ethnic

[1] For example, since 2021, a subsidy program for underemployment has been implemented for the first time in Korea (Ministry of Employment and Labor 2021).

groups (South Korea Ministry of Justice 2019). Region is not included because the regional variation of income in small and rich countries (like Korea) is less significant than in large and poor countries (Streeten 1993; Felsenstein and Portnov 2005). Finally, occupation and industry type are not included because our agricultural and non-agricultural sector classifications have already accounted for the majority of variations in occupation and industry.

Table 1.1 shows descriptive statistics of key variables used in this study for the years 2009, 2012, and 2015. Given the limited space available, the descriptive statistics are presented only for the selected three years to show how the key variables change over time (a full description of data for all years used in this study is available from the authors upon request). The average household per capita income gradually increases over time in both sectors. However, the average household per capita income from the non-agricultural sector is always higher than per capita income from the agricultural sector, while significant income differences between sectors are continuously observed over time. The age over 65 ratio (AR) shows an increasing aging trend overall and a significantly more aged population in the agricultural sector than in the non-agricultural sector. In 2015, for instance, the AR from the agricultural sector was 53.32%, while the same ratio from the non-agricultural sector was only 27.10%. This skewed age structure could significantly affect the income disparity between agricultural and non-agricultural sectors (Gavrilov and Heuveline 2003; Weil 2006). The underemployment ratio (UN), calculated using skill level- and income-based criteria (Friedland and Price 2003; Wilkins 2007), shows an overall decreasing trend. From 2009 to 2015, it is observed that UN from full sample decreased from 13.48% to 10.26%. It is also observed that UNs in the agricultural sector are significantly higher than those in the non-agricultural sector. For example, UNs in 2015 were 17.62% and 9.81% in the agricultural and non-agricultural sectors, respectively. The statistics clearly show that underemployment is more prevalent in the agricultural sector than in the non-agricultural sector. The prevalence of underemployment in the agricultural sector could be one of the major factors of low agricultural income because the under-employed labor force provides a significantly lower economic contribution than the employed labor force (Warren 2015). The unemployment ratio (UE) overall shows an increasing trend across time: from 2009 to 2015, UE from the full sample increased from 8.29% to 9.01%. In the agricultural sector, UE increased from 9.47% to 17.69%. It is noted that UE increases faster in the agricultural sector than in the non-agricultural sector. The out of the labor force ratio (OL) increases over time in both sectors and is significantly larger in the non-agricultural sector for all years: from 2009 to 2015, OL increased from 34.59% to 40.59% in the full sample. Two types of household assets, financial and real estate assets, are considered in our study. Relevant statistics show that households in both sectors invest more in real estate than in financial assets. However, agricultural households invest more in real estate assets than non-agricultural households do. For instance, in 2015, the ratio of real estate assets to total assets in the agricultural sector was 82.6%, while the same ratio was 53.8% in the non-agricultural sector. The level of household head's education differs significantly, particularly in the "More than college" level. In 2015, for example, about 40% of non-agricultural household heads had at least a college degree, while almost half of agricultural household heads did not even finish middle school. The significant difference in a household head's education level could also affect the income disparity between the two sectors.

5. Results

5.1. Estimation Results from Longitudinal Regressions

Table 1.2 reports results from longitudinal data analysis. The dependent variable is the annual per capita household income in one million Korean won (approximately $882.41 based on $1 = 1133.26 Korean Won). The joint normal distribution assumption between the endogenous variables (AR, UN, UE, and OL) and error term makes it difficult to derive asymptotic standard errors of estimates.

Therefore, all standard errors are computed using a bootstrapping procedure (Park and Gupta 2012; Gui et al. 2019).

Overall, results are similar across the three different samples. Most estimates are statistically significant, at least at the 10% level. Year effects (from Year 2010 to 2016) indicate a significantly increasing time trend of household per capita income from all regressions. In addition, the age over 65 ratio (AR), underemployment ratio (UN), unemployment ratio (UE), and out of labor force ratio (OL) negatively affect income when only direct effects are assessed without considering the interaction terms. Asset values (financial and real estate) and a household head's education level show a positive correlation with household income, as expected.

Table 1.3 reports the significant test for coefficient difference between agricultural and non-agricultural households based on Table 1.2 results. Overall, the test result shows significant differences in coefficients of aging ratio (AR), unemployment ratio (UE), and an interaction term between aging and out of labor force ratio (AR*OL). This result suggests that the income disparity is due to aging but may not be the role of underemployment. However, since we employ the interaction terms between aging ratio and employment statuses, comparing the difference in marginal effect would be more appropriate to compare the impact of aging and employment status between sectors.

To compare the importance of aging and household members' employment status in determining household income with the consideration of both direct and indirect (interaction) effects, we calculated the elasticities of household income (HI) with respect to each of AR, UN, UE, and OL. In general, the log-log functional form would be plausible to obtain elasticities measuring the unit-free marginal effects (Kilpatrick 1973; Wellington 1991; Espey et al. 1997). However, the double log functional form could not be used in our study because our ratio variables (e.g., aging ratio, underemployment ratio, etc.) contain a large number of observations with zero values. These observations would have been excluded if we used the double-log functional form. Therefore, considering our data status, the elasticity calculation based on linear model estimates would be preferable.

For example, the elasticity of HI with respect to AR is calculated as:

$$\eta_{HI,AR} = \frac{\partial HI_{it}}{\partial AR_{it}} \frac{\overline{AR}_{it}}{\overline{HI}_{it}} = \left(\hat{\beta}_1 + \hat{\beta}_5 \overline{UN}_{it} + \hat{\beta}_6 \overline{UE}_{it} + \hat{\beta}_7 \overline{OL}_{it}\right) \frac{\overline{AR}_{it}}{\overline{HI}_{it}}, \tag{4}$$

where $\overline{HI}_{it}$, $\overline{AR}_{it}$, $\overline{UE}_{it}$, $\overline{UN}_{it}$, and $\overline{OL}_{it}$ are mean values of HI, AR, UN, UE, and OL, respectively. Calculated elasticities via Equation (4) are reported in Table 1.4.

Among the variables considered in Table 1.4, AR and UN are the top two factors that determine agricultural household income, while UN and OL are the top two determining factors of household income in full and non-agricultural samples. Effects from AR and UN are greater in the agricultural sector than in the non-agricultural sector. Stallmann et al. (1999) and Seok et al. (2018) also find that the agricultural sector has higher proportions of elderly laborers, and its negative economic outcome is greater in the agricultural sector than in the non-agricultural sector.

Table 1.5 shows income differences between the agricultural and non-agricultural sectors (i.e., non-agricultural income minus agricultural income) and their statistical significance that are estimated from longitudinal and cross-sectional models. Overall, agricultural income is considerably lower than non-agricultural income. All mean differences are calculated using predicted income. The difference in annual household income per capita throughout the study period is 658,000 Korean Won (\$580.63) from the longitudinal model, while the differences are 354,000, 930,000, and 752,000 Korean Won (\$312.37, \$820.64, and \$663.5) in the year 2009, 2012, and 2015, respectively. All differences are statistically significant except the difference in 2009 from the cross-sectional model.

5.2. Simulation Results

Tables 1.4 and 1.5 indicate that there exists a great degree of income disparity between agriculture and non-agriculture, and aging labor force and underemployment in agriculture are major contributing factors. One way to reduce this income disparity might be to implement government policies targeting lower aging and underemployment ratios in the agricultural sector. Such efforts include promoting employment opportunities (particularly for young adults) and fostering business investments in agriculture through various tax policies and investment subsidies. To show the effects of these efforts, Equation (3), with estimates from the longitudinal model, is simulated under five scenarios of reduced aging and underemployment ratios in agriculture. The five scenarios include a 2%, 4%, 6%, 8%, and 10% decrease of AR, UN, and both AR and UN, and simulation results are reported in Table 1.6. Results suggest that government policies reducing AR and UN could be effective in reducing the income disparity.

For example, when AR decreases by 2% in the agricultural sector (Scenario 1), the income disparity decreases from 0.658 to 0.604, which is a 8.21% decrease in the income difference. With a 10% decrease of UN (Scenario 5), the disparity decreases by 42.71%. When both AR and UN are reduced by 10% (Scenario 5), agricultural income becomes higher than non-agricultural income. Finally, as expected from Table 1.4, AR decreasing policy appears to be more effective than UN reducing policy under all scenarios.

6. Discussions and Conclusions

Our study investigates the role of aging and underemployment on household income and income disparity between agricultural and non-agricultural sectors. We measure aging as the ratio of the number of 65 years or older people in the household to the total number of household members

(Sicular et al. 2007). We also measure the status of household underemployment as the ratio of the number of underemployed people in the household to the total number of household members. Underemployment is defined using skill and income-level criteria (Friedland and Price 2003; Heyes et al. 2017), which helps clarify underemployment, especially in the agricultural sector (Loughrey and Hennessy 2013, 2014).

This study applied a longitudinal model to eight-year longitudinal data to estimate the causal effect of aging and underemployment on household income per capita. We used the Gaussian copula correction method to address the potential endogeneity problem of aging and underemployment (along with unemployment and out of the labor force). Our estimation results show negative and significant coefficients of aging and underemployment variables from both agricultural and non-agricultural household samples. Marginal effects of aging and employment status (considering both direct and indirect effects), i.e., elasticities of household income with respect to each of the aging and employment status variables, indicate that aging and underemployment significantly lower household income in both sectors, but the negative effect of aging and underemployment is more severe for agricultural households. Our simulations result in a substantial reduction of income disparity between the two sectors with decreased aging and underemployment ratios in agriculture.

Our results suggest that the implementation of proper government policies could address aging and underemployment problems in agricultural households and significantly reduce the income disparity between agricultural and non-agricultural sectors. The implementation of proper government policies (e.g., promote employment opportunities for young laborers) can attract more young adults and employment and business opportunities to agricultural regions. Aging and underemployment problems in agriculture could also be improved through influx of young foreign workers into the agricultural sector by immigration policies, as suggested by many studies in the literature (e.g., United Nations 2001; Marois et al. 2020).

Increasing immigrant workers has been considered one of the most effective ways to improve employment problems and age structure in the labor force (Bijak et al. 2008; Bloom et al. 2011). However, these studies also point out that large-scale immigration would incur significant costs such as political, social, health, and economic inequality problems. Therefore, a future research direction might be to conduct a cost-benefit analysis of immigration labor, particularly focusing on aging and employment status in the agricultural sector.

Table 1.1. Descriptive Statistics at the Household Level.

Variables		2009 Full Sample (N = 6721)	2009 Agriculture (N = 452)	2009 Non-Agriculture (N = 6269)
Per capita income (one million Won)		11.79	9.54	11.96
		(12.15)	(7.17)	(12.41)
Age over 65 ratio (AR) (%)		19.73	43.09	18.05
		(35.74)	(42.16)	(34.64)
Underemployment ratio (UN) (%)		13.48	32.39	12.11
		(26.49)	(38.69)	(24.84)
Unemployment ratio (UE) (%)		8.29	9.47	8.19
		(20.97)	(23.25)	(20.79)
Out of the labor force ratio (OL) (%)		34.59	17.22	35.84
		(34.63)	(23.52)	(34.97)
Financial asset value (one million Won)		17.43	15.89	17.54
		(66.02)	(41.50)	(67.44)
Real estate asset value (one million Won)		30.33	87.26	26.22
		(112.78)	(187.09)	(104.25)
Household head's education level (%)	Less than Elementary	21.41	19.13	53.10
	Middle	12.74	12.36	17.92
	High	32.81	33.63	21.46
	More than college	33.05	34.89	7.52

Variables	2012 Full Sample (N = 6434)	2012 Agriculture (N = 422)	2012 Non-Agriculture (N = 6012)
Per capita income (one million Won)	14.35	12.11	14.5
	(12.09)	(9.09)	(12.25)
Age over 65 ratio (AR) (%)	24.03	48.05	22.34
	(38.92)	(42.02)	(38.13)
Underemployment ratio (UN) (%)	11.13	23.14	10.29
	(24.78)	(34.93)	(23.69)
Unemployment ratio (UE) (%)	8.42	11.55	8.19
	(22.14)	(27.23)	(21.72)
Out of the labor force ratio (OL) (%)	37.08	17.90	38.43
	(36.39)	(25.86)	(36.64)
Financial asset value (one million Won)	1950.15	2005.36	1946.27
	(4488.57)	(4399.99)	(4495.06)
Real estate asset value (one million Won)	3950.63	11,245.73	3438.56
	(14,348.46)	(18,259.19)	(13,891.83)

Household head's education level (%)	Less than Elementary	20.42	18.23	51.66
	Middle	12.17	11.74	18.25
	High	32.13	32.78	22.75
	More than college	35.28	37.24	7.35

		2015		
		Full Sample (N = 6577)	**Agriculture (N = 380)**	**Non-Agriculture (N = 6197)**
Per capita income (one million Won)		16.26	14.18	16.39
		(14.39)	(14.86)	(14.36)
Age over 65 ratio (AR) (%)		28.61	53.32	27.10
		(42.16)	(42.31)	(41.68)
Underemployment ratio (UN) (%)		10.26	17.62	9.81
		(24.29)	(32.41)	(23.64)
Unemployment ratio (UE) (%)		9.01	17.69	8.48
		(22.98)	(31.09)	(22.29)
Out of the labor force ratio (OL) (%)		40.59	18.91	41.92
		(37.80)	(25.83)	(38.02)
Financial asset value (one million Won)		2810.92	2689.73	2818.35
		(7381.87)	(4644.53)	(7517.55)
Real estate asset value (one million Won)		3832.70	12,799.34	3282.87
		(14,682.86)	(22,633.83)	(13,865.03)
Household head's education level (%)	Less than Elementary	19.04	17.28	47.63
	Middle	11.51	10.99	20.00
	High	31.47	31.98	23.16
	More than college	37.98	39.75	9.21

Table 1.2. Parameter Estimates from Longitudinal Regressions

Variables	Parameters	Full Sample	Agriculture	Non-Agriculture
Age over 65 ratio (AR)	β_1	−3.403 *** (0.538)	−7.795 *** (1.941)	−2.608 *** (0.613)
Underemployment ratio (UN)	β_2	−11.278 *** (0.509)	−12.869 *** (1.292)	−11.591 *** (0.580)
Unemployment ratio (UE)	β_3	−8.229 *** (0.527)	−2.418 (1.794)	−8.884 *** (0.562)
Out of labor force ratio (OL)	β_4	−8.867 *** (0.398)	−11.305 *** (2.439)	−9.126 *** (0.398)
AR*UN	β_5	1.415 *** (0.510)	1.401 (1.445)	3.107 *** (0.609)
AR*UE	β_6	0.902 (0.589)	−0.692 (1.998)	0.977 (0.669)
AR*OL	β_7	0.318 (0.501)	3.603 (2.539)	−0.343 (0.589)
Financial asset value	β_8	0.114 *** (0.014)	0.195 *** (0.060)	0.110 *** (0.014)
Real estate asset value	β_9	0.028 *** (0.002)	0.012 *** (0.004)	0.031 *** (0.002)
Middle[1]	β_{10}	2.029 *** (0.194)	1.198 * (0.677)	2.070 *** (0.199)
High	β_{11}	2.459 *** (0.160)	1.274 ** (0.576)	2.416 *** (0.179)
More than college	β_{12}	5.469 *** (0.198)	1.745 ** (0.869)	5.445 *** (0.206)
Year 2010[2]	α_{2010}	0.886 *** (0.189)	0.592 (0.501)	0.889 *** (0.201)
Year 2011	α_{2011}	1.455 *** (0.186)	1.037 ** (0.515)	1.461 *** (0.194)
Year 2012	α_{2012}	2.230 *** (0.198)	1.409 *** (0.519)	2.244 *** (0.201)
Year 2013	α_{2013}	2.927 *** (0.208)	2.248 *** (0.675)	2.921 *** (0.232)
Year 2014	α_{2014}	3.128 *** (0.215)	2.469 *** (0.840)	3.119 *** (0.214)
Year 2015	α_{2015}	3.852 *** (0.229)	2.792 *** (0.842)	3.871 *** (0.227)
Year 2016	α_{2016}	4.725 *** (0.238)	2.812 *** (0.640)	4.798 *** (0.243)

*** indicates statistical significance at the 1% level, respectively. Numbers in parentheses are bootstrap standard errors with 1000 replicates.

[1] Less than elementary school is omitted to avoid the perfect correlation.

[2] Year 2009 is omitted to avoid the perfect correlation.

Table 1.3. Coefficient Difference between Agricultural and Non-agricultural Sectors.

	t-statistics
Age over 65 ratio (AR)	-2.55**
Underemployment ratio (UN)	-0.63
Unemployment ratio (UE)	4.60***
Out of the labor force ratio (OL)	-1.16
AR*UN	-0.69
AR*UE	-1.07
AR*OL	1.88*

*, **, and *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 1.4. Household Income Elasticities with respect to Aging, Underemployment, Unemployment, and Out of the Labor Force.

	Full Sample	Agriculture	Non-Agriculture
Age over 65 ratio (AR)	−0.055	−0.308	−0.036
Underemployment ratio (UN)	−0.085	−0.246	−0.078
Unemployment ratio (UE)	−0.049	−0.000	−0.050
Out of the labor force ratio (OL)	−0.230	−0.162	−0.243

Table 1.5. Income Disparity between Agricultural and Non-agricultural Sectors.

	Disparity from Longitudinal Model	Disparity from Cross-sectional Model		
		2009	2012	2015
Income difference	0.658 ***	0.354	0.930 ***	0.752 **
	(0.135)	(0.283)	(0.343)	(0.362)

Note: both cross-sectional and longitudinal models use the same explanatory variables. Numbers in parentheses are standard errors. ** and *** indicates statistical significance at the 5% and 1% levels, respectively.

Table 1.6. Expected Income Disparity between Sectors with Decreased Aging and Underemployment Ratios from the Agricultural Sector.

Target Variable	Scenario 1: −2% Shock	Scenario 2: −4% Shock	Scenario 3: −6% Shock	Scenario 4: −8% Shock	Scenario 5: −10% Shock
AR	0.604 (−8.21%)	0.528 (−19.76%)	0.452 (−31.31%)	0.375 (−43.01%)	0.299 (−54.56%)
UN	0.619 (−5.93%)	0.559 (−15.05%)	0.498 (−24.32%)	0.437 (−33.59%)	0.377 (−42.71%)
AR and UN	0.543 (−17.48%)	0.406 (−38.30%)	0.270 (−58.97%)	0.133 (−79.79%)	−0.004 (−100.61%)

Note: Numbers in parentheses are percentage changes of income disparity from the baseline disparity, 0.658, reported in Table 1.4.

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CHAPTER II

SOCIAL NETWORKING AND TECHNOLOGY ADOPTION: AN ANALYSIS OF TWITTER DATA

Abstract

This study examines the effect of information-intensive social networking, a proxy for social learning effect, on technology adoption decisions using 231 turfgrass professionals' Twitter accounts data between June 1, 2018 and December 31, 2019. To address the reflection problem in social networking analysis, we account for the networking heterogeneity that confounds in social networking process. The confounding effects are decomposed into individual- and group-level similarities, herd behavior, and clustering effects. To account for network structure-based heterogeneities (herd behavior and clustering effects), we employ the spatial autoregressive probit model that directly incorporates network structures into the model as a matrix system (i.e., adjacency matrix). A Bayesian estimation method (with priors from earlier studies) is applied in our study to address the convergence problem that arises due to the complexity of model specifications. Empirical results show positive and significant information-intensive networking effect, observation-based networking effects (herd behavior), and group-specific effects (group-level similarity) on turfgrass professionals' decision-making process. The results also indicate that the information-intensive networking effect is larger than the observation-based networking effect.

The interaction term between group-specific effects and observation-based networking effects explains the networking effect could significantly differ by each professional group. These results suggest policy and marketing strategy for new technology adoption should target individuals who are actively exchanging information through networking, while considering the networking behavior by groups to which the individuals belong

Keywords: social network analysis, new technology adoption, turfgrass, social media, Twitter, network structure measure, spatial autoregressive probit model, Bayesian estimation.

1. Introduction

Factors affecting technology adoption have been key interests of many stakeholders such as breeders, producers, and marketers in the agricultural production system. New technology development is a long-term project that requires large amount of inputs, and its return largely depends on consumer adoption of the newly developed technology. Nevertheless, technology adoption is often unpredictable, which causes significant uncertainties that hinder development and investment in the next phase (Bhaskaran and Krishnan 2009). Particularly, the adoption of new technology in agriculture has been more crucial than in other industries due to its effects on the environment, welfare, and sustainability of the applied region (Doss 2006; Saitone and Sexton 2017; Beaman et al. 2021). Earlier studies in social network analysis indicate that consumers' networking behavior via social media has become an important factor for the new technology adoption decision in the agricultural sector as information exchange through internet emerges as a key communication and networking tool (Bandiera and Rasul 2006; Doss 2006; Centola 2010; Peng and Mu 2011; Ramirez 2013; Miller and Mobarak 2015; Morris and James 2017; Mills et al. 2019).

Information-intensive networking has been considered an important source of gathering information that many consumers use during the new technology adoption process. Therefore, without appropriate information exchange through networking, the technology diffusion process could be slow and unsustainable or even result in a negative cycle of non-adoption (Munshi 2004; Straub 2009). Therefore, identifying the information-intensive networking (i.e., network with active information exchange) effect shows whether a sustainable new technology adoption process would be feasible for target network. This information is also useful to improve marketing and sustainability of new technology diffusion in agriculture.

However, it is challenging to sort out the information-intensive networking effect from overall social networking effect (Manski 2000). As Manski (1993, 2000) discuss, the social networking effect is likely ambiguous when one does not have sufficient information on social networking processes. For example, unobservable information such as private attributes (e.g., social preference) could significantly affect each individual's decision, especially in online network (Acquisti and Grossklags 2005; Pan et al. 2017; Adnan et al. 2019). Accordingly, without accounting for the unobservable information, it would be difficult to distinguish an intensive social networking, i.e., learning effect (Manski 1993; Golub and Jackson 2010; Maertens and Barrett 2013; Miller and Mobarak 2015), and other effects such as mimicking (i.e., imitating, social pressure, herd behavior) from social networking effect i.e., the reflection problem (Manski 1993; Liu et al. 2014; Hsieh and Lee 2016).

Many studies attempt to resolve the ambiguity in social network effects through several pathways to provide clear implications (Bandiera and Rasul 2006; Santos and Barrett 2008; Conley and Udry 2010; Liu et al. 2014; Boucher and Fortin 2016; Hsieh and Lee 2016; Maertens 2017; Beaman et al. 2021; Johnsson and Moon 2021). For instance, Johnsson and Moon (2021) suggest how one can account for unobserved information via a two-stage estimation method, yet they assume the unobservable information are only oriented in individual-level aspects such as demographics. This individual-level only approach may neglect the other networking effects, such as the effects that based on the network structure itself (Snijders 2001). Besides, previous studies argue that there are several sources of networking effects at individual- and group-levels, which could hinder the information exchange process via social network (Bandiera and Rasul 2006; Santos and Barrett 2008; Lobel and Sadler 2016). Moreover, this diversity issue could be more severe in online networks since social media is less-constraint and more heterogeneous than in-person networks (Li 2011). Thus, neglecting this diverse nature of social networking effects on decision-making could occur a reflection problem and may result in biased networking effects.

This study examines an information-intensive social networking effect by accounting for all effects that confound social networking process. This information suggests how to leverage online social networks to increase adoption rate of new technologies. Therefore, this research provides guidance on the use of social networking for extension specialist, marketers, and policy makers who are interested in educating, selling, and distributing new technologies to agricultural stakeholders.

To achieve this goal, we decompose the social networking effect into several categories (i.e., information-intensive networking, group- and individual-level similarities, herd behavior, and clustering effects) by employing the revealed information based on the professionals' online networking system in our model with social media data collected from a Twitter group that includes turfgrass professionals, input suppliers, university researchers, consultants from private firms. Therefore, our study contributes to the literature by proposing a method to solve the reflection problem by analyzing and filtering group- and individual-level networking heterogeneities, i.e., group- and individual-level similarities, herd behavior, and clustering effects that are difficult to control with observational or survey data completely, by accounting for networking characteristics that represents each networking heterogeneity.

We assume that information-intensive networking is formed by the most potent social signal in the online network platform, e.g., the retweet action on Twitter (Rath et al. 2017; Mills et al. 2019). We consider the networking heterogeneities are composed of (a) group-level similarity effect by institutional similarities (e.g., norms or traditions shared by practitioners) within each profession, (b) individual-level similarity effect by socioeconomic similarities (e.g., socioeconomic attributes) between individuals, (c) herd behavior effect by observing others ideas or opinion (e.g., social norm) in the network to which each individual belongs, and (d) clustering effects by social contiguity between individuals (Snijders et al. 2010; Jackson and López-Pintado 2013; Liu et al. 2014; Cohen-Cole et al. 2018; Mele 2021).

To capture and measure the individual-level similarity, group-level similarity, herd behavior, and clustering effects, we employ the demographic variables, professional group-specific effects, several types of networking systems (i.e., multiple adjacency matrices based on different networking), and clustering coefficient that indicates the degree of social proximity of peers, respectively (Lacombe 2004; Opsahl and Panzarasa 2009; LeSage and Pace 2010; Lin 2010; Snijders et al. 2010; Liu et al. 2014).

To clarify herd behavior effects, we apply the network structure through a weak social signaling channel (e.g., reply action in Twitter platform) based on the following assumption: herd behavior is based on networking by weak social signal, the network that individuals instead observe and imitate than exchange information with others (Dutta et al. 2021). To account for networking-specific effects (i.e., herd behavior), we employ the Spatial Autoregressive (SAR) probit model, which directly incorporates the network structure into a model as a matrix system (Zhang et al. 2013; Liu et al. 2014). To remedy the convergence issue by empirical complexity, we apply the Bayesian estimation method with priors following suggestions from previous studies (Smith and LeSage 2004; Zhang et al. 2013; Liu et al. 2014).

Our results show the positive and significant group-level similarity effect (golf course superintendents), herd behavior effect, and information-intensive networking effect on new technology adoption decision. We find that the information-intensive networking is more effective than the observation-based networking, which suggests that targeting individuals who are involved in information exchange process more actively could be more effective in increase adoption rates and probability of sustainable adoption process than targeting those who involved in the observation-based networking. Our estimation results also find that the advisor networking (with researchers from universities and private consulting firms, and input suppliers) is not effective in affecting consumers' adoption decision. The results suggest that consumers mostly rely on the information from online social networking over the advisor's suggestions. The model specification with interaction terms between group-specific effect and observation-based networking suggests that the overall networking effects (direct effect) and group-specific networking effects (indirect effect) could significantly differ. Therefore, it is important to consider the networking behavior characteristics of each group when designing a policy or marketing strategy. Overall, our study shows the significance of learning effect (i.e., sustainable adoption process), and relative superiority between other networking effects in the decision-making process through online social networking. Therefore, this information explains which networking characteristic should be considered to increase a technology adoption rate in sustainable process. Our findings could be applicable to various agricultural commodity producers, policy makers, and marketers who are considering the online social network as a marketing tool.

2. Literature Review

2.1. Overview of Social Network Analysis Studies on New Technology Adoption Studies

The literature discusses that a new technology adoption decision in the agricultural sector impacts not only the agricultural stakeholders also welfare, development, and sustainability (Doss 2006; Saitone and Sexton 2017; Beaman et al. 2021). However, as Sunding and Zilberman (2001) argue, the technology adopters' perception of benefits of new technologies could vary across individuals or groups due to the heterogeneous information and understanding of new technologies by differences in preference, perception, and networking effect (Ryan and Tucker 2012). Chavas and Nauges (2020) discuss these differences in acknowledgment of new technology among individuals could bring uncertainty upon a new technology adoption, hindering a prediction of the new technology impact. This ambiguity may reduce the potential benefits of new technologies or even impede the new technology development (Royzman et al. 2017). Therefore, it is crucial to predict the stakeholders' new technology adoption decision-process to ensure efficiency on new technology research and its benefits (Batz et al. 2003).

Technology adoption decisions had been considered to be hinged on individual-level attributes such as gender, education level, financial status, and behavioral belief (e.g., Lynne et al. 1995). Nonetheless, recent studies argue that social networking has an important role in information flow of new technologies at the individual- and group-level, further a new technology adoption decision (Bandiera and Rasul 2006; Conley and Udry 2010; Miller and Mobarak 2015; Maertens 2017). However, Manski (1993) points out the social networking effect on decision-making process is hard to identify; it is because social networking process involves a variety of casual process and effects driven by many factors such as personal preference. (Manski 1993, 2000). This identification is important because distinguishing between learning (e.g., adoption decision based on the expected benefits of the introducing a new technology) and imitation (e.g., adopt a new technology by mimicking behavior of others) is important for new technology adoption (Conley and Udry 2010; Maertens and Barrett 2013).

In technology adoption process, imitation does not guarantee to generate rational expectation of new technology adopters; implies the inefficient use (e.g., fail to fully utilize a new function of equipment or variety) of new technologies (Manski 2000). Conversely, Lee et al. (2013) argue that innovation effect, i.e., adopt a new technology to enjoy its benefit, is more sustainable for adoption rate over time than imitation effect. In addition, Wang et al. (2020) argue information exchange through social networking has an important role to make efficient adoption (e.g., learn how to fully utilize a new function of equipment or variety) decision. Therefore, identifying the effectiveness of information exchange through networking processes is critical for exploring sustainable new technology development and decision-making processes. Nonetheless, social networking effect is difficult to identify particular effects (e.g., information-intensive networking effect) due to its complexity; social networking between individuals often depends on personal preferences and corresponding attributes, which are hardly observable in data due to practical complications such as privacy issues (He et al. 2017). This omitted information problems on networking effect would likely lead to biased estimates, and thus incorrect inferences of social networking effect on a new technology adoption decision.

In the previous literature, various attempts have been made to filter out reflection effects from the social networking effect on new technologies adoption decision: rich dataset that accounts for most of the networking-related information (Conley and Udry 2010; Maertens 2017), experimental design that controls externalities on networking effect (Santos and Barrett 2008), proxy variables for personal attributes (e.g., a degree of desire to achieve goals) that accounts for unobservable private information (Boucher and Fortin 2016), and Bayesian network that gauges networking-based unobservable information (Hsieh and Lee 2016) are applied to remedy the reflection problem. These approaches hinge on the quality of the dataset, researcher's choices of proxy variables, or underlying assumptions (e.g., for Bayesian network and experimental designs). Thus, these approaches may lack accessibility to research due to high cost and lack of external validity by a subjective framework (e.g., a choice of proxy variables for personality).

Besides, most of previous studies considered the networking effect as a proportion of adopters in each individual's network, i.e., linear-in-mean model (e.g., Kline and Tamer 2014). This mean-effect approach captures the influence by other adopters, but could not fully account for the individual-level interaction within the network system in general. Moreover, the previous studies have rarely discussed the group-level variations in networking effect on adoption decision other than homophily (i.e., tendency to associate with peers) (e.g., Aral et al. 2009).

2.2. The Inherent Heterogeneity of Social Networking and Its Implications

The previous literature of social network analysis argues that individual- and group-level differences could lead to heterogeneous social networking effects on a new technology adoption decision, which may occur an inaccurate inference on networking effect for adoption decision (Bandiera and Rasul 2006). Especially the group-level difference in networking, i.e., homophily, is considered one of the most basic and significant factors on social networking effect (Jackson and López-Pintado 2013). By definition, homophily means the tendency for people to seek out or be attracted to those who are similar to themselves, and this group-based heterogeneity may occur heterogeneous networking effect on adoption decision (Jackson et al. 2017). Based on this concept, McPherson et al. (2001) discuss that employing the socioeconomic variables (e.g., income, education level, occupation) could control the heterogeneity that is caused by similarities between individuals and groups on social networking and its outcome. Nonetheless, as Bandiera and Rasul (2006) argue, socioeconomic variables alone may not be capable of accounting for all heterogeneities by differences in networking behavior between individuals. Besides, sociology and corresponding social network analysis articles argue that heterogeneities in networking is not only caused by the socioeconomic similarity between individuals but also by other factors such as social norms and preferences (Krivitsky et al. 2009; Zhou et al. 2009; Li 2011; Zhou 2011; Liu et al. 2014; Yang et al. 2020; Mele 2021). Therefore, the previous studies' results only with similarity-based measures (e.g., demographics) to control the network heterogeneities may undergo the omitted variable issue in networking effect, which could lead to a reflection problem (Manski 2000; Bandiera and Rasul 2006). Accordingly, this uncontrolled heterogeneity issue raises the necessity for a more systematic investigation into the individual- and group-level networking heterogeneities.

Miaz et al. (2016) discuss that in terms of social network, individual-level differences are based on not only by socioeconomic attributes but also networking behaviors, especially in online network (Katona et al. 2011). Also, Monge et al. (2003) explain that the patterns of all interactions between individuals in the network, which form a structure of that particular network, influence each individual's networking decision. For example, Gruhl et al. (2004) show the positive correlation between concentration level of network and overall interaction rate in that network. This point of view suggests examining more realistic networking and its effect by considering the endogenous social interaction between individuals for better inference. However, this approach raises more complexity in social network analysis as the potential factors of these interactions are enormous and difficult to observe (Himelboim et al. 2017). Besides, for online networks, the underlying reason for social interaction could be more complicated than in-person network since the organizing, joining, and leaving the network is relatively less bounded to material conditions (e.g., physical distance) than in-person network. (Li 2011). To overcome this issue, several studies attempt to employ the network structure measures, which represents the networking characteristic of each individual in a particular network, as a proxy of this networking pattern (Liu et al. 2014; Maiz et al. 2016; Himelboim et al. 2017; Jackson et al. 2017). Nevertheless, only a few studies provide empirical evidence of this approach in terms of a new technology adoption process. Also, fewer studies consider that the detailed individual- and group-level networking heterogeneities should be considered as well.

3. Methodology

In this study, we estimate a technology adoption decision model to examine the effect of social networking on a new turfgrass variety adoption decision of professionals. In order to assess the intensive networking effect, we control the individual- and group-level social networking effects by employing the several measures as follows: (a) networking effect based on strong communication, which could be interpreted as the proxy for learning effects, (b) another networking effect based on weak communication, represents the herd behavior effects, (c) profession group variables that represent the group-level similarity effects, (d) demographic variables that account for individual-level similarity effects, and (e) network structure measures, which represents each individual's networking behavior, including clustering effects. This method is purposed to separate the confounding effects, individual- and group-level networking heterogeneities (b), (c), (d), and (e) from social networking effect (a) to provide an accurate intensive networking effect.

3.1. Networking Heterogeneities

According to the previous studies' discussions, individual- and group-level networking heterogeneities could be divided into four main categories Figure 1 (e.g., McPherson et al. 2001; Leenders 2002; Bandiera and Rasul 2006; Snijders et al. 2006; Snijders et al. 2010; Liu et al. 2014; Himelboim et al. 2017).

In general, group- and individual-level similarities could be captured with observational data such as socioeconomic variables. Nonetheless, herd behavior and clustering effects are based on group- and individual-level networking behavior and preference, which only could be captured through the network structure and corresponding statistics (Shalizi and Thomas 2011; Himelboim et al. 2017). Each aforementioned network effect could obscure networking effects by each following reason:

1-1) Group-level Similarity (i.e., network fixed effects) is the tendency that individuals in the network may behave in similar way under a similar institutional environment. Such institutional similarity may lead mimicking behavior among members of each institution, thereby contaminating the information exchange process[2] (Manski 1993; Lin 2010). Moreover, the presence of similarity may hinder the network from convergence of consensus (e.g., evaluating the usefulness of new technology), especially when individuals tend to follow the average level of information obtained through networking (Golub and Jackson 2012).

1-2) Individual-level similarities such as demographic status may occur imitating effect for people who shares same individual status by homophily (Durrett and Levin 2005). Besides, networking process based on individual-level aspects (e.g., gender) are unlikely to be relevant to a new technology and corresponding utility (Santos and Barrett 2008). Therefore, just as group-level similarity, individual-level similarity may cause noise in networking effect and hinder the information exchange process in network (Santos and Barrett 2008; Lin 2010; Golub and Jackson 2012).

2-1) Herd behavior is a tendency that individuals in network acting collectively towards aggregated opinion such as social norm (Bernheim 1994; Kameda and Hastie 2015; Cohen-Cole et al. 2018; Ushchev and Zenou 2020; Mele 2021). More specifically, Herd behavior is based on

[2] Lobel and Sadler (2016) argue that homophily could benefit the learning process in network only if the improvement principle (If an individual can identify a neighbor with similar preferences, their social signal can improve neighbor's selection) holds. However, this principle is based on the assumption that each individual is strongly influential to their neighbor and the preference of individuals is homogenous within the network. Considering these assumption are too strong for online network, we suggest the similarity would likely hinders the learning process in network in general.

the idea that the difference between each individual's choice or behavior and the average value of the whole network's performance would penalize the person's utility level due to collective idea (e.g., social norms or public opinion) (Bernheim 1994; Rook 2006). Therefore, this assumption suggests that if herd behavior exists in a particular network, each individual would tend to regress to their neighbor's aggregated opinion rather make their own choice through social learning (Bernheim 1994).

2-2) In graph theory, clustering (i.e., transitivity) explains the people's tendency to likely to be acquainted with friend's friends[3] (Oliveira and Gama 2012; Mele 2021). The clustering tendency could have significant effect on new technology adoption process through more dense information exchange (Katona et al. 2011). This tendency could be driven influential individual as a center or by each individual's neighbor's propensity to expand the network (Wu et al. 2013).

It may seem similarity measures and other effects (herd behavior and clustering) represent same inference. However, the underlying logic for similarity, herd behavior, and clustering effects differ: unlike similarity, herd behavior and clustering represents the tendency to congregate due to individuals' social proximity rather than similarity in institution or social status. Therefore, similarity and clustering effects needs to be controlled differently. These four concepts and their effects on social networking do not necessarily align with each other, especially in online network (Katona et al. 2011). For example, Zhou (2011)'s study shows that people's social identity (e.g., race, gender, ethnicity) is not significantly correlated with subjective norms (i.e., influence by significant individuals, which could be interpreted as clustering effect) and partially correlated with group norms (i.e., herd behavior by social norm). Nevertheless, social identity and group norms significantly affect the students' participation

[3] The difference between homophily and clustering effect is their scale: homophily describes a tendency to gather with similar others in terms of any kind of similarities, and clustering effect explains a tendency to gather with others in terms of social contiguity (e.g., more likely to interact with friend's friend than others) only.

intention for online social networking. Thus, employing socioeconomic status as control variables in the model or subgrouping by social status may be insufficient to remedy the heterogeneity in social networking effect on a new technology adoption decision. A few studies suggest the idea that is directly incorporating the networking systems with different specifications in the model, which can be represented as adjacency matrix, to account for these group-level networking effects (LeSage and Pace 2009; Liu and Lee 2010; Zhang et al. 2013; Liu et al. 2014). Nevertheless, the concept of herd behavior and clustering as network heterogeneities has rarely been discussed in social network analysis studies regarding a new technology adoption decision.

Overall, specifying and controlling all individual- and group-level heterogeneous networking effects is essential to assess the accurate information-intensive networking effect and provide practical policy implications. In the literature, several studies hint that applying the adjacency matrix and network structure measures could resolve this major issue in social network analysis (e.g., Leenders 2002; Butts 2008; Hsieh and Lee 2016; Galeott et al. 2020).

3.2. Specification of Adjacency Matrices and Corresponding Network Measures

Adjacency matrix (i.e., weight matrix, contiguity matrix) represents networking system, which based on the social distance or contiguity between individuals. Distance or contiguity could be either geographical, economical, or social due to researcher's assumption on this networking system (Liu and Lee 2010; Badinger and Egger 2011). Previous studies suggest that directly incorporate networking system in model and measures that correspond to social network structure could provide more accurate networking effects; this approach provides more detailed policy implications than other networking measures, such as average (mean effect) networking behavior of reference groups or number of social connection (Leenders 2002; Pinkse and Slade 2010; Zhang et al. 2013). Several studies discuss the advantages of directly incorporating the networking system in the model. LeSage and Pace (2009) explain that by considering the whole networking system, adjacency matrix could account for all individual-level direct (e.g., the effect of interaction between my friends and I) and indirect (e.g., the effect of interaction between my friends and their neighbors on me) connections and their networking effects on each individual's decision. In addition, Leenders (2002) argues that the specification of adjacency matrix could represent networking operations and its outcome due to the underlying assumption of each specification. Moreover, Lacombe (2004), Badinger and Egger (2011), and Liu et al. (2014) suggest applying more than one adjacency matrices could capture several types of networking system effects (e.g., consider the effect of economic relationship and geographical relationship between regions on income per capita simultaneously), which is hardly detectable through conventional approaches (Elhorst et al. 2012).

In fields aside from economics, particularly in sociology and education disciplines, social network analysis studies claim that the network measures (e.g., eigenvector centrality) reflect networking characteristic of each individual (e.g., how actively someone communicates with other people in the network) (Freeman 1978; Snijders et al. 2006; Snijders et al. 2010). The network measures are based on the network structure that is built by each individual's choice of networking toward others in the network. Borgatti and Halgin (2011) explain that the networking choice is based on personal information, including unobservable factors such as preference, and it determines how information flow in the network (Borgatti 2005; Himelboim et al. 2017). Besides, Jackson et al. (2017) discuss the potential of network structure measures as an appropriate proxy to describe economic decision-making processes through social network such as diffusion of new technology in communities. This concept is more suitable in online social network cases because subjective criteria (e.g., preference) have more important role than in-person social network. Considering online networks have a wide range of information sources that are less restricted to geographical or temporal conditions, each individual's networking choices are highly dependent on individual preferences (Gallos et al. 2012; Himelboim et al. 2017). Therefore, directly incorporating network measures in the model could account for the unobservable individual-level information that could cause reflection problems. In addition, this approach would provide more accurate implications with online social network cases.

Comprehensively, the literature presents ample evidence that applying multiple adjacency matrices and employing network structure measures could provide more accurate networking effect through information exchange by assessing and dissecting the various social networking effects. In the next chapter, we will explain how to conceptually implement this method in details.

3.3. Model Specification

In this study, we employ a Bayesian Spatial Probit model to estimate the networking effect on a new technology adoption decision[4]. Consider the following regression model,

$$Y^* = \rho_1 W_1 Y^* + \rho_2 W_2 Y^* + X\beta + e, \qquad e \sim N(0, \sigma^2 I), \tag{1}$$

where Y^* is a vector $(n \times 1)$ of latent variable that links to the observed binary outcome y_i (If $y_i = 1$, adopt a new variety (i.e., $y_i^* > 0$). Otherwise, $y_i = 0$ $(i.e., y_i^* \leq 0)$) of individual i $(i = 1, \dots, n)$, W_1 and W_2 are adjacency matrices[5] $(n \times n)$ with zero-diagonal elements of information-intensive and observation-based networking, respectively, ρ_1 and ρ_2 are scalar networking coefficients correspond to W_1 and W_2 to, respectively, X represents covariate matrix

[4] Other methods such as Maximum Simulated Likelihood (MSL) estimation could provide more efficient estimates than Bayesian approach. However, these methods have several challenges in spatial modelling, such as a huge computational burden (Franzese et al. 2016). Therefore, as an alternative, we employ the Bayesian method for a stable convergence (Wilhelm and de Matos 2013).

[5] The literature argue that an adjacency matrix is prone to endogeneity issue since unobservable factors (e.g., social preference) can affect networking process, leading to inconsistent estimates (Pinkse and Slade 2010; Qu and Lee 2015; Jackson et al. 2017). Even though our study employ the network structure measures that account for the unobservable information (i.e., networking behavior of each individual) in networking process, this endogeneity issue could still remain (Chandrasekhar and Lewis 2011; Hsieh and Lee 2016). Nevertheless, the use of adjacency matrices is essential in our framework, as directly applying network structure (i.e., adjacency matrix) in model is the most effective way account for all direct and indirect interactions between individuals in network (Leenders 2002; Liu and Lee 2010; Zhang et al. 2013; Liu et al. 2014; Hsieh and Lee 2016).

with k variables ($n \times k$), β is corresponding coefficient vector ($k \times 1$), and e is a normal error term vector ($n \times 1$)[6,7].

Adjacency matrices W_1 and W_2 are based on the social interaction between individual i and j ($i \neq j$). For instance, if individual i are socially adjacent with individual j, $W_{i,j} = 1$, otherwise, $W_{i,j} = 0$.

Let us consider the simple adjacency matric with three individuals. In Figure 2, $W_{12} = 1$ explains the individual 1 is socially adjacent with individual 2 and $W_{23} = 1$ explains individual 2 is adjacent to individual 3 as well. This example shows the social interaction between individual 1 and 2 and between 2 and 3, but there is no direct interaction between individual 1 and 3. Nonetheless, indirect networking effect between 1 and 3 exists through individual 2 as waypoint. Therefore, this adjacency matrix framework accounts for all direct and indirect interaction between individuals in network (LeSage and Pace 2009).

In this framework, we assume the adjacency matrix W_1 represents the information-intensive networking effect and W_2 is to capture herd behavior effect. To represent herd behavior effect, we apply W_2 that based on the observation-based social signaling. This framework is based on the previous studies' discussion that retweets works as the main channel for information exchange in Twitter, while the other channels (e.g., reply) are prone to imitating behavior by observing other's option without actual information exchange (Boyd et al. 2010; Mills et al. 2019; Dutta et al. 2021). Thus, we could assume the network based on retweet would represent the networking effect based on active information exchange, and thus a proxy for learning effect[8].

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[6] For brevity and parameter identification, we consider the σ^2 is equal to one (LeSage and Pace 2009; Wilhelm and de Matos 2013).
[7] Error components e are conditionally independent with given network parameters ρ_1 and ρ_2 (Smith and LeSage 2004).
[8] This approach is based on the idea that each network captures each unique effect on dependent variable (Kelejian and Prucha 1998; Elhorst et al. 2012).

Accordingly, we could consider the network with observation-based (less information exchange), weak signaling such as reply would rather represent imitating behavior of individuals. This could be interpreted as herd behavior under the insufficient information (Maertens and Barrett 2013; Hill et al. 2016; Shen et al. 2016).

$$X_i = [D_{i1}, D_{i2}, D_{i3}, D_{i4}, Price_i, White_i, Male_i, Deg_i, Cent_i, Clus_i, Cent_i^{adv}, \\ D_{i1} * W_1,\ D_{i2} * W_1,\ D_{i3} * W_1,\ D_{i4} * W_1, \\ D_{i1} * W_2,\ D_{i2} * W_2,\ D_{i3} * W_2,\ D_{i4} * W_2] \tag{2}$$

For each individual *i*, the vector X_i $(1 \times k)$ includes dummy variables of j professional groups for each individual *i* (if individual *i* belongs to group j, $D_{ij} = 1$. Otherwise, $D_{ij} = 0$), purchased sod price by each individual ($Price_i$), degree centrality (Deg_i), eigenvector centrality ($Cent_i$), clustering coefficient ($Clus_i$), gender ($Male_i$), race ($White_i$), eigenvector centrality measure between individuals and with advisor group, i.e., advisor networking effect ($Cent_i^{adv}$), and interaction term between group dummy variables and adjacency matrices.

Sod price ($Price_i$) variable explains how each individual will response the price of turfgrass to make a new variety adoption decision. Gender ($Male_i$) and Race ($White_i$) variables account for individual-level similarities based demographic status, and professional group variable controls the group-level similarity based on occupational environment.

Degree centrality ($Cent_i$) indicates each *i*'s the number of direct connections (i.e., tie), which explains each individual's degree of influence on networking (Maharani and Gozali 2014). On the other hand, the eigenvector centrality is the degree that describes each individual's level of influence in overall network, including direct (e.g., my friends) and indirect (i.e., friends' friends) connections both (Bonacich 2007; Wu et al. 2013)[9].

[9] Degree centrality and eigenvector centrality could indicate different inference due the nature of network (Oldham et al. 2019). For example, in a strictly hierarchical network structure such as a corporation, people

The clustering coefficient ($Clus_i$) explains the degree of clustering behavior of each individual's peers. This coefficient has a value between 0 and 1: clustering coefficient of 0 means none of individual's peers interact to each other, and clustering coefficient of 1 means all of individual's peers are socially adjacent (Watts and Strogatz 1998). Thus, the higher value of clustering coefficient indicates each individual's peers are more likely to connect with people who are socially closer than others, and thus clustering effect, i.e., more likely to interact only with people who are close.

Advisor networking effect variable ($Cent_i^{adv}$) is the simultaneous group-s individual centrality measure with respect to the advisor groups (Bonacich 1991; Brass et al. 2004). Advisors (e.g., consultant, faculty, and researcher) are not included in our model since they are not decision-makers for new variety adoption (i.e., Y^* is neither 1 nor 0 in equation (1)). Nonetheless, advisors could transfer the information and suggestions through networking process, and thus significantly affect a new variety adoption decision (Wheeler 2008; Wossen et al. 2013; Wang et al. 2020). Thus, accounting for the advisors' effect on adoption decision is essential to ensure the validity of this model and provide meaningful policy implication. The main idea of this measures is to show how much each individual is influential to the groups and vice versa in the network through the eigenvector centrality in dual (group-individual) approach (Everett and Borgatti 2013). The derivation of this network measure is as follows (Bonacich 1991):

$$\lambda \begin{pmatrix} g \\ p \end{pmatrix} = \begin{pmatrix} 0 & A^t \\ A & 0 \end{pmatrix} \begin{pmatrix} g \\ p \end{pmatrix}, \tag{3}$$

where g is the eigenvector (i.e., centrality score) of *j* groups, p is the eigenvector of *i* individuals, λ is the eigenvalue (scalar), A is the rectangular matrix ($i \times j$) that showing the membership of individual *i* in group *j*, and A^t is the transpose of A. This approach provides the simultaneous

who at the top rank (e.g., Chief Executive Officer) will be very influential to overall network (high eigenvector centrality), yet they would have only a few direct connections (low degree centrality).

centrality measure between individual and groups, including advisor groups in our case, rather than centrality within individuals or groups. Therefore, this individual centrality measure p would represent the degree of each individual's social interaction with the network including advisor groups[10].

We expect W_1, W_2, Deg_i, $Cent_i$, $Clus_i$, $White_i$, and $Cent_i^{adv}$ would have positive, and $Price_i$ and $Male_i$ would have negative effect on a new variety adoption decision across models (Bandiera and Rasul 2006; Moser and Barrett 2006; Wood et al. 2014; Magnan et al. 2015; Wang et al. 2020). In addition, we expect W_1 would have larger impact than W_2 on adoption decision (Boyd et al. 2010; Mills et al. 2019). The interaction terms would indicate how social networking process varies for each group. For example, observation-based networking (W_2) is expected to be effective in new variety adoption across the board, but may be marginal for some groups that prefer in-depth social interaction. Also, advisors' opinion ($Cent_i^{adv}$) may insignificant for particular groups that value their own experience over the extension specialist's suggestions (Conley and Udry 2010). Therefore, identifying group-specific networking effects is essential to design an effective policy of marketing strategy. However, the interaction terms between covariates and group dummy variables would explain how networking system (adjacency matrices), individual-level similarities (race and gender), and networking behavior (network structure measures) would differ to each group. However, the model including all interaction terms as Equation (2) hardly converges due to its computational complexity. Therefore, as an alternative, we apply the following Equation (4) and (5) to provide a proxy of aforementioned implications.

$$X_i = [D_{i1}, D_{i2}, D_{i3}, D_{i4}, Price_i, White_i, Male_i, Deg_i, Cent_i, Clus_i, Cent_i^{adv},], \quad (4)$$

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[10] Note that $Cent_i$ explains the effect of each individual's social influence on decision-making process, and $Cent_i^{adv}$ explains the effect of each individual's interaction with advisors on decision-making process.

$$X_i = [D_{i1}, D_{i2}, D_{i3}, D_{i4}, Price_i, White_i, Male_i, Deg_i, Cent_i, Clus_i, Cent_i^{adv}, \\ D_{i1} * W_2,\ D_{i2} * W_2,\ D_{i3} * W_2,\ D_{i4} * W_2] \quad (5)$$

Equation (4) and (5) are restricted versions of Equation (2). Equation (4) assume all interaction terms have no effect on a new variety adoption decision. Thus, parameter estimates would explain the overall effect on decision-making process. Equation (5) incorporate the interaction terms between group dummy variables and weak-networking system, i.e., contextual effect of group-level similarity (Liu et al. 2014; Cohen-Cole et al. 2018)[11]. The interaction terms would explain how observation-based networking differ to each group (e.g., does networking with less information would increase the odds golf course superintendents to adopt a new variety?).

Although these models converge properly, multicollinearity between adjacency matrices and network structure measures (degree centrality, eigenvector centrality, clustering coefficient, and advisor networking effect) can raise the likelihood of type II error due to inflated variance. The Variance Inflation Factor (VIF) of network structure measures indicates less than 5 (i.e., no serious multicollinearity between network structure measures) and none of eigenvalues of weight matrix in data generating process[12] $(I - W_1 - W_2)$ are close to 0 (i.e., no serious collinearity between adjacency matrices). Nonetheless, the strong collinearity between adjacency matrices and network structure measures could exist and occur to fail to reject the false null. To identify this potential collinearity problem, we compare the coefficients by applying sub-models for each Equation (3) and (4) with stronger constraints (e.g., the network structure measure coefficients are zero).

[11] We do not include interaction terms with W_1 since incorporating interaction terms for both adjacency matrices occur perfectly singular covariance matrix issue.
[12] See Appendix for details.

4. Data

To illustrate the impact of social networking on technology adoption, particularly, effect of information-intensive networking and social networking with advisor group, we collected 231 turfgrass professionals' Twitter account data, which include the selected professionals' all tweet history, contents, and tweet interactions (retweets and reply) among professionals for the period from June 1, 2018, to December 31, 2019. The Twitter accounts were owned by confirmed turfgrass professionals such as university sports facility managers, national football, baseball, and soccer league field managers, sod producers, golf course superintendents, and public turf managers. There were originally 1,143 Twitter followers, but we had to exclude 742 followers from our dataset who were not engaged in the turfgrass profession, not had been active on Twitter, or were not racially and gender identifiable. In addition, since our econometric models are to predict a new variety adoption decision of turfgrass users, i.e., decision-makers, we initially excluded 170 advisors (turfgrass management suppliers, university faculties and professionals, and private researchers and consultants) who did not participate in decision-making process in our network. However, the network data between the 170 advisors and decision makers are used later to calculate the centrality between the advisor groups and decision makers and to evaluate the effect of the advisor-decision maker networking on technology adoption (Bonacich 1991)[13].

The network structure measures, degree centrality, eigenvector centrality, and clustering coefficient are derived based on the retweet network between professionals that is illustrated in Figure 3. Figure 3 shows how professionals interact through Twitter platform. The network structure indicates a few dense groups in the middle, smaller groups around the outskirts of the structure, and a few isolated individuals[14] that do not interact. This grouping behavior in our data

[13] See section 3.3 for details.
[14] Isolated individuals in network, i.e., isolates are considered as dead-end of network that do not deliver or receive information from others, which would be discarded as an outlier. Nonetheless, online network environment allows the isolates to observe the behavior of others, whether or not they interact with them

suggests controlling the group-level networking heterogeneities as discussed in the previous section.

Table 2.1 reports descriptive statistics of our network data at overall- and group-levels. The total number of connections between individuals in network (i.e., node) is 990, and the average number of connections between individuals in network (i.e., tie) is 4.285. It explains each individual in this network has at least four directional connections on average. Group degree centrality indicates the degree of networking between groups: the number of non-group nodes that are connected to group members (Everett and Borgatti 1999). It explains that golf course superintendents (group 4) are the most active and national football, baseball, and soccer league field managers (group 2) are the least active in between-group communication. The number of ties in between (off-diagonal elements in matrix) and within (on-diagonal elements in matrix) groups shows the frequency of between- and within- interactions of each group. The between- and within-group statistics show that golf course superintendents (group 4) have the largest and the densest within network, while national football, baseball, and soccer league field managers (group 2) have the smallest and thin within-network. Overall, the network descriptive statistics show the golf course superintendents are the most influential group among all groups as they are the largest group and the most actively interacting in this network.

Table 2.2 shows eigenvector centrality measures between individuals and groups, including advisor groups; turfgrass management suppliers, university faculty and professionals, and Private researchers and consultants, and individuals. Among the decision maker groups (from group 1 to group 5), golf superintendents (group 4) are the most influential group for individuals in the network, and private researchers and consultants (group 8) are the most active group among the advisors (from group 6 to group 8). It explains the group golf superintendents are the most

(Himelboim et al. 2017). Therefore, isolates were not discarded from the study to reflect the nature of online network.

influential in between-groups and between individual-groups both. Also, the high centrality score of private researchers and consultants group hints the advisor could affect the decision-makers' adoption decision process (Prokopy et al. 2015).

We collect the demographic information by inquiring the Twitter profile pictures of the corresponding professionals. The identification of personal details, gender and race[15], of professionals was carried out as follows: first, we visited each professional Twitter account and check the profile. In Twitter platform, the Twitter users can upload their picture on their profile and brief introduction about their status. When the photo is clear enough to identify race and the self-introduction matched the information we had, we determined the individual's race and gender. For professionals who cannot identify gender or race through their profile picture (e.g., people who use company logo in profile picture and do not mention their personal status in their bio), we execute the additional survey for that professionals through Twitter Direct Message (DM) function. As a result, we collect race and gender information of 203 professionals through Twitter account monitoring and 28 professionals through DM survey. Our key variable, a new variety adoption decision of professionals is verified by three-stage classification. First, we extract the tweets of professional with keywords that implies the professional's new decision to adopt a new variety (cite "Twitter-aided decision making: a review of recent developments"). If the tweet contains the keywords either (a) "turfgrass" and "adoption" (or "adopt"), (b) "turfgrass" and "installation" (or "install"), or (c)[16] "Latitude 36" or "NorthBridge" or "TifTuf Bermuda," we consider the tweet as a signal of adoption decision. Second, we monitor the tweets of professionals that classified from the first stage. If any of tweets contains keywords from the first stage with graphical evidence (e.g., Figure 4) of new variety application, we consider that

[15] The response rate for other demographic variables, such as education level or income were too low to include in our study.
[16] These are the most up-to-date turfgrass varieties during data collection period, from June 1, 2018, to December 31, 2019.

professional adopt a new variety (either in their field or for their clients) during our data collection period. In this stage, we confirm 43 professionals who adopt a new variety. Third, to identify professionals who have introduced new varieties have not posted on Twitter, we send survey questions to professionals other than those verified in the second stage via DM. If the professional answer "Yes" to question 2 and mention the applied varieties in question 3, we consider that professional adopt a new variety. Through this process, we confirm additional 42 professionals. Afterwards, the sum of the verified professionals in stages 2 and 3, 85 out of 231 professionals are considered as the total of number of professionals who made adoption decision.

Table 2.3 shows descriptive statistics of key variables used in this study. The percentages of professional group which profession is the majority from this network: Golf course superintendents (group 5) indicates the highest proportion among the network (52.38%) and National football, baseball, and soccer league field managers (group 2) shows the lowest percentage (5.19%). It clues the golf course superintendents would have significant influence on adoption decision in this network. The "White" and "Male" variables indicate that the turf industry is racially and sexually uniformed profession: more than nine out of ten turf professionals are white men. The price indicates 36.59 of mean, similar to the average price of warm season sod (34.93) (USDA 2020), and 2.58 of standard deviation. It shows our price data is consistent to the market price level and the sod price has small variability. The eigenvector centrality indicates small mean and corresponding standard deviation values: it denotes that each individual is unlikely to be influential to others in this network. However, the maximum of Eigenvector centrality shows 0.34, which implies there are a few but highly influential individuals exist in this network. The clustering coefficient shows each individual's peers have moderate level of clustering behavior. However, just as eigenvector centrality, the maximum value of clustering coefficient implies there are a few individuals whose peers are actively interact to each other.

5. Results

Table 2.4 reports results from Bayesian spatial probit analysis of equation (4) model specification. The dependent variable is turfgrass professional's new variety adoption decision that verified through Twitter tweet extraction, tweet monitoring, and Direct Message (DM) survey. The estimates indicate the posterior means by Markov Chain Monte Carlo (MCMC) with 10,000 sampling size with 1,000 burn-in per chain for 3 chains. Gelman-Rubin statistics for all estimates indicates close to 1, implying an appropriate mixing of Markov chains, i.e., the MCMC convergences were successful for all parameters (Gelman and Rubin 1992). For professional group variables, we choose public turf managers (group 5) as a baseline. Thus, the coefficient of the professional group variables indicate how larger or smaller the probability of adopting a new technology is in those groups than the public turf manager group. We employ the parameter restrictions for adjacency matrix coefficients (ρ_1 and ρ_2) that ensures the convergence of the model (Smith and LeSage 2004; LeSage and Pace 2009)[17]. Therefore, the interpretation for ρ_1 and ρ_2 should be under the consideration of their bounds[18]: the ρ_1 and ρ_2 do not range between -1 and 1 as in SAR model with single adjacency matrix (LeSage and Pace 2009; LeSage and Pace 2010).

Model 1 is the base model with no restriction, and Model 1-2, Model 1-3, and Model 1-4 extends the base model with restrictions regarding the collinearity issue between network structure measures and adjacency matrices (see section 3.3 for details). To compare a model fit between specifications, posterior log-likelihood for each model are also reported (Agiakloglou and Tsimpanos 2021). Overall, results are similar across Model 1 to Model 1-4. In Model 1, golf

[17] In prior distribution setting, the inverse of maximum and minimum eigenvalues of adjacency matrix as a upper and lower bound of four parameter beta distribution, respectively. As a result, the bounds of ρ_1 and ρ_2 are with our network dataset (see Appendix for details).

[18] $-0.025 < \rho_1 < 0.016$ and $-0.004 < \rho_2 < 0.004$ by the inverse of minimum and maximum eigenvalues of each corresponding matrix (Smith and LeSage 2004).

course superintendents (group 4), degree centrality, information-intensive networking effect (W_1), and Observation-based networking effects (W_2) significantly increases probability to adopt a new variety[19]. As expected, information-intensive networking effect (W_1) has larger effect than observation-based networking effects (W_2) on a new variety adoption decision. The posterior log-likelihood explains that the most restricted model (Model 1-4) best fits to data and prior information among all specifications[20].

The positive and significant golf course superintendents (group 4) coefficient explains that the group with relatively large size, has many connections, and highly influential between groups and individuals (see Table 2.1 and Table 2.2) is more likely to adopt a new technology than reference group (i.e., public turf managers). This implication is aligned with the positive and significant degree centrality coefficient: individuals with more direct connections are more likely to adopt a new technology (Bandiera and Rasul 2006).

We assume the information-intensive network (W_1), the networking structure based on the strongest social signal in social media platform (i.e., "retweet" action in Twitter) would represent how intensive information exchange through networking affect new technology adoption decisions (Rath et al. 2017; Mills et al. 2019). As Manski discusses (2004), social

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[19] Significant coefficients for both adjacency matrices supports the suitability of our model specification. Moreover, under the restriction that there is no observation-based networking effects ($\rho_2 = 0$), the estimation results change signs in significant coefficients such as golf course superintendents (group 4). Since descriptive statistics in section 4 hint the golf course superintendents are influential in networking process and adoption decision both, we could assume including both adjacency matrices would prevent the omitted variable bias.

[20] Increasing posterior log-likelihood by adding more restrictions (i.e., less parameters) implies the prior of restricted parameters may have significant role in posterior distribution in our model.

$$P(\theta|Y) = \frac{P(Y|\theta)P(\theta)}{P(Y)},$$

where $P(\theta|Y)$ is posterior distribution, $P(Y|\theta)$ is likelihood of parameter with obtained data, $P(\theta)$ is prior distribution, and $P(Y)$ is data information. $P(Y)$ is fixed by given data, $P(Y|\theta)$ is most likely increase by adding more parameters, and a change of $P(\theta)$ depends on a setting of prior. Therefore, the only reason of increasing posterior log-likelihood by adding more restriction is that increase in $P(\theta)$ by change in prior (e.g., $\theta = 0$ by restriction) may outweigh the decrease in $P(Y|\theta)$. It implies the selection of prior is significant in our framework.

learning is the process by which each individual sequentially obtaining and updating information through the network. This learning process (i.e., converge to a consensus) could be hindered by structural condition of network of network such as clustering behavior (Golub and Jackson 2012). Therefore, positive and significant ρ_1 after filtering the confounding effects (similarities, herd behavior, and clustering effects) that hinder learning process would represent the social learning process by information exchange through networking process (Golub and Jackson 2010; Ramirez 2013; Dong et al. 2018). Therefore, this result explains that our target network has a possibility to maintain a sustainable adoption process for a new technology.

Observation-based network (W_2), the networking structure based on a weak signaling that mainly delivers the neighbors' choice, not underlying reasons nor feedback regarding that choice (i.e., 'reply' action in Twitter), also indicate positive and significant coefficient ρ_2, but the effect is smaller than ρ_1. It explains mimicking other's choice or opinion (herd behavior) would also significantly affect an adoption decision, but less effective than information-exchange networking process especially for the knowledgeable individuals such as turfgrass professionals (Munshi 2004; Straub 2009; Ki and Kim 2019).

The insignificant advisor networking effect (β_{11}) suggests three possible situations. First, the advisor groups are not actively interacting with decision makers on average (dual centrality measures in Table 2.2 hints this possibility). Second, decision-makers could be skeptical with advisor groups' suggestion on a new technology, especially if they are experienced individuals (Conley and Udry 2010; Prokopy et al. 2015). Third, the decision-makers may rely on the information from online social networking process (e.g., information-intensive networking) rather than advisors' suggestion or opinion (Wood et al. 2014). For instance, if decision-makers think the information exchange with their colleagues through social media is more helpful than the experts' education program, they would not pay much attention to experts' opinion, i.e., insignificant coefficient of advisor networking effect. Therefore, it suggests that experts should consider more actively incorporating into the online social networks (e.g., social media) for their education program.

The insignificant individual-level similarities (β_1 and β_2) show that individual-level aspects is irrelevant to a new technology adoption decision for professionals, especially for who are participate in demographically homogeneous profession (e.g., turfgrass) (Santos and Barrett 2008).

The network measures results varies: the degree centrality (β_7) coefficient indicates significant coefficient whereas eigenvector centrality (β_8) and clustering coefficients (β_9) shows insignificant coefficient. It explains the individuals with high social connections (e.g., popular individuals among co-workers) are likely to adopt a new technology, whereas individual with higher influence (e.g., senior manager of firm) on network or higher cluster tendency (e.g., individuals who primarily interact with their peers) are irrelevant to adoption decision. The model with restrictions that no advisor networking effect (Model 1-2; $\beta_{11} = 0$), no network structure effects (Model 1-3; $\beta_7 = \beta_8 = \beta_9 = 0$), and no advisor networking nor network structure effects (Model 1-4; $\beta_7 = \beta_8 = \beta_9 = \beta_{11} = 0$) show same implication as Model 1. Thus, along with low VIF (<5) between network structure measures and no close to 0 eigenvalues of adjacency matrices, the negligible differences between models confirms no serious multicolliearnity issue between covariates and adjacency matrices.

In SAR model specification, some covariates may not only directly but also indirectly affect dependent variable through imposed matrix system (e.g., an adjacency matrix based on social network) (LeSage and Pace 2009; Vega and Elhorst 2013). Moreover, since adjacency matrices are directly incorporated in data generating process (see equation (A-1) in Appendix), interpreting the covariate estimates without networking influence may inappropriate (LeSage and Pace 2009; Lacombe and LeSage 2018). Although many social network studies do not consider the marginal effects important (e.g., Leenders 2002; Paez et al. 2008; Zhang et al. 2013; Liu et al. 2014), it would be necessary to derive marginal effect for better inference in terms of networking process (Cohen-Cole et al. 2018). Accordingly, we calculate the marginal effect of estimates regarding the overall network structure we impose (LeSage and Pace 2009).

Table 2.5 reports the (average) direct (i.e., the effect of my behavioral characteristic on my decision via networking process), indirect (i.e., the effect my neighbor's behavioral characteristic on my decision via networking process), and total effects (i.e., direct plus indirect effects) of each variable through overall networking (i.e., information-intensive and observation-based networking both) process of the model 1: baseline in Table 2.4. Overall, direct and total effects are consistent with Table 2.4 results whereas indirect effect is insignificant for all variables. It explains peers' demographic (male and white), perceived price (sod price), profession (group 1 to group 4), and networking behavior (network structure measures) are irrelevant to decision-making process of each individual through network.

Table 2.6 reports results from Bayesian spatial probit analysis of equation (5) model specification, which includes interaction terms between group dummy variables and observation-based networking effect (W_2). Therefore, each interaction term shows how much the group that participated in an observation-based networking is affected by that network compare to public turf managers. Just as Table 2.4, Model 2 is a base model with no restriction, and Model 2-2, Model 2-3, and Model 2-4 are the estimation result with each corresponding restrictions to confirm the collinearity issue between network structure measures, adjacency matrices, and interaction terms. Posterior log-likelihood reports the base model (Model 2) has the best fits among all specifications.

From Model 2 to Model 2-4, the estimation results aside from interaction terms are similar to the Table 2.4: Significant effects of golf course superintendents (group 4), degree centrality, and information-intensive networking effect (W_1), and Observation-based networking effects (W_2) on probability to adopt a new variety. In Model 2, interaction terms between university sports facility managers and observation-based networking effects (Group 1*W_2) indicates negative and significant coefficient, and Golf course superintendents and observation-based networking effects (Group 4*W_2) shows positive and significant coefficient. On the contrary, from Model 2-2 and 2-4 shows the negative and significant coefficient for interaction term between national sport league field managers and observation-based networking effects (Group 2*W_2). Therefore, the difference in significance for coefficient β_{13} between Model 2 and restricted models (Model 2-2, Model 2-3, and Model 2-4) suggests there could be an inflated variance issue by multicollinearity.

The results from interaction terms between group-specific variables and observation-based networking (W_2) explain as follows: First, although a particular networking process (e.g., observation-based networking) positively affect overall adoption decisions, it may significantly differ by each group's perspective toward that network. Second, some groups may get skeptical (e.g., insignificant coefficient β_{14}), to information from particular network. These implications suggest applying the uniform policy or marketing strategy (e.g., promote new technology only through observation-based network) may ineffective. Thus, considering the group-specific attitude toward each networking type would be essential to design marketing strategy or extension education program.

Table 2.7 reports the marginal effects of model 2: baseline in Table 2.6. Due to the inclusion of interaction terms, none of the variables indicate significant direct or indirect effects expect for Group 1*W_2, Group 2*W_2, and Group 4*W_2. It explains that under the consideration of relative networking effect of groups participating in a particular network, none of the variable has significant marginal effect on decision-making process. However, the insignificant marginal effects for most of variables hint the presence of inflated variance by collinearity between interaction terms and other variables. Therefore, the model specification with interaction term would be inadequate to explain decision-making process, especially in terms of marginal effect.

6. Conclusions

Our study investigates the role of social networking on a new variety adoption decision using a Twitter data from turfgrass professionals. To identify information-intensive (i.e., actively exchange information) networking effect, which could be considered as a proxy of social learning effect, among the confounding networking effect, we decompose networking effect into group- and individual-similarities, clustering, and herd behavior effects. This approach is purposed to filter-out the networking confounding effects that may cause reflection problem. To classify and control group-similarity, individual-similarity, herd behavior, and clustering effects, we employ the professional group-specific effects, demographic variables (race and gender), the weak signaling (observation-based) networking system, and degree centrality, eigenvector centrality, clustering coefficient in spatial autoregressive model specification, respectively (Liu and Lee 2010; Snijders et al. 2010; Liu et al. 2014; Cohen-Cole et al. 2018). To account for the advisors networking effect on individuals' adoption decision, we employ the simultaneous group and individual centrality measures that represents the degree of social interaction between individuals and advisor groups (Bonacich 1991). The adjacency matrix that based on retweet, the strongest social signal in Twitter platform would represent a proxy of social learning effect on a new technology adoption decision (Mills et al. 2019). To clarify herd behavior effect, we use employ the additional adjacency matrix that based on reply interaction, the weak communication between individual in Twitter platform, which represents a tendency to imitate neighbors' opinion, i.e., herd behavior (Shen et al. 2016; Aarstad et al. 2018; Dutta et al. 2021). For faster and stable estimation process, we employ the Bayesian estimation method with priors that based on the previous literature, which ensure the invertible covariance matrix. (Sun et al. 1999; Smith and LeSage 2004; LeSage and Pace 2009; Wilhelm and de Matos 2013). We confirm there is no serious mutlicollienarity issue by (a) small Variance Inflation Factor (VIF < 5) between covariates, (b) no close to 0 eigenvalues for adjacency matrices, and (c) no significant difference in estimates between models with different parameter restrictions. The Gelman-Rubin statistics for all estimates indicate adequate convergence of MCMC process for Gibbs-sampling (Gelman and Rubin 1992).

Our estimation results show positive and significant coefficients for information-networking networking and herd behavior effects both, and the effect of information-intensive networking is larger than herd behavior effect, degree centrality, and golf course superintendents (group 4) variables across all model specifications. On the other hand, the advisor networking effects indicate significant coefficient. These results explain (a) the significant learning about the new technology through information exchange, the likelihood to result in a sustainable adoption process.(b) Information exchange networking is more effective than observation-based networking. (c) Individuals with more close connections are more likely to adopt a new variety. (d) Large and socially active group (e.g., golf course superintendents) are more active in introducing new technologies than other groups. (e) Decision-makers may prefer the information from online social networking to suggestions from advisor groups.

The model with interaction terms between group dummy variables and observation-based networking effects, i.e., the indirect effect of observation-based networking by each group, shows positive and significant coefficient for golf course superintendents, and negative and significant coefficients for university sports facility managers and national sport league field managers. This result suggests the observation-based networking may have less significant effect on a new variety adoption decision of sport field managers (university sports facility managers and national sport league field managers), whereas have more significant effect on golf course superintendents than reference group (public turf managers).

These results suggest following policy implications: first, advertising to individuals who are more involved in information-intensive networking (e.g., participate in discussion about new technology through social media) than observation-based networking (e.g., observe others behavior without contemplation) would, on average, be more effective in increasing the new technology adoption rate as well as ensuring a sustainable adoption process (Bandiera and Rasul 2006; Wang et al. 2020). Second, advertising for individuals and groups who are active and have more connections in networking, i.e., higher degree centrality would ensure to increase new technology adoption (Bandiera and Rasul 2006; Wossen et al. 2013). Third, advisor groups (e.g., extension specialists) may need to engage more in online social networking to provide relevant information about new technologies for sustainable new technology adoption process (Munshi 2004; Straub 2009; Wood et al. 2014). Fourth, networking effects could significantly differ by each professional group: some groups may make adoption decision through observation-based networking, and others may oppose the information or opinion from observation-based networking process. Therefore, when designing a policy or marketing strategy, group-specific behaviors and responses to each networking type should be considered.

Although efforts have made to remedy the reflection problem and identify precise networking effects, this study still has some limitations. First, selecting the observation due to network could be problematic. Just as snowball sampling, our data is based on the connection between individuals, i.e. networking structure. It implies our sample is not randomly selected, thereby this study result could not be interpreted in terms of population. Second, the aforementioned selection bias could also raise endogeneity issue. Since our data is not randomly selected, individual-specific attributes toward networking behavior, such as gender-specific tendency to participate networking, would not be considered. Third, we assume the adjacency matrices are given, yet stating the fixed social networks could be a strong assumption that may reduce the validity of this study (Pinkse and Slade 2010). Fourth, strong parameter restrictions could limit the validity of this study as well. Although the parameter restrictions for networking coefficients (ρ_1 and ρ_2) are based on the previous studies' suggestion (e.g., Smith and LeSage 2004), study results under the strong assumptions may cast doubt in our findings and their implications. Fifth, our definition of weak networking would not weak enough to represent the observation-based herd behavior. For instance, Twitter has other networking and signaling channel such as "Like" action, and the networking effects of the other channels are not considered in this study. Thus, our definition of weak networking is not clear until compare the networking effects of different channels (e.g., comparison of networking effect between "Reply," "Like," and "Following" action channels via Twitter platform). Sixth, we conclude that the group with relatively larger size and more active in social interaction than other groups is more likely to adopt a new technology. Nonetheless, the large group may socially active due to its size and vice versa; this simultaneity may occur reflection problem (Manski 1993). Seventh, despite our effort, the inconsistent estimate issue due to endogenous adjacency matrices is not fully accounted (Pinkse and Slade 2010; Qu and Lee 2015; Hsieh and Lee 2016). The literature suggests the instrument variable (IV) estimation via a rich dataset could solve this endogeneity issue (Kelejian and Prucha 2010; Yoganarasimhan 2012). However, our data does not have information to obtain an appropriate instrument variable for endogenous networking system. Therefore, the estimation result in this study is limited to be interpreted in causal relationship. Finally, our study does not provide a sufficient guideline for extension specialists. Although we suggests extension specialists need to be more active in online social network, we could not suggest how to approach in details that important to design an effective extension education program (e.g., what kind of social signals from farmers indicate that they are well informed by education program or not?).

Therefore, future research directions might be to consider applying a large network dataset, which has enough observation number to represent the population of specific community (e.g., a network of all lawn owner in town). Another possible direction might be to apply methodologies that mitigate the selection bias problem. For instance, Bayesian hierarchical modelling with individual-level random effects could account for the unobserved individual-specific attributes, such as demographic specific effects (Khattak and Khattak 2021). Unlike conventional random-effects model, Bayesian hierarchical approach would have no low degree of freedom issue due to small sample size. Employing the concept of random graph theory, such as Exponential Random Graph Model (ERGM) could be useful to remedy endogenous adjacency matrices and non-random network issues both. ERGM consider each interaction in network is random, thereby allow to predict the network structure in terms of probability of interaction between individuals (e.g., a probability that person A interacts with person B in network is a function of network characteristic) (Snijders et al. 2006; Robins et al. 2007). Thus, applying a predicted network structure (i.e., adjacency matrix) via ERGM as IV estimator could account for the randomness and remedy endogeneity issue of adjacency matrices simultaneously. Further, simulating the network structure changes due to policy or environmental shock could be an interesting option. For instance, when stakeholders engage more actively with consultants or extension specialist through government program, the network structure among stakeholders will change and will affect stakeholders' decision-making processes through social network. Moreover, applying other network structure measures other than centralities could provide more practical policy implications. For example, network measures considering the direction of social interaction could suggest which type of interaction could be the most efficient way to transfer information (e.g., one-way interaction vs two-way interaction).

Despite aforementioned caveats, our study is the first based on online network structure and its measures, which account for networking behavior that unobservable through data, in the agricultural technology adoption literature. Moreover, our study introduce a method to filter-out and estimate an information-intensive networking effect rather than confounding networking effects that barely explains stakeholders networking behavior. Thus, this study would provide a practical stepping stone upon for future related studies by suggesting an accurate methodology to predict new technology adoption decision.

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Table 2.1. Network Descriptive Statistics.

Overall Network Descriptive Statistics					
Total number of nodes (individuals in network)					231.000
Total number of ties (connections between individuals in network)					990.000
Average degree (number of ties)					4.285
Group Degree Centrality[1]					
University sports facility managers (group 1)					0.257
National football, baseball, and soccer league field managers (group 2)					0.168
Sod producers (group 3)					0.209
Golf course superintendents (group 4)					0.481
Public turf manager (group 5)					0.444
Number of Ties: between- and within-groups					
	Group 1	Group 2	Group 3	Group 4	Group 5
Group 1	**24**	17	12	24	34
Group 2	17	**10**	4	10	20
Group 3	12	4	**24**	23	32
Group 4	24	10	23	**320**	74
Group 5	34	20	32	74	**112**

[1]: Normalized by the sum of total degree: values lies between 0 and 1 (Everett and Borgatti 1999).

Table 2.2. Network Descriptive Statistics: individual-group dual centrality[1]

Individual-Group Degree Centrality	
University sports facility managers (group 1)	0.001
National football, baseball, and soccer league field managers (group 2)	0.004
Sod producers (group 3)	0.001
Golf course superintendents (group 4)	1.000
Public turf manager (group 5)	0.018
Turfgrass management suppliers (group 6)	0.003
University faculty and professionals (group 7)	0.001
Private researchers and consultants (group 8)	0.419

[1]: The dual centrality explains the degree of social influence of each group on individuals in the network (Bonacich 1991).

Table 2.3. Data Descriptive Statistics (Obs = 231)

Dependent Variable	Mean	S.D.	Max	Min
New variety adoption (%)	36.79	48.32	-	-
Explanatory Variables				
University sports facility managers (group 1) (%)	7.35	26.16	-	-
National football, baseball, and soccer league field managers (group 2) (%)	5.19	22.24	-	-
Sod producers (group 3) (%)	9.09	28.81	-	-
Golf course superintendents (group 4) (%)	52.38	50.05	-	-
Public turf managers (group 5) (%)	25.97	43.94	-	-
White (%)	95.67	20.39	-	-
Male (%)	97.40	15.94	-	-
Price[2] (cents per square foot)	36.59	2.58	28.00	54.33
Degree centrality[2]	0.03	0.04	0.34	0.00
Eigenvector centrality[3]	0.02	0.09	0.78	0.00
Clustering coefficient	0.54	0.82	1.00	0.00

[1]: Source: National Quarterly Sod Report (USDA 2020) and sod producer survey (Miller 2022).
[2,3]: This measure is normalized by dividing each value by the largest value (Zaki et al. 2014).

Table 2.4. Parameter Estimates from Spatial Probit Regression.
※ Dependent Variable: a new variety adoption decision (Obs = 231)

	Parameters	Model 1[1]: baseline	Model 1-2[2]: $\beta_{11} = 0$	Model 1-3[2]: $\beta_7 = \beta_8 = \beta_9 = 0$	Model 1-4[2]: $\beta_7 = \beta_8 = \beta_9 = \beta_{11} = 0$
Intercept	β_0	1.016	0.974	1.023	1.220
Male	β_1	-0.397	-0.319	0.431	-0.576
White	β_2	0.263	0.239	0.115	0.356
University sports facility managers (group 1)[3]	β_3	0.058	0.161	-0.064	0.245
National sport league field managers (group 2)	β_4	-0.480	-0.418	-0.585	-0.404
Sod producers (group 3)	β_5	-0.476	-0.392	-0.466	-0.368
Golf course superintendents (group 4)	β_6	0.354*	0.431*	0.398*	0.439**
Degree centrality	β_7	7.221***	7.174***	-	-
Eigenvector centrality	β_8	-0.589	-0.405	-	-
Clustering coefficient	β_9	-0.151	-0.189	-	-
Sod price	β_{10}	-0.019	-0.021	-0.038	-0.025
Advisor networking effect	β_{11}	0.005	-	0.126	-
Information-intensive networking effect (W_1)	ρ_1	0.008*	0.007*	0.007*	0.008*
Observation-based networking effects (W_2)	ρ_2	0.002*	0.002*	0.002*	0.001*
Posterior log-likelihood	-	-229.494	-220.894	-200.391	-198.729

*, **, and *** indicate the Bayesian estimates does not include zero in credible interval of 90%, 95%, and 99%, respectively.
[1]: Four-parameter Beta prior setup: $a = b = c = d = 2$ (the other prior settings are identical between models).
[2]: Four-parameter Beta prior setup: $a = b = c = d = 1$.
[3]: Public turf manager (Group 5) is omitted to avoid the perfect correlation.

Table 2.5. Marginal Effects of Model 1: baseline.

	Direct Effect	Indirect Effect	Total Effect
Male	-0.090	-0.008	-0.099
White	0.061	0.007	0.068
University sports facility managers (group 1)	0.002	-0.001	0.001
National sport league field managers (group 2)	-0.179	-0.018	-0.196
Sod producers (group 3)	-0.156	-0.013	-0.169
Golf course superintendents (group 4)	0.143*	0.013	0.156**
Degree centrality	2.246***	0.206	2.452***
Eigenvector centrality	-0.157	-0.016	-0.173
Clustering coefficient	-0.045	-0.004	-0.049
Sod price	-0.008	-0.001	-0.008
Advisor networking effect	0.032	0.003	0.036

*, **, and *** indicate the Bayesian estimates does not include zero in credible interval of 90%, 95%, and 99%, respectively.

Table 2.6. Parameter Estimates from Spatial Probit Regression: with interaction terms.
※ Dependent Variable: a new variety adoption decision (Obs = 231)

	Parameters	Model 2[1]: baseline	Model 2-2[1]: $\beta_{11} = 0$	Model 2-3[1]: $\beta_7 = \beta_8 = \beta_9 = 0$	Model 2-4[1]: $\beta_7 = \beta_8 = \beta_9 = \beta_{11} = 0$
Intercept	β_0	0.049	0.058	0.002	-0.052
Male	β_1	-0.461	-0.457	-0.465	-0.402
White	β_2	0.560	0.673	0.727	0.686
University sports facility managers (group 1)[2]	β_3	0.309	0.520	0.249	0.599
National sport league field managers (group 2)	β_4	-0.669	-0.244	-0.686	-0.382
Sod producers (group 3)	β_5	-0.571*	-0.318	-0.555	-0.401
Golf course superintendents (group 4)	β_6	0.233	0.343*	0.386*	0.334*
Degree centrality	β_7	-0.340	-0.267	-	-
Eigenvector centrality	β_8	0.384	0.006	-	-
Clustering coefficient	β_9	-0.157	-0.145	-	-
Sod price	β_{10}	0.001	-0.003	-0.004	-0.001
Advisor networking effect	β_{11}	0.142	-	0.192	-
Information-intensive networking effect ($\boldsymbol{W_1}$)	ρ_1	0.008*	0.007*	0.008*	0.008*
Observation-based networking effects ($\boldsymbol{W_2}$)	ρ_2	0.002*	0.002*	0.002*	0.002*
Group 1*$\boldsymbol{W_2}$	β_{12}	-0.163*	-0.204**	-0.133*	-0.161*
Group 2*$\boldsymbol{W_2}$	β_{13}	-0.209	-0.284*	-0.209*	-0.206*
Group 3*$\boldsymbol{W_2}$	β_{14}	-0.067	-0.107	-0.114	-0.131
Group 4*$\boldsymbol{W_2}$	β_{15}	0.025**	0.029**	0.027**	0.021**
Posterior log-likelihood	-	-317.234	-368.837	-339.661	-324.441

*, **, and *** indicate the Bayesian estimates does not include zero in credible interval of 90%, 95%, and 99%, respectively.
[1]: Four-parameter Beta prior setup: $a = b = c = d = 2$ (the other prior settings are identical between models).
[2]: Public turf manager (Group 5) is omitted to avoid the perfect correlation.

Table 2.7. Marginal Effects of Model 2: baseline.

	Direct Effect	Indirect Effect	Total Effect
Male	-0.136	-0.010	-0.146
White	0.162	0.013	0.175
University sports facility managers (group 1)	0.089	0.008	0.097
National sport league field managers (group 2)	-0.193	-0.015	-0.208
Sod producers (group 3)	-0.165	-0.013	-0.178
Golf course superintendents (group 4)	0.067	0.005	0.072
Degree centrality	-0.099	-0.009	-0.108
Eigenvector centrality	0.109	0.010	0.119
Clustering coefficient	-0.045	-0.004	-0.050
Sod price	0.000	0.000	0.001
Advisor networking effect	0.041	0.003	0.044
Group 1*$\boldsymbol{W_2}$	-0.047*	-0.004	-0.051*
Group 2*$\boldsymbol{W_2}$	-0.060*	-0.005	-0.065*
Group 3*$\boldsymbol{W_2}$	-0.019	-0.002	-0.021
Group 4*$\boldsymbol{W_2}$	0.007*	0.001	0.008*

* indicates the Bayesian estimates does not include zero in credible interval of 90%.

Figure 2.1. Primary sources of network heterogeneities.

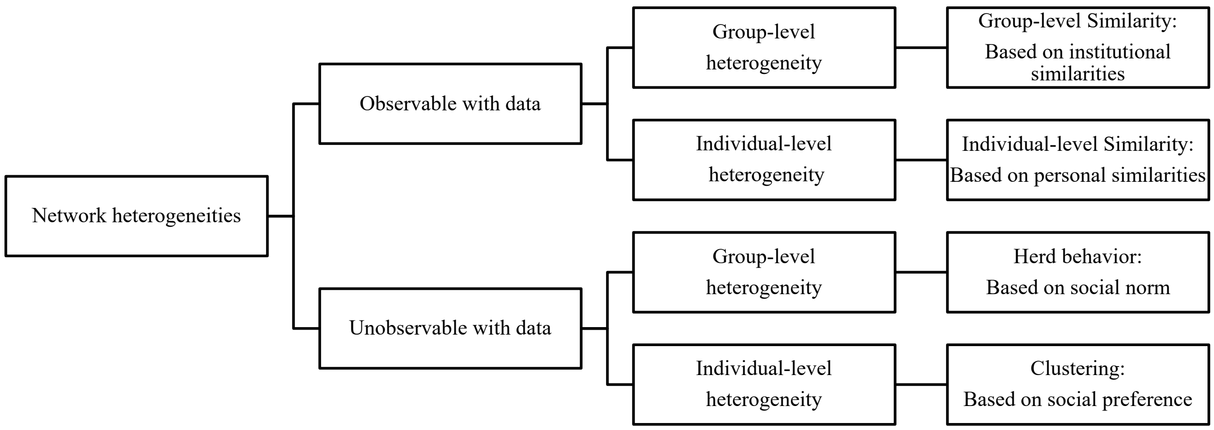


Figure 2.2. Network Example.

$$W = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

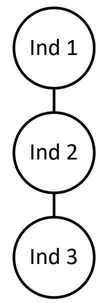


Figure 2.3. Social Network Structure of Professionals based on Twitter Interaction.

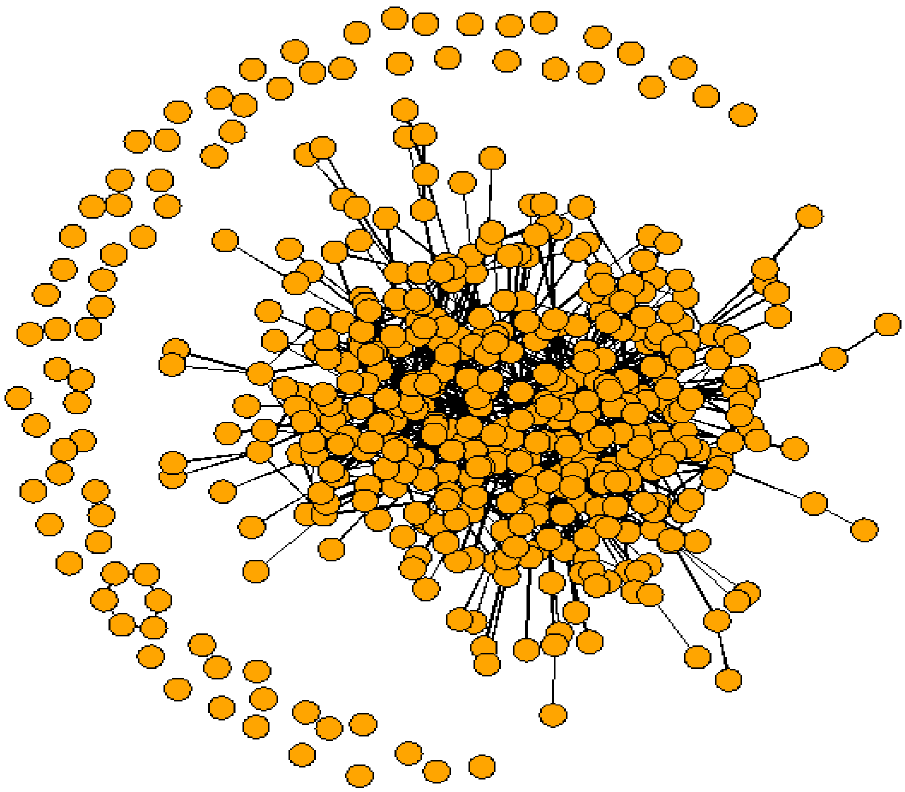
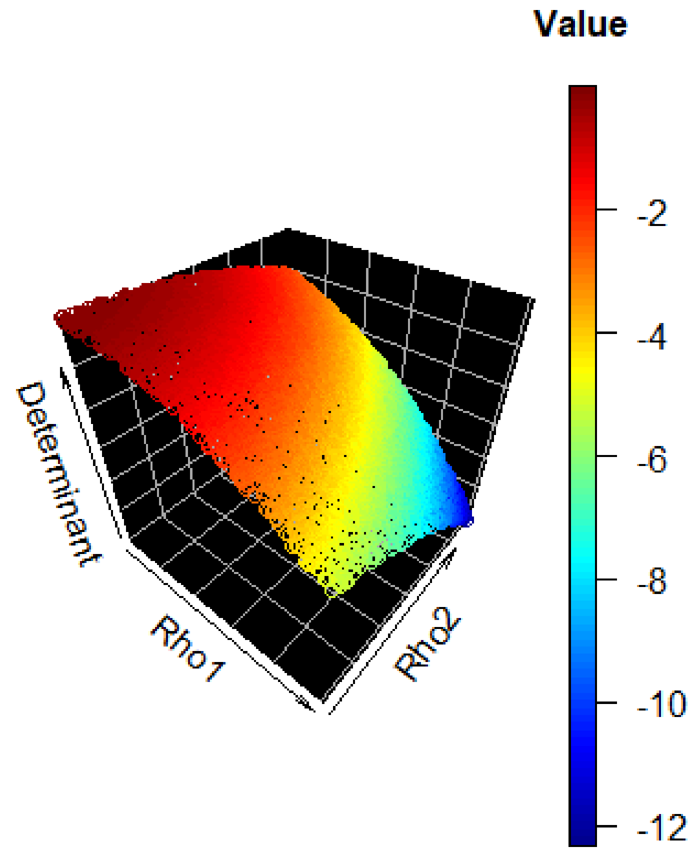


Figure 2.4. Example of Tweet to Verify New Variety Adoption.

Figure 2.5. Grid Search Plot of $|I - \rho_1 W_1 - \rho_2 W_2|$.



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APPENDIX

Based on the Equation (2.1), the data generating process for Y_i^* is as follows (LeSage and Pace 2009):

$$Y^* = S^{-1}(X\beta + e) \tag{A-1}$$

$$Y^* \sim N\left[S^{-1}(X\beta), S^{-1}ee'S^{-1\prime}\right],$$

$$S = (I - \rho_1 W_1 - \rho_2 W_2),$$

where I is an identity matrix. The rearrangement from Equation (1) to (A-1) is purposed to (a) express as a solution for adoption decision, Y, (b) avoid potential singular matrix issue by sparse matrices W_1 and W_2, and most importantly, (c) remedy the endogeneity by reducing the W_1Y and W_2Y parts that cause simultaneity bias (Anselin 2001). In addition, this framework accounts for the non-linear nature of networking effect (Bandiera and Rasul 2006). Nonetheless, the non-linearity in ρ_1 and ρ_2 would cause complexity to estimate these parameters. Therefore, instead of using S^{-1}, we employ the quadratic Taylor expansion that is a proxy of S^{-1} but has no non-linearity issue in parameter estimation (Kelejian and Prucha 1998; LeSage and Pace 2010; LeSage and Pace 2011).

In this framework, convergence issue may arise due to non-invertible covariance matrix: if covariance matrix of latent variable is non positive-definite, it may result in singular matrix and thus inappropriate posterior distribution for adjacency matrix parameters (Smith and LeSage 2004). To avoid this critical issue, the previous literature suggests to employ parameter restriction for ρ. For spatial probit model in particular, Sun et al. (1999) and Smith and Lesage (2004) suggest that if W is square matrix and diagonal elements are zero, the spatial dependence parameter of probit model should lie in between inverse of maximum and minimum eigenvalues of corresponding adjacency matrix. Nonetheless, since there are two adjacency matrices in our model, this restriction would not be sufficient to ensure convergence. Therefore, we need to employ stronger constraints than in previous studies to prevent singular matrix problem. In the previous literature, Lee and Liu (2010) argue that if SAR model has more than two adjacency matrices, it is appropriate to employ the interdependent parameter restriction such as $|\rho_1| + |\rho_2| < 1$ to ensure the invertible covariance matrix. Also, Wilhelm and Matos (2013) and Liu et al. (2014) suggest non-negativity parameters restriction for better convergence and Zhang et al. (2013)'s empirical analysis with normal distribution prior indicates the positive and significant adjacency matrix parameters.

By combining all of these suggestions in the previous literature, we employ the parameter restriction for ρ_1 and ρ_2 as follows:

$$\frac{1}{2}\varphi_{1,min}^{-1} + \frac{1}{2}\varphi_{2,min}^{-1} < \rho_1 + \rho_2 < \frac{1}{2}\varphi_{1,max}^{-1} + \frac{1}{2}\varphi_{2,max}^{-1}. \tag{A-2}$$

where φ_{min}^{-1} and φ_{max}^{-1} are the inverse of minimum and maximum eigenvalues of corresponding adjacency matrix, respectively. This restriction would satisfy the sufficient condition for convergence by providing a narrow region that guarantees positive definite for both adjacency matrices. In addition, this constraint ensures the non-zero determinant in likelihood function, which is essential for sampling ρ_1 and ρ_2 in Bayesian framework. We employ this restriction by utilizing prior distribution of corresponding parameters (details are provided in the further part of this section).

The basic idea of Bayesian estimation is sampling from a posterior distribution of parameters $P(\beta, \rho_1, \rho_1, Y^*|Y)$ given the data *Y* and prior distributions. We consider the β follows multivariate normal distribution and ρ_1 and ρ_2 follow four parameters beta prior[21] as follows (LeSage and Pace 2009):

$$\begin{gathered}\beta \sim N(c, T), \\ \rho_1 \sim Beta4\left(a, b, \frac{1}{2}\varphi_{1,min}^{-1}, \frac{1}{2}\varphi_{1,max}^{-1}\right), \\ \rho_2 \sim Beta4\left(c, d, \frac{1}{2}\varphi_{2,min}^{-1}, \frac{1}{2}\varphi_{2,max}^{-1}\right),\end{gathered} \tag{A-3}$$

where c and T are hyper-parameters, mean and variance for normal prior, *a*, *b*, *c*, *d*, are shape parameters[22] for four parameter beta prior distribution, and $\frac{1}{2}\varphi_{min}^{-1}$ and $\frac{1}{2}\varphi_{max}^{-1}$ are range parameters, i.e., lower and upper bounds of the corresponding beta distribution, respectively. With these prior settings, we could implement the aforementioned restriction, the parameter space of $\rho_1 + \rho_2$ as in Equation (A-2) to ensure convergence as a support of parameter distribution.

Based on the prior information in Equation (A-3), the posterior distribution of parameters, i.e., the joint distribution of data likelihood and prior distribution functions, could be represented as follows:

$$p(\beta, \sigma^2, \rho_1, \rho_2, Y^*|Y) \propto p(Y|\beta, \rho_1, \rho_2, Y^*) * \pi(\beta, \sigma^2) * \pi(\rho_1) * \pi(\rho_2). \tag{A-4}$$

[21] The four parameters beta distribution has an advantage in (a) flexible range in the level of information in prior, from uniform (a=1, b=1) to normal-like (a>1, b>1) distribution, and (b) flexible range in parameter than conventional Beta distribution (Hanson 1991). In particular, this flexible parameter range is suitable to employ the networking parameter restrictions that ensures the positive definite covariance matrix of latent variable.

[22] In practice, we apply different shape parameters by each model specification to control the degree of information by prior (see footnotes in Table 2.4 and Table 2.6).

In general, the posterior distribution is unlikely obtainable through analytical approach due to its complexity. Therefore, the practical way of sampling parameter via posterior distribution is Gibbs sampling through Markov Chain Monte Carlo (MCMC) process on conditional density of each parameter distribution (Wilhelm and de Matos 2013). For instance, the Gibbs sampling process for latent variable $Y^* = (Y_1^*, Y_2^*, \ldots, Y_i^*)$ is based on the conditional density distribution of Y^* with observed data $Y = (Y_1, Y_2, \ldots, Y_i)$ is as follows (LeSage and Pace 2009):

$$p(Y^*|\beta, \rho_2, \rho_2, Y) \sim N\left[S^{-1}X\beta, S^{-1}ee'S^{-1'}\right]. \qquad \text{(A-5)}$$ [23]

The steps of Gibbs sampling are follows:

1) Assign the initial values for parameters, $\beta^0, \rho_1^0, \rho_2^0$ (Y is given as data).

2) Draw a sample from conditional distribution based on the initial values $p(Y^{*,1}|\beta^0, \rho_1^0, \rho_2^0, Y)$.

3) Apply the drew value from step 2 to draw other conditional distributions such as $p(\beta^1|\rho_1^0, \rho_2^0, Y^{*,1}, Y)$.

4) Repeat the steps 1 to 3 for all parameters given sampling time *t*.

Therefore, Gibbs sampling process generates posterior samples without deriving a high-dimensional joint distribution function of posterior distribution (Geman and Geman 1984). For sampling β, posterior distribution of β is proportional to the multivariate normal distribution with conditional mean and variance. We sample β from a multivariate normal conditional density as

$$p(\beta|\rho_1, \rho_2, Y^*, Y) \propto N(c^*, T^*), \qquad \text{(A-6)}$$

$$c^* = (X'X + T^{-1})^{-1}(X'SY^* + T^{-1}c),$$

$$T^* = (X'X + T^{-1})^{-1},$$

[23] $Y^*$is truncated normal due to the property of latent variable that the range of Y^* changes by each selection (If $Y_i = 1$ then $Y_i^* > 0$, if $Y_i = 0$ then $Y_i^* \leq 0$).

where c^* is conditional mean and T^* is marginal variance-covariance of posterior distribution of β. These parameter are derived based on the given initial value from prior information (c and T), given dataset ($X, Y, Y^*, and\ W$), and corresponding parameters (ρ_1 and ρ_2) (see Chapter 5 of Lesage and Pace (2009) for details).

The sampling for of ρ_1 and ρ_2 are based on following conditional densities as

$$p(\rho_1|\rho_2, \beta, Y^*, Y) \sim |S| \exp\left[-\frac{1}{2\sigma^2}(SY - X\beta)'(SY - X\beta)\right], \qquad \text{(A-7)}$$
$$p(\rho_2|\rho_1, \beta, Y^*, Y) \sim |S| \exp\left[-\frac{1}{2\sigma^2}(SY - X\beta)'(SY - X\beta)\right].$$

For brevity, we assume both parameters follow same distributional form that conditional to each other. For faster computational process, we employ the grid-search method for *S* that based on the aforementioned parameter restrictions of ρ_1 and ρ_2: compute the determinant of S for all grid points in given parameter space for ρ_1 and ρ_2 (see Equation (A-6)) in advance, and search the derived determinant that matches each step in Gibbs-sampling process as Figure 5 (LeSage and Pace 2009; Wilhelm and de Matos 2013).

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