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Using Artificial Neural Network techniques to improve the description and prediction of household financial ratios

Wookjae Heo [a], Jae Min Lee [b], Narang Park [c,*], John E. Grable [d]

[a] Department of Consumer Sciences, South Dakota State University, Brookings, SD, United States of America
[b] Department of Family Consumer Science, Minnesota State University, Mankato, MN, United States of America
[c] Department of Financial Planning, Housing, and Consumer Economics, University of Georgia, 205 Dawson Hall, 305 Sanford Dr. Athens, GA 30602, United States of America
[d] Department of Financial Planning, Housing, and Consumer Economics, University of Georgia, Athens, GA, United States of America

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ABSTRACT

The purpose of the study described in this paper was to shed light on the need for alternative methods to improve descriptions and predictions of household financial ratios. Using data from the 2013, 2015, and 2017 Panel Study of Income Dynamics (PSID), this study examined the descriptive and predictive power of an Artificial Neural Network (ANN) model and an Ordinary Least Squares (OLS) model when evaluating household savings-to-income ratios and debt-to-asset ratios cross-sectionally and across time. Results suggest that ANN models provide a better overall model fit when describing and forecasting financial ratios. Findings confirm that machine learning procedures can provide a robust, efficient, and effective analytic method when an educator, researcher, financial service professional, lender, or policy maker needs to describe and/or predict a household's future financial situation. Suggestions for the implementation of ANN modeling procedures by household finance researchers, practitioners, and policy makers are provided.

1. Introduction

Financial ratios have been a staple financial analysis tool in the corporate world for the better part of two centuries. The adaption of financial ratios to the assessment and evaluation of households, however, is relatively recent. Altman (1971) is generally considered to be the first person to advocate the use of business ratio analytical techniques to the assessment of household financial stability, although it was Griffith (1985) who formalized the use of widely used household ratios (DeVaney, 1994). Essentially, a household level financial ratio is a mathematical derived tool that (a) objectively measures a household's financial situation; (b) provides a way to track financial progress over time; and (c) allows a lender, financial service professional, or educator a platform to determine the financial wherewithal of a household to take on more debt or spending obligations (Lytton et al., 1991)

The use of current and projected household level financial ratios is pervasive across the financial sector of the economy. Banks, credit unions, and other lending institutions, for example, use financial ratios as a key determinant of loan originations, with financial ratios often being used as an input into credit risk scores (Duca and Rosenthal, 1994). Financial service professionals, financial counselors, financial therapists, and financial coaches often use financial ratios to gain insights into the current and future financial stability of a household (Harness et al., 2008; Lytton et al., 1991). In some cases, weak financial ratios can result in reduced access to financial service products and services, higher costs associated with services, and an increased likelihood of entering bankruptcy (Birkenmaier, 2012).

Two financial ratios stand out as being widely used by institutions and financial service professionals when evaluating the financial condition of a household: the savings-to-income ratio and the debt-to-asset ratio. The savings-to-income ratio refers to the sum of household savings divided by annual gross income (Grable et al., 2012). The debt-to-asset ratio provides a measure of a household's ability to meet financial obligations assuming all assets are liquidated (DeVaney, 1994; Kim and Lyons, 2008). The debt-to-asset ratio is measured as total debts divided by total assets (e.g., Garman and Forgue, 2018). Together, these

* Corresponding author.
E-mail address: narang.park25@uga.edu (N. Park).

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ratios provide descriptive information about the current financial status of a household. The savings-to-income and debt-to-asset ratios can also be used to gauge how well a household manages monetary resources (Grable et al., 2012; Harness et al., 2008).

Financial ratios serve another role in addition to being indicators of current financial status. Financial ratios can be used as prescriptive tools to help guide household decision makers when making choices about debt accumulation, saving, and general spending (Harness et al., 2008). Although somewhat simplistic, a financial decision maker – or her or his financial advisor – can use financial ratios as benchmarks to plan how to manage financial and monetary resources (Greninger et al., 1996).

As noted by Deacon and Firebaugh (1988) and Grable et al. (2012), describing – let alone predicting – the financial status of a household is complicated and oftentimes problematic. Traditional tools used to describe the determinants of the savings-to-income ratio and the debt-to-asset ratio do not always work well, primarily because these ratios can be impacted by various under- or un-identified influential factors. For instance, a household with a strong savings-to-income ratio may experience economic hardship in the future because of uncontrolled spending, the loss of income, death of an income earner, or any number of other factors that make traditional prediction models somewhat unreliable. This helps explain, to some extent, why lending institutions often experience credit risks that surpass original estimations. This also illustrates why some households exhibit a projection bias by extrapolating current ratios into the future in a way that leads to problematical outcomes (e.g., bankruptcy).

As the discussion thus far has indicated, financial ratios are very valuable household financial management tools. While effective in describing a household's current financial situation, financial ratios are not static. This means that financial ratios are difficult to predict, primarily because the strength of a financial ratio can be altered over time by interactions with other factors. Consider the debt-to-asset ratio. It is generally thought that households managed by those in their 20 s should have a higher level of debt compared to households managed by those nearing or entering retirement. As such, in a simple prediction model, one would assume that as the age of a household financial manager increases, the debt-to-asset ratio should decrease. A key problem with this assumption is that traditional prediction models are generally unable to fully account for other household and individual factors that can alter the direction and strength of the debt-to-asset ratio. Factors that can cause a linear pattern to change include job varieties, income level, marital status, homeownership, health condition, the number of dependents living in a household, education of the household head, and changes in financial circumstances at the household and macroeconomic level (Chen and Finke, 1996; Godwin, 1996; Joo and Grable, 2004; Kim and Lyons, 2008; Lee and Kim, 2016; Scannell, 1990).

The insight that financial ratios are difficult to describe and forecast is not new. What is noteworthy, however, is information on new methodologies that can be used to improve the prediction accuracy of household financial ratios. The main purpose of this study paper is to describe a method, based on an artificial neural network (ANN) modeling technique that can be used to significantly improve the description and prediction of the savings-to-income ratio and the debt-to-asset ratio. Specifically, this paper describes a machine learning technique and compares the technique to a baseline linear regression procedure when describing and forecasting savings-to-income and the debt-to-asset ratios for US households. As will be shown later in the paper, the machine learning procedure provides a robust, efficient, and effective analytic method to describe and forecast a household's future financial position.

2. Literature review

The use of financial ratios originated in corporate finance and accounting, where financial ratios were used to evaluate a company's profitability, liquidity, and solvency (DeVaney, 1994; Prather, 1990). In 1985, Griffith suggested that financial educators, financial counselors, and financial service professionals should adopt the financial ratio technique to evaluate the financial stability of households. She recommended 16 financial ratios for use when measuring liquidity, solvency, and the overall status of a household's financial situation (Garrett and James, 2013; Prather, 1990). Additional research on the use and value of household financial ratios led to wide acceptance among financial educators, financial service professionals, and researchers. Today, financial ratios are almost universally used as the basis for making and tracking financial recommendations made by financial service professionals when working with clients (DeVaney, 1994; Garman and Forgue, 2018; Grable et al., 2012; Lee and Kim, 2016), as well as a key determinant of loan originations (Duca and Rosenthal, 1994; Zanin, 2017).

As previously noted, financial ratios are widely used as a diagnostic tool to assess the financial strengths and weaknesses of households. In this sense, financial ratios tend to be used as descriptors, rather than predictors, of a household's financial situation. It is important to note, however, that another value associated with the use of financial ratios is trend analysis. Given the dynamics within and between variables over time, financial ratios can provide an accurate picture of the spending and saving habits of a household. By extension, the accurate prediction of financial ratios should provide household financial managers, and those who provide financial services to households, a way to gauge the financial position of a household in future years.

Although conceptually true, the accurate prediction of financial ratios, based on traditional linear modeling techniques, has been elusive. Rather than making projections about spending and saving based on highly accurate estimates, household financial managers, lending institutions, and other financial service professionals have been forced to make "guestimates" of a household's future financial status, based on trends, judgments, and expectations. The lack of reliability when predicting the values of financial ratios highlights limitations associated with traditional linear estimation techniques. As explained above, there are many factors that can have direct, as well as indirect, interactional, and mediating relationships with the financial resources of a household. Conventional estimation models (e.g., Ordinary Least Squares regression, logistic regression, probability models, etc.) are not particularly well suited to capture the underlying interactions and unobserved influences among factors typically associated with financial ratios (Medio, 1992; Shapiro and Gorman, 2000). The primary outcome associated with the current study is to provide an alternative to these methodologies that can be used to enhance the value and use of financial ratios at the household level.

2.1. The savings-to-income ratio

Among the large number of financial ratios used on a day-to-day basis, the savings-to-income ratio is among the most popular and widely used indicators of prudent financial management practice. The saving-to-income ratio is calculated as the percentage of gross income being saved annually for future financial goal achievement. The ratio is calculated as the sum of household savings divided by annual gross income (Grable et al., 2012). The definition of savings includes any employee and employer contributions to goal directed activities (e.g., defined contribution pension plans) as well as any income surplus (Greninger et al., 1996). While financial experts generally recommend that the ratio be equal to or greater than 10% (Greninger et al., 1996), there is not a "hard-and-fast rule" regarding the appropriate level of the ratio. Financial experts typically suggest that interpretation of the ratio should be flexible depending on the life stage of the household (Grable et al., 2012). For example, younger individuals and families might not save as much given debt repayment obligations and the costs associated with raising children, whereas households managed by older adults may save far more than normative rules recommend. Assuming a household's gross income and employer saving contributions are relatively stable, the volatility of the savings-to-income ratio relies on each household's saving motives and behavior.

Previous research on financial ratios has indicated that saving is related to several socio-demographic features of a household (e.g., age, gender, race/ethnicity, marital status, education, having a child), economic status (e.g., household income, net worth, homeownership, possession of other type of financial products), and personal characteristics (e.g., health status, risk tolerance, planning horizon, locus of control, self-control). For example, being female, Black (or Hispanic), single, less educated, and living with a dependent child are known to be associated lower savings rates (DeVaney et al., 2007; Kim and Lyons, 2008; Lunt and Livingstone, 1991; Lyons and Yilmazer, 2005; Yuh and Hanna, 2010). Age shows mixed in describing the ratio because some research suggests that households on both extremes of the life-cycle save less (Yuh and Hanna, 2010), while other researchers have indicated that the young are less likely to save compared to those in older generations (DeVaney et al., 2007; Lyons and Yilmazer, 2005). With regards to economic status, higher levels of income and net worth, investment levels, having insurance, and homeownership are known to be positively associated with a higher level of savings (DeVaney et al., 2007; Kim and Lyons, 2008; Lunt and Livingstone, 1991; Lyons and Yilmazer, 2005; Yuh and Hanna, 2010). When it comes to personal characteristics, DeVaney and her associates (2007) indicated that risk tolerance and a longer planning horizon tend to be positively related to household savings. Lunt and Livingstone (1991) noted that savers often believe they have control over their personal financial situation. In the literature, self-control – the ability to control impulsiveness – is generally positively linked to saving behavior (Strömbäck et al., 2017). Also, poor health condition has been shown to be a predictor of lower levels of savings (Kim and Lyons, 2008; Lyons and Yilmazer, 2005).

2.2. The debt-to-asset ratio (solvency ratio)

The debt-to-asset ratio, also known as the solvency ratio, is widely used to assess the overall financial security of a household. The debt-to-asset ratio provides a measure of a household's ability to meet financial obligations upon the liquidation of all household assets (DeVaney, 1994; Kim and Lyons, 2008). The debt-to-asset ratio is measured by dividing total debts (liabilities) by total assets (e.g., Garman and Forgue, 2018; Garrett and James, 2013; Kim and Lyons, 2008; Lee and Kim, 2016). The higher the resulting ratio, the greater the debt burden. Although benchmark standards differ by source, nearly all researchers and financial educators suggest a ratio equal to or less than one, meaning that after liquidating all assets and paying debt, a household would either have nothing left or a positive amount (Kim and Lyons, 2008; Lee and Kim, 2016). If total debts exceed total assets (i.e., debt-to-asset ratio > 1.0), a household is considered to be lacking sufficient assets to pay off liabilities, and thus is considered technically insolvent.

The debt-to-asset ratio, or likelihood of being insolvent, is related to the socio-economic and demographic characteristics of a particular household. Age, homeownership, income level, and having adequate health insurance are known to be positively related to solvency (Joo and Grable, 2004; Kim and Lyons, 2008; Lee and Kim, 2016). For example, the debt-to-asset ratio is known to be higher for poor households across age groups compared to the ratio for wealthier households (Yilmazer and DeVaney, 2005). Additionally, health condition (i.e., poor, serious chronic), having more dependents, being a non-married household, living in a household where the household head is a racial/ethnic minority, being credit constrained, and lacking a college degree are known to be negatively related to solvency (e.g., Joo and Grable, 2004; Kim and Lyons, 2008; Lee and Kim, 2016). There is less evidence that solvency is related to age, gender, marital status, and employment status (e.g., Kim and Lyons, 2008), although there is robust evidence that behavioral and attitudinal variables, such as monetary transfers to children, low risk tolerance, and overspending are related to the solvency ratio (e.g., Kim and Lyons, 2008; Lee and Kim, 2016).

2.3. Factors associated with household financial ratios

Household demographic characteristics are of importance whenever models are developed to predict a household's savings-to-income ratio and the debt-to-asset ratio across time. In the literature, age, education, household income, and marital status are generally known to be significantly associated with saving motives and the likelihood of saving (Chang et al., 1997; DeVaney et al., 2007; Lee and Hanna, 2015; Lee et al., 1997; Yuh and Hanna, 2010; Xiao and Noring, 1994). However, there is less consensus among researchers in relation to other household demographic factors. To date, no definite gender, ethnicity, health status, or number of children in a household patterns have emerged in the literature. Researchers continue to debate these variables' significance on saving motives and the likelihood of saving (DeVaney et al., 2007; Fisher, 2010; Lee et al., 1997; Yuh and Hanna, 2010; Xiao and Noring, 1994).

The literature does indicate that many demographic characteristics of households are related to debt decisions, such as the amount of debt held by households and the likelihood of having debt (e.g., Baek and Hong, 2004; Bryant, 1990; Flores and Vieira, 2014; Godwin, 1998; Yilmazer and DeVaney, 2005). Generally, age, income, assets (financial and non-financial), and net worth are known to be related to the likelihood of holding debt (e.g., Baek and Hong, 2004; Flores and Vieira, 2014; Yilmazer and DeVaney, 2005). However, the effects of education, gender, ethnicity, family structure, presence of children in the household, homeownership, and health status differ across research studies (Baek and Hong, 2004; Yilmazer and DeVaney, 2005).

Family structure (e.g., household size and marital status), income, and assets are generally thought to be associated with the amount of debt held by households, whereas no consensus opinion is evident in relation to the effects of education and ethnicity on the amount of debt (Baek and Hong, 2004; Godwin, 1998) or in relation to other types of behavioral indicators (e.g., exercise and healthy eating) (Carr et al., 2012). Household attitudes and behavioral characteristics are known to be related to debt decisions (e.g., likelihood of holding a debt, debt amount, changes in debt amounts). For example, spending behavior, compulsive buying, saving for a goal, expectations about future income and the economy (e.g., real income and inflation), time preference, credit limits, and credit attitudes are commonly reported to be associated with debt decisions (e.g., Baek and Hong, 2004; Godwin, 1998; Vieira et al., 2016).

As noted here, some of the factors that have traditionally been used to explain and/or predict saving behavior (i.e., household income, and marital status) are quite robust across studies, whereas other variables have been shown to have greater levels of effect variation depending on the type of study and population being surveyed. In this study, the relevant and historically significant variables from the literature were included as controls in the models used to predict household savings-to-income ratios and debt-to-asset ratios.

3. Theoretical background

At the individual and household level, Deacon and Firebaugh (1988) introduced the concept of an ecological system of family resource management. The main concept underlying the Deacon and Firebaugh framework is that there are diverse systems around an individual/household and that individuals and households interact within and between multi-level systems. Deacon and Firebaugh argued that diverse behavioral and managerial factors from these systems are associated with each other via inter- and intra-processes. Conceptually, Deacon and Firebaugh noted that researchers should account for the various interactions and compounding effects across systems when making household predictions. At the time the systems framework was proposed, it was not really possible to account for multi-system interactions in descriptive and prediction models. Today, however, analytic and computing power can be used to test research questions, based on the Deacon and Firebaugh model, in a way that fully incorporates the possibility that an individual/household moves among and across systems without being constrained by restrictions embedded in traditional analytic methodologies. For example, Walters et al. (2016) highlighted the extended application of an ecological approach for finance research. While this approach has been used mainly in the fields of computer science, such as artificial intelligence and robotics, Walters et al. suggested that further attempts to test analytic models in finance are needed and that advances in analytical techniques can be made by extrapolating from natural systems and processes in ways that explain financial behavior, such as investor actions in the stock market.

Conventional analytic tools used to (a) identify factors associated with an outcome variable and (b) forecast levels of an outcome variable, including ordinary least squares and logistic regression techniques, require that those making an analysis adhere to strict methodological guidelines (Medio, 1992; Meyers, 2007; Taylor and McGuire, 2007). For example, financial ratios are observed at the personal or household level. As such, there can be an issue of methodological individualism (Herreiner, 1999) that can make descriptions and predictions imprecise. When this occurs, a traditional modeling technique may overlook and/or purposely exclude variables that add to a model's explanatory power. This often occurs because of interactions, compounding effects, and multicollinearity. On the other hand, an unconventional analytic tool, such as machine learning – based on the use of an artificial neural network (ANN) – can sometimes be used to better capture under- or un-identified interactions within and among a multitude of variables included in a model, regardless of traditional constraints related to interaction or compounding effects or multicollinearity. In effect, machine learning is a robust non-parametric, large data technique that can be used reliably to increase descriptive and forecasting validity.

Machine learning techniques have been widely used by researchers working in computer science, marketing, the broad social sciences, and economics (Brock, 1996; Bukovina, 2016; Farmer and Sidorowich, 1988; Ince et al., 2019; Medio, 1992) but rarely among those who study consumer and household financial issues. As will be shown in this study, artificial neural networks using dynamic nonlinear estimations (i.e., machine learning) can be adapted to other fields. Machine learning does not necessarily depend on conventional assumptions about observed effects between and among the variables in one system. Dynamic nonlinear estimation techniques assume that there are holistic systems that are not confined to a one directional relation between x and y. In this sense, machine learning models are similar to the conceptual models originally proposed and described by Deacon and Firebaugh (1988).

The research conducted in this study follows a procedure outlined by Heo (2020). He combined two theoretical concepts based on ecological systems theory (see Deacon and Firebaugh, 1988) and dynamic nonlinear estimation procedures. According to Heo, the complexities of human behavior, including financial decision making, can be modeled based on two assumptions. First, within holistic systems there are general rules, and second, the observed patterns within most systems can be altered by stochastic features. For instance, it is reasonable to assume that the more a household saves, the greater the wealth exhibited by the household; however, this is not always the case. Households that overspend or experience an external macroeconomic shock may simultaneously increase savings while experiencing a decline in wealth. This decline is generally unpredictable using traditional analytic methods.

On the other hand, an artificial neural network (ANN) can be used to anticipate stochastic shocks, especially when the tested model combines concepts from a household's ecological system with aspects of dynamic nonlinear estimation. ANN is a useful tool for data classification and future-pattern prediction (Berson et al., 2000; Hand et al., 2001; Herbrich et al., 1999; Ince et al., 2019; Kovalerchuk and Vityaev, 2000; Kudyba and Kwatinetz, 2014; Linoff and Berry, 2011; Ye, 2014). As shown below, sequential functions of ANN (1) and (2) can be combined to account for a wide assortment of variables in an effort to increase the accuracy of descriptions and predictions:

$$u = \sum_{i=1}^{n} \omega_i \chi_i \tag{1}$$

$$y = f(u - \theta) \tag{2}$$

where, u is the activation unit to reach the function (f), χ_i denotes input factors, ω_i is related to the weight for each factor, and θ is a threshold level to trigger the function (f); the output (y) is calculated when the unit (u) has a number over threshold (θ).

When conceptualized this way, it is possible for a nonlinear estimation procedure to work effectively when describing and forecasting a behavioral phenomenon or outcome like a household's savings-to-income ratio or debt-to-asset ratio. As such, in this study, ANN was employed as the nonlinear estimation procedure for predicting financial ratios.

4. Methods

4.1. Data and program

Data from the 2013, 2015, and 2017 Panel Study of Income Dynamics (PSID) were used in this study. These years were selected based on (a) the purpose of the study which was to describe and forecast the future saving-to-income ratio and debt-to-asset ratio of those living in the United States, and (b) the unique time period represented by these years. Specifically, the period 2013 through 2017 represented the full recovery from what many in the media have called the Great Recession or global financial crisis. The number of respondents for each year was 1048 in 2013, 908 in 2015, and 959 in 2017.

Table 1
Measurement and operationalization: Predictors.

Measurement	
	Demographics
Education of head and spouse	Length of school year (1–16, e.g., 8 = completed the eighth grade) by head and spouse.
Age of head and spouse	Age of head and spouse.
Job status of head	Categorical variable: working, housekeeping, student, and not working.
Race/ethnicity of head and spouse	Categorical variable: White, African American, Asian, Pacific Islander and Native American, and Others/No answer.
Gender	Male; Female
	Expenditure of family
Interest rate of mortgage	Actual interest rate on mortgage or fixed loan.
Expenditures for housing	Annual dollar amount spent for mortgage and loan payments, rent, property tax, insurance, utilities, cable TV, telephone, internet charges, home repairs, and home furnishings.
Expenditures for transportation	Annual dollar amount spent on vehicle loan, lease, and down payments, insurance, other vehicle expenditures, repairs and maintenance, gasoline, parking and carpool, bus fares and train fares, taxicabs and other transportation.
Expenditures for food	Annual dollar amount spent on food (in home, delivery, and out of house).
Expenditures for vacation	Annual dollar amount spent on trips and vacations, including transportation, accommodations, and recreational activities.
Expenditures for clothing	Annual dollar amount spent on clothing
Expenditures for education	Annual dollar amount spent on education
Expenditures for childcare	Annual dollar amount spent on childcare
Expenditures for health	Annual dollar amount spent on hospital and nursing home, doctor, prescription drugs, and insurance.
	Financial and economic factors on family
Equities	Equities' value such as stock market products
Governmental subsidies	Yes, receive government subsidy; No.
House market value[a]	House's market value (dollar) − remaining mortgage
Net worth[a]	Total amount of farm and business wealth, checking/savings, other real estate, equities, vehicle value, other assets, and annuities (dollar) − total debt
Total debt[b]	Total amount of outstanding credit debt, student loan, medical bill, legal bill, and auto loan (dollar)
	Health factors
Mental health status of head and spouse	Yes, have psychological problem; No.
Health activities of head and spouse	
Vigorous physical activities	Annual total hours spent on vigorous physical exercise, head and spouse.
Light physical activities	Annual total hours spent on light or moderate physical exercise, head and spouse.
Physical activities for muscle	Annual total hours spent on physical exercise to improve muscle, head and spouse.
Risky behavior of head and spouse	
Smoking	Number of cigarettes taken per a day (head and spouse).
Alcohol	Annual total amount (e.g., bottles, glasses) of alcohol consumption (head and spouse).

[a]House's market value and net worth were used as predictors only for saving-to-income ratio model.
[b]Total debt was used as predictor only for debt-to-assets ratio.

4.2. Outcome variables

The first outcome variable was the savings-to-income ratio. The savings-to-income ratio was calculated using the following function (3):

$$\begin{aligned} &\textit{Savings-to-Income Ratio} \\ &= \textit{Total Savings Amount}/\textit{Annual Total Family Income} \end{aligned} \tag{3}$$

In this study, savings and family income were coded as natural logarithms of household saving and household income, respectively. The transformation of each variable was made to create ratio variables that were normally distributed. The ratio used in the analyses was defined as a subtraction of logarithms (i.e., $\ln(x) - \ln(y) = \ln(x/y)$).

The second outcome variable was the debt-to-asset ratio. The debt-to-asset ratio was calculated using the following function (4):

$$\textit{Debt-to-Asset Ratio} = \textit{Total Liabilities}/\textit{Total Assets} \tag{4}$$

As was the case with the savings-to-income ratio, total liabilities and total assets were transformed into natural logarithms based on total household debt (i.e., liabilities) and total household assets. The ratio was defined as a subtraction of logarithms (i.e., numerator and denominator in the fraction).

4.3. Independent variables

Based on the review of the literature, the following variables were included in the analytic models used to describe and predict household savings-to-income and debt-to-asset ratios: education of the household head, spouse education, age of household head, spouse age, interest rate on current loans, expenses paid for housing, expenses paid for transportation, expenses paid for travel and vacation, expenses paid for clothing, expenses paid for education, expenses paid for child care, expenses paid for health care, whether or not the household received governmental assistance, whether or not the household head or spouse exhibited a problematic psychological condition, health activities of the household head and spouse, smoking and alcohol consumption of the household head and spouse, family income, family savings, dollar amount held in equities, debt amount, net worth, job status of household head and spouse, race/ethnicity of household head and spouse, and gender of household head. Table 1 shows how each variable was operationalized in the study.

4.4. Analytic models and procedure

As described previously, the purpose of this study paper is to describe a method, based on an ANN modeling technique, that can be used to significantly improve the description and

Table 2
Descriptive table for demographics of samples.

	2013 ($n = 1048$)		2015 ($n = 908$)		2017 ($n = 959$)	
	Mean	SD	Mean	SD	Mean	SD
Head education	15.33	1.83	15.26	1.91	15.30	1.90
Spouse education	14.98	3.33	14.63	3.74	14.52	4.07
Head age	45.67	11.31	48.77	13.26	47.63	12.99
Spouse age	42.65	13.73	45.08	15.90	43.67	16.29
	Freq.	%	Freq.	%	Freq.	%
Head race/ethnicity						
White (Ref.)	931	88.84	785	86.45	829	86.44
African American	80	7.63	75	8.26	88	9.18
American Indian	9	0.86	8	0.88	10	1.04
Asian	16	1.53	23	2.53	18	1.88
Others/No answer	12	1.15	17	1.87	14	1.46
Spouse race/ethnicity						
White (Ref.)	953	90.94	795	87.56	860	89.68
African American	75	7.16	78	8.59	68	7.09
American Indian	4	.38	2	0.22	0	.00
Asian	11	1.05	26	2.86	26	2.71
Others/No answer	5	.48	7	0.77	5	.52
Head job status						
Working	544	51.91	471	51.87	496	51.72
Housekeeping	34	3.24	31	3.41	37	3.86
Student	52	4.96	30	3.30	31	3.23
Now working	418	39.89	376	41.41	395	41.19
Head gender (Ref: Male)	515	49.14	443	48.79	480	50.05

prediction of the savings-to-income ratio and the debt-to-asset ratio. In this study, the ANN model was a assumed to be a representative machine learning technique. The ANN procedure works by identifying hidden layers within a model. The best fit model is determined when the error variance is at the lowest level. In effect, an ANN methodology searches in a non-parametric, atheoretical manner for meaningful relationships between and among variables without regard to compounding or interaction effects or multicollinearity. In this study, the ANN model was hypothesized to improve validity and predictability of an empirical model by iteration. In this study, Stata 15.1 was used to run ANN models over 500 iterations. The result was a formalized model that optimized the description and prediction of household savings-to-income ratios and debt-to-asset ratios.

The analytic process was comprised of two steps. At the first step, OLS models were compared to ANN models to determine which procedure offers the highest degree of descriptive power. Since there were three years of prediction and two methods (i.e., OLS and ANN), six initial prediction examinations were made. The procedure and results from the analytic processes employed in this study are presented as follows:

(1) Estimation of an OLS and ANN model for each year (i.e., 2013, 2015, and 2017) with two models (i.e., savings-to-income ratio and debt-to-asset ratio);
(2) Calculation of the accuracy from the six models (i.e., saving ratio in 2013, 2015, and 2017 and debt ratio in 2013, 2015, and 2017);
(3) Calculation of how the values from the model differed from the observed values by following the estimation of root mean squared error (RMSE) and mean absolute error (MAE) (shown below in function (5)); and
(4) Comparison of the RMSE and MAE scores between the OLS and ANN models.

The second step in the analytic process involved determining the robustness of the OLS and ANN methods when predicting the level of future financial ratios. Specifically, respondent data from 2015 were used to predict the savings-to-income ratio and debt-to-asset ratio of respondents in 2017. This test was made to compare the prediction accuracy between the two methodologies.

As noted at (4) in the first step of the analytical procedure, the ANN model was designed to estimate a RMSE and MAE score. RMSE and MAE are used to measure how well the models (i.e., OLS and ANN) were able to describe and forecast the two financial ratios. For the purposes of this study, forecast errors were calculated to estimate RMSE and MAE, as shown in function (5):

$$e_{ti} = \text{observed financial ratio}_{ti} - \text{predicted financial ratio}_{(t-1)i} \quad (5)$$

where, i denotes the financial ratio (i.e., savings-to-income ratio and debt ratio) and t_n is the survey year ($n : 1 = 2013, 2 = 2015$, and $3 = 2017$). By using the error (i.e., residuals) between the predicted ratio and the observed ratio, it is possible to calculate the comparison values, including RMSE and MAE, from the function (6) and (7):

$$\text{RMSE} = \{\sum(e_{ti}^2)/(n-1)\}^{1/2} \quad (6)$$

$$\text{MAE} = \sum(|e_{ti}|)/(n-1) \quad (7)$$

The RMSE and MAE are common tools used to evaluate model performance when making complex descriptions and forecasts (Hyndman and Koehler, 2006; Wooldridge, 2013). For interpretation purposes, the lower the RMSE and MAE, the more robust the model. However, because the RMSE uses two stages of squared terms (see function (6)) and thus is sensitive to outliers (Armstrong, 2001), sometimes RMSE reports distort results when outliers produce large fluctuations in error terms (Willmott and Matsuura, 2005). This is the reason MAE is used in conjunction with RMSE (e.g., Armstrong, 2001; Willmott and Matsuura, 2005). Essentially, MAE acts as a robustness check when evaluating a prediction model.

5. Results and findings

5.1. Demographic characteristic of respondents

The demographic features of respondents for each survey year are shown in Table 2. Comparable to the US population, years of education was approximately 15 years for those in the sample, across all survey years. The mean age of both the household head and spouse of those in the sample fell between 43 and

Table 3
OLS results: Savings-to-income ratio.

	2013 (n = 1048)		2015 (n = 908)		2017 (n = 959)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Head education	−.05	.03	−.05	.03	.00	.03
Spouse education	.13***	.02	.08***	.02	.02	.02
Head age	.05***	.01	.05***	.01	.00	.01
Spouse age	−.03**	.01	−.03***	.01	.01	.01
Loan interest rate	−.05*	.02	−.04	.03	−.08**	.03
Expenses						
Housing	.00**	.00	.00	.00	.00	.00
Transportation	.00	.00	.00**	.00	.00	.00
Travel/Vacation	.00	.00	.00*	.00	.00	.00
Food	.00	.00	.00	.00	.00***	.00
Clothing	.00	.00	.00	.00	.00**	.00
Education	.00*	.00	.00***	.00	.00*	.00
Childcare	.00**	.00	.00	.00	.00	.00
Health	.00	.00	.00	.00	.00	.00
Gov. subsidy (Ref: Yes)	.00	.00	.98*	.41	−.19	.78
Financial position						
Total debt	.00	.00	.00	.00	.00	.00
Equity amount	.00	.00	.00	.00	.00	.00
House value	.00	.00	.00	.00	.00	.00
Net worth	.00***	.00	.00***	.00	.00***	.00
Head health						
Mental health status	.73***	.19	−.72**	.21	−.31	.20
Vigorous exercise	.00	.00	.00*	.00	.00***	.00
Light exercise	.00***	.00	.00	.00	.00	.00
Muscle exercise	.00	.00	.00	.00	.00	.00
Head risky behavior						
Cigarette	.01	.02	−.05**	.02	−.06***	.01
Alcohol	.00	.00	.00**	.00	.00	.00
Spouse health						
Mental health status	.25	.16	−.03	.17	−.18	.16
Vigorous exercise	.00	.00	.00**	.00	.00	.00
Light exercise	.00***	.00	.00	.00	.00	.00
Muscle exercise	.00	.00	.00	.00	.00	.00
Spouse risky behavior						
Cigarette	−.06***	.01	−.01	.02	.06**	.02
Alcohol	.00***	.00	.00	.00	.00	.00
Head job status (Ref: Working)						
Housekeeping	.34	.25	.60*	.25	.03	.23
Student	.07	.21	−.44	.25	−.05	.25
Not working	.27***	.09	.08	.09	.09	.09
Head race/ethnicity (Ref: White)						
African American	.23	.35	.40	.38	.40	.26
American Indian	.91	.47	−.21	.49	.44	.44
Asian	−1.00**	.38	−.01	.33	−.76*	.36
Others/No answer	.19	.55	.34	.45	1.71***	.37
Spouse race/ethnicity (Ref: White)						
African American	−.59	.36	−.91	.37	−1.10***	.29
American Indian	1.12*	.45	−.27	.98	–	–
Asian	−1.13	.70	−.76	.32	−.04	.31
Others/No answer	−.05	.87	−.76	.68	−1.11	0.61
Head gender (Ref: Male)	−.03	.09	−.09	.09	−.07	.08
Constant	−4.02***	.56	−3.08	.54	−2.32***	.48
R^2	.27		.23		.22	

Note. * p < .05; ** p < .01; *** p < .001.

49 years. Most respondents (around 86% to 90%) were White, and approximately half of the sample was comprised of working males.

5.2. Estimating results: OLS regression

Table 3 shows the results from the OLS regression model by each survey year for the savings-to-income ratio. The education level of a spouse, age of head, expenses for housing, expenses for education, expenses for childcare, net worth, the mental health status of a household head, light exercise, spouse alcohol consumption, head of household employment status (not working), and race/ethnicity of spouse (i.e., American Indian) were positively related to the savings-to-income ratio in 2013. In 2015, positively significant descriptors of the savings-to-income ratio were: education level of spouse, age of household head, expenses for transportation, expenses for travel/vacation, expenses for education, receipt of a government subsidy (yes), net worth, vigorous exercise, household head alcohol consumption, and the employment status of the household held as a housekeeper. In 2017, expenses for food, expenses for clothing, expenses for education, net worth, vigorous exercise by the household head, number of cigarettes consumed by a spouse, and race/ethnicity of head (i.e., others/no answer) were positively related to the savings-to-income ratio.

Some factors (and in some cases categories of factors) were found to be negatively related to the savings-to-income ratio each survey year. In 2013, age of spouse, interest rate of loans, number of cigarettes consumed by a spouse, and race/ethnicity of head (i.e., Asian) were negatively associated with the savings-to-income ratio. In 2015, age of spouse, the mental health status

Table 4
OLS results: Debt-to-asset ratio.

	2013 ($n = 1048$)		2015 ($n = 908$)		2017 ($n = 959$)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Head education	−.02	.03	.04	.03	−.08**	.03
Spouse education	−.01	.02	.10***	.02	.06**	.02
Head age	−.06***	.01	−.02*	.01	−.02**	.01
Spouse age	−.01	.01	−.04***	.01	−.03***	.01
Loan interest rate	.05*	.02	.08**	.03	.01	.03
Expenses						
Housing	.00***	.00	.00**	.00	.00**	.00
Transportation	.00***	.00	.00*	.00	.00**	.00
Travel/Vacation	.00	.00	.00	.00	.00	.00
Food	.00	.00	.00	.00	.00	.00
Clothing	.00	.00	.00	.00	.00	.00
Education	.00	.00	.00	.00	.00*	.00
Childcare	.00	.00	.00***	.00	.00**	.00
Health	.00**	.00	.00	.00	.00	.00
Gov. subsidy (Ref: Yes)	.00	.00	−1.40**	.41	.95	.79
Financial position						
Family income	.00	.00	.00*	.00	.00	.00
Saving amount	.00*	.00	.00*	.00	.00	.00
Equity amount	.00**	.00	.00**	.00	.00***	.00
Head health						
Mental health status	−.28	.17	.40	.21	−.22	.20
Vigorous exercise	.00***	.00	.00	.00	.00**	.00
Light exercise	.00	.00	.00*	.00	.00	.00
Muscle exercise	.00	.00	.00	.00	.00**	.00
Head risky behavior						
Cigarette	.00	.02	.01	.02	−.04**	.01
Alcohol	.00	.00	.00	.00	.00**	.00
Spouse health						
Mental health status	−.18	.15	.06	.17	.45**	.16
Vigorous exercise	.00**	.00	.00	.00	.00	.00
Light exercise	.00	.00	.00	.00	.00	.00
Muscle exercise	.00**	.00	.00*	.00	.00	.00
Spouse risky behavior						
Cigarette	.02	.01	.00	.02	.05*	.02
Alcohol	.00*	.00	.00*	.00	.00	.00
Head job status (Ref: Working)						
Housekeeping	−.42	.24	−.01	.25	−.25	.23
Student	−.05	.19	.13	.25	−.33	.25
Not working	.02	.09	.01	.09	−.11	.09
Head race/ethnicity (Ref: White)						
African American	1.53***	.33	.09	.38	.29	.26
American Indian	−.54	.43	−.90	.49	.77	.45
Asian	.36	.36	−.93**	.32	−.34	.36
Others/No answer	−1.19*	.51	−.13	.45	.25	.38
Spouse race/ethnicity (Ref: White)						
African American	−.46	.34	.41	.37	−.04	.29
American Indian	−.57	.42	−.71	.98	–	–
Asian	.32	.65	−.47	.32	−.72*	.31
Others/No answer	−.57	.81	.48	.68	−.38	.62
Head gender (Ref: Male)	−.02	.08	−.06	.09	.05	.09
Constant	1.06*	0.52	−2.02***	.53	−.22	.48
R^2	.43		.39		.41	

Note. * $p < .05$; ** $p < .01$; *** $p < .001$.

of a household head, and number of cigarettes consumed by the household head showed a negative association with the savings-to-income ratio. In 2017, the interest rate of loans, number of cigarettes consumed by the household head, and race/ethnicity of the household head (i.e., Asian) and her/his spouse (i.e., African American) were negatively associated with the savings-to-income ratio. However, the education level of the household head, expenses for health care, total debt amount, dollar amount of equities, house value, a category of exercise (i.e., muscle exercise), a category of employment status (i.e., student), some racial/ethnic categories for the household head (i.e., African American, American Indian) and racial/ethnic categories for a spouse (i.e., Asian, Others/no answer), and the gender of the household head were not significant.

Table 4 shows the results from the OLS regression model test by each survey year for the debt-to-asset ratio. Numerous factors and categories of factors were found to be positively related to the ratio. Specifically, in 2013, interest rate of loans, expenses for housing, expenses for transportation, expenses for health care, saving amount, amount of equities, vigorous exercise, muscular exercise of a spouse, alcohol consumption by a spouse, and having a household head who was African–American were positively related to the debt-to-asset ratio. In 2015, positively significant predictors of the debt-to-asset ratio were: education level of spouse, interest rate of loans, expenses for housing, expenses for transportation, expenses for childcare, family income, saving amount, amount held in equities, light exercise of household head, muscular exercise of a spouse, and alcohol consumption by a spouse. In 2017, education level of a spouse, expenses for housing, expenses for transportation, expenses for education, expenses for childcare, amount held in equities, vigorous muscular exercise of household head, alcohol consumption by household head, the mental health status of a spouse, and number

Table 5
ANN model selection associated with the number of hidden layers.

	Savings-to-income ratio			Debt-to-asset ratio		
Hidden layer #	2013 Mean of error^2	2015 Mean of error^2	2017 Mean of error^2	2013 Mean of error^2	2015 Mean of error^2	2017 Mean of error^2
1	2.1457	1.6218	1.4762	1.4758	1.5889	2.6745
2	1.5722	1.3101	1.5593	1.2411	1.2657	1.2415
3	.9830	1.3849	1.0603	.9071	.9524	1.0413
4	1.2989	1.0251	1.0017	.8066	.8539	1.0963
5	.7184	.8482	.7870	.5765	.6755	1.2126
6	.6123	.7689	.6236	.6330	.5559	.6232
7	.4051	.5812	.5551	.7865	.4324	.7410
8	.3873	.5474	.4757	.4702	.4041	.4497
9	.3611	.5176	.5711	.3705	.4227	.3316
10	.3170	.4948	1.2551	.2749	.3877	.5350
11	.3517	.4695	.5741	.6067	.2301	.3786
12	.4011	.4448	.4639	.3146	.4239	.4225
13	.2725	.4741	.7246	.3164	.3468	.3114
14	.3440	.3340	.4225	.4011	.2734	.2869
15	.2584	.4741	.7246	.1997	.3468	.3114
16	.3354	.3718	.8342	.2083	.2336	.3632
17	.2415	.3041	.7246	.2092	.1870	.3114
18	.2201	.2379	.4675	.3105		.2317
19	.2444		.3986	.1940		
20	.2193					

of cigarettes consumed by a spouse were positively associated with the debt-to-asset ratio.

Some factors exhibited a negatively significant association with the debt-to-asset ratio each survey year. In 2013, age and a race/ethnicity category (i.e., others/no answer) of the household head were negatively associated with the debt-to-asset ratio. In 2015, age of household head and spouse, receiving a governmental subsidy, and a household head who was Asian showed a negative association with the debt-to-asset ratio. In 2017, education level of household head, age of household head and spouse, number of cigarettes consumed by the household head, and the race/ethnicity of a spouse being Asian were negatively associated with the debt-to-asset ratio. However, expenses for travel/vacation, food, and clothing, light exercise of a spouse, job status of household head, some categories of household head race/ethnicity (i.e., American Indian) and spouse (i.e., African American, American Indian, Others/no answer), and gender of the household head were not significant.

5.3. Estimating results: ANN

The optimal number of hidden layers within an ANN model can be identified when the error variance is at the lowest level. In order to estimate a stable model in this study, a random seed of 1 was selected. As explained in the theoretical background discussion, it was assumed that all independent variables had a degree of covariance when predicting the outcome. Covariance occurs when two or more factors are sharing a similar distribution or are correlated within the analytic sample (Adams and Lawrence, 2018). Therefore, it is generally recommended that covariance be adjusted in the analytic procedure (Trochim and Donnelly, 2006). Thus, although some of the independent variables were not significant, each could still have an indirect – but meaningful – role in shaping the predictive power of the model. In other words, unlike a traditional analytic model where non-significant variables are typically excluded from discussion, in an ANN model, the role of non-significant variables can be still meaningful in shaping the model's predictive validity by creating compounding effects with other independent variables. As such, ANN models tend to be less focused on identifying coefficients or significance levels associated with individual variables. As such, ANN models can be more efficient when predicting outcomes using a large number of variables.

The following is an important question to answer when using an ANN model: is the model a good fit to the data? In alignment with the literature, the answer to this question in this study was based on the number of hidden layers identified in the ANN modeling process. The optimal model was the one that produced the lowest mean squared error (MSE) based on function (5).[1] As shown in Table 5, as many as 20 different hidden layers were used to improve the accuracy of estimations in 2013, 2015, and 2017. In the case of the savings-to-income ratio, the MSE was .2193 based on 20 hidden layers in 2013, .2379 based on 18 hidden layers in 2015, and .3986 based on 19 hidden layers in 2017. In the case of the debt-to-asset ratio, the optimal number of hidden layers was 19 (MSE = .1940), 17 (MSE = .1870), and 18 (MSE = .2317) in 2013, 2015, and 2017, respectively.

Table 6 shows the variables associated with each ANN model by year. As shown in Table 6, variables are presented with weights. Weights indicate the relative importance or the influence of a variable when estimating the savings-to-income ratio. The greater the weight value means the more the variable influenced the overall model. A weight close to zero indicates weak or no effect as a ratio predictor. Although specific or directional effects of the variables differed by models, some predictors showed consistently high levels of association with large weight values. The following variables were of particular importance when describing the savings-to-income ratio, across all three models: education level of household head and spouse, age of household head and spouse, race/ethnicity of the household head and spouse, net worth, debt, and expenditures for housing and clothing.

Some variables exhibited a small or weak association with the savings-to-income ratio across the three models. For example, receiving a governmental subsidy, household head and spouse minority status (i.e., American Indian, Asian, other/no answer), head of household being a student or housekeeper, and the mental health status of the household head and spouse exhibited a weak effect on the savings-to-income ratio. Some variables showed considerable variability in descriptive magnitude across the models, including house value and health expenses. For example, the house value variable was the third most influential factor in 2013 and 2017, however, the house value variable was the second least influential factor in 2015. These findings suggest

[1] MSE $= 1/n * \sum_{i=1}^{n}$(predicted financial ratio$_{(t-1)i}$ − observed financial ratio$_{ti}$)^2.

Table 6
ANN results: Savings-to-income ratio.

2013 ($n = 1048$)		2015 ($n = 908$)		2017 ($n = 959$)	
Predictor	Weight value	Predictor	Weight value	Predictor	Weight value
Spouse educ.	3.9295	Spouse educ.	2.0770	Head hvy exer.	.5049
Head age	1.2220	Head age.	.6076	Expend. cloth	.4604
House value	.4586	Net worth	.2239	House value	.2870
Net worth	.3486	Expend. transp	.2119	Expend. health	.1925
Not working	.2552	Expend. cloth	.1431	Net worth	.1705
Expend. housing	.2397	Expend. educ.	.1133	Equities	.1127
Loan interest	.2030	Head hvy exer.	.1113	Spouse White	.0971
Expend. cloth	.0735	Head muscular	.1067	Spouse muscular	.0756
Head alcohol.	.0706	Head light exer.	.0908	Head Afri.-Am.	.0611
Head working	.0616	Debt total	.0225	Head gender	.0493
Head gender	.0583	Equities	.0142	Expend. transp.	.0435
Light exercise	.0513	Spouse cigarette	.0103	Spouse alcohol	.0422
Expend. transp.	.0463	Spouse A-Indian	.0054	Expend. food	.0264
Expend. educ.	.0444	Head student	.0053	Spouse cigarette	.0070
Spouse muscular	.0291	Head gender	.0036	Govern. subsidy	−.0034
Equities	.0269	Spouse Asian	.0018	Head Asian	−.0044
Head Afri.-Am	.0232	Head A-Indian	.0009	Head cigarette	−.0045
Head student	.0136	Head housekeep	−.0001	Head student	−.0055
Spouse A-Indian	.0094	House value	−.0002	Spouse Asian	−.0059
Head A-Indian	.0092	Spouse othr race	−.0011	Head alcohol	−.0089
Head housekeep	.0072	Govern. subsidy	−.0049	Head othr race	−.0121
Head othr race	.0047	Spouse alcohol	−.0082	Head A-Indian	−.0128
Spouse mental	.0028	Expend. Health	−.0089	Head mental	−.0156
Spouse hvy exer.	.0004	Head othr race	−.0134	Spouse A-Indian	−.0225
Govern. subsidy	.0000	Spouse mental	−.0205	Head housekeep	−.0247
Spouse Asian	−.0033	Head cigarette	−.0221	Expend. child	−.0249
Spouse othr race	−.0069	Head alcohol	−.0250	Spouse mental	−.0448
Expend. food	−.0103	Head mental	−.0346	Expend. educ.	−.0768
Head mental	−.0113	Head Asian	−.0353	Expend. travel	−.0970
Head cigarette	−.0157	Loan interest	−.0395	Head muscular	−.1072
Head Asian	−.0294	Spouse light exer.	−.0530	Spouse Afri.-Am.	−.1275
Expend. travel	−.0307	Spouse muscular	−.0612	Head working	−.1509
Head muscular	−.0390	Head Afri.-Am.	−.0636	Spouse age	−.1622
Head light exer.	−.0479	Expend. travel	−.0725	Head not working	−.1901
Spouse alcohol	−.0643	Expend. child	−.0874	Spouse light exer.	−.1967
Spouse Afri-Am.	−.0692	Spouse Afri.-Am.	−.0961	Spouse hvy exer.	−.2302
Spouse cigarette	−.0736	Head working	−.1473	Expend. housing	−.2318
Expend. child	−.0918	Head not working	−.1503	Head light exer.	−.3223
Debt total	−.1147	Spouse hvy exer.	−.1524	Loan interest	−.3513
Head hvy exer.	−.1323	Expend. housing	−.1712	Head White	−.3606
Head White	−.1849	Spouse White	−.5131	Debt total	−.3756
Spouse White	−.4121	Head White	−.6315	Head educ.	−.5973
Expend. health	−.4572	Expend. food	−.7972	Spouse educ.	−.8251
Head educ.	−.5536	Head educ.	−1.1444	Head age.	−.9101
Spouse age	−1.2806	Spouse age	−1.9051		

Note. American Indian group for spouse race was not included in 2017 analysis due to lack of observations. The variable was also omitted from the OLS model.

that variables of importance are not stable when viewed from an ecological system perspective.

As shown in Table 7, the debt-to-asset ratio was associated with various variables across the three model years. Some variables, such as household head and spouse education level, transportation expenses, clothing expenses, and interest rate of loans, exhibited a consistently large effect when describing the debt-to-income ratio. For example, the age of a household head and spouse was found to be negatively associated with the ratio across all three models.

On the other hand, other variables exhibited a smaller or weaker association with the debt-to-asset ratio across three models. For example, variables such as receiving a governmental subsidy, household head minority status (i.e., American Indian, Asian, other/no answer), being a student or housekeeper head of household, and mental health status exhibited a weak relationship with the debt-to-income ratio. Some variables showed considerable variability from one year to the next, including health care expenses, childcare expenses, clothing expenses, and family income. For example, expenses paid for health care was identified as having a negative association with the ratio in 2013 and 2015 models but a positive relationship in 2017. Family income had a strong, negative relationship with the ratio in 2013 and 2015 but a weak positive relationship in 2017.

Similar to the savings-to-income ratio results, the role of the independent variables used in the models varied across survey years. This reflects the dynamics within and between the variables used to describe financial ratios from an ecological system perspective.

5.4. RMSE and MAE comparisons

The findings from the OLS and ANN comparisons highlight an important point: the variables of importance used to describe the savings-to-income and debt-to-asset ratios differed across the models. The only consistent variable across the two procedures when describing the savings-to-income ratio was net worth. The variables identified as important in terms of the debt-to-asset ratio differed using the two approaches. In a purely descriptive framework, one can rightly ask which methodology provides a better description of a household's financial status? In order to answer this question, the ratios were compared to predicted financial ratio estimates using RMSE and MAE approximations. As a reminder, RMSE is an efficient method that can be used to compare the accuracy of a model when the residuals being compared

Table 7
ANN results: Debt-to-asset ratio.

2013 ($n = 1048$)		2015 ($n = 908$)		2017 ($n = 959$)	
Predictor	Weight value	Predictor	Weight value	Predictor	Weight value
Spouse educ.	.7931	Head educ.	1.7274	Expend. transp.	.7009
Expend. transp.	.5996	Expend. transp.	1.4451	Spouse educ.	.5554
Spouse White	.1319	Loan interest	1.1913	Head hvy exer.	.2198
Loan interest	.0958	Head hvy exer.	.2678	Expend. health	.1539
Head African	.0916	Spouse hvy exer.	.2549	Expend. child	.1280
Head educ.	.0869	Spouse White	.1730	Expend. cloth	.1167
Spouse alcohol	.0558	Expend. cloth	.1424	Family income	.0715
Head alcohol	.0539	Head not working	.1364	Expend. educ.	.0595
Spouse light exer.	.0479	Spouse African	.0954	Spouse alcohol	.0487
Head mental	.0292	Head working	.0941	Spouse African	.0449
Head gender	.0148	Expend. travel	.0561	Head gender	.0358
Head student	.0080	Head White	.0497	Head African	.0288
Head Asian	.0065	Head othr race	.0455	Spouse mental	.0257
Spouse Asian	.0034	Expend. educ.	.0401	Head alcohol	.0199
Expend. child	.0029	Head African	.0163	Head A-Indian	.0057
Govern. subsidy	.0000	Head student	.0156	Govern. subsidy	.0034
Head housekeep	−.0008	Head A-Indian	.0150	Head othr race	−.0027
Head cigarette	−.0010	Head housekeep	.0127	Spouse White	−.0057
Spouse A-Indian	−.0022	Spouse othr race	.0107	Spouse Asian	−.0077
Spouse othr race	−.0064	Spouse muscular	.0099	Head student	−.0086
Head A-Indian	−.0104	Head mental	.0068	Head housekeep	−.0155
Head othr race	−.0205	Spouse A-Indian	.0039	Head cigarette	−.0264
Head working	−.0214	Head alcohol	.0038	Spouse cigarette	−.0267
Spouse hvy exer.	−.0252	Govern. subsidy	−.0016	Head Asian	−.0301
Spouse cigarette	−.0303	Spouse mental	−.0019	Head mental	−.0309
Spouse mental	−.0330	Spouse cigarette	−.0036	Expend. house	−.0502
Savings amount	−.0428	Head Asian	−.0091	Spouse muscular	−.0605
Spouse hvy exer.	−.0469	Spouse Asian	−.0091	Spouse A-Indian	−.0696
Expend. educ.	−.0477	Spouse alcohol	−.0221	Head muscular	−.0860
Head not working	−.0630	Expend. child	−.0228	Spouse hvy exer.	−.1200
Equities	−.0693	Head gender	−.0239	Savings amount	−.1214
Spouse African	−.0713	Head cigarette	−.0446	Head not working	−.1390
Head muscular	−.0757	Head muscular	−.0552	Expend. travel	−.1440
Expend. travel	−.0873	Spouse educ.	−.0561	Expend. food	−.1533
Expend. cloth	−.1082	Expend. health	−.1107	Head light exer.	−.1780
Head light exer.	−.1247	Expend house	−.1140	Head working	−.2065
Head White	−.1358	Equities	−.1488	Spouse light exer.	−.2740
Expend. health	−.1826	Expend. food	−.1819	Equities	−.3203
Family income	−.2422	Savings amount	−.2121	Loan interest	−.4073
Head hvy exer.	−.2760	Head light exer.	−.2283	Head White	−.6187
Expend. food	−.3052	Spouse light exer.	−.2441	Head age	−1.0783
Expend. house	−.5868	Family income	−.2482	Head educ.	−1.1703
Spouse age	−.9181	Spouse age	−.3514	Spouse age	−1.5509
Head age	−1.4377	Head age	−.8072		

Note. American Indian group for spouse race was not included in 2017 analysis due to lack of observations. The variable was also omitted from the OLS model.

are tightly grouped (Hyndman and Koehler, 2006), while MAE tends to be a more efficient approximation procedure when the residual outcomes show broad distributions (Armstrong, 2001; Willmott and Matsuura, 2005).

Generally, smaller RMSE and MAE estimates are considered better indicators of model fit (Armstrong, 2001; Hyndman and Koehler, 2006; Samsudin et al., 2010; Willmott and Matsuura, 2005; Wooldridge, 2013). As shown in the first 11 columns of Table 8, the RMSE and MAE estimates associated with the ANN methodology were comparatively smaller than the estimates for the OLS regression for both the savings-to-income and debt-to-asset ratios.[2] This means that the ANN methodology did a better job of describing the savings-to-income ratio and debt-to-asset ratio.

The MAE estimates are particularly telling in this regard. MAE is calculated as an absolute number of subtractions between observed values and predicted values. As shown in Table 8, there was a significantly larger difference between the observed savings-to-income ratio and the predicted savings-to-income ratio when OLS estimates were compared to ANN estimates in 2013, 2015, and 2017. The differences were statistically significant ($t = 22.59$, $p < .001$; $t = 21.84$, $p < .001$; $t = 18.26$, $p < .001$, respectively). The same pattern was noted in relation to the debt-to-asset ratio ($t = 26.13$, $p < .001$; $t = 21.93$, $p < .001$; $t = 23.77$, $p < .001$, respectively). This means that across the three time periods, the ANN approach offered greater descriptive power compared to the traditional OLS procedure.

While describing the savings-to-income and debt-to-asset ratios is methodologically interesting, in practice, description of key variables associated with financial ratios tends to be of primary importance to lenders and policy makers who are looking for

2 Estimating the significance difference between models was assessed empirically using the following technique: (1) estimate the RMSE for the OLS model; (2) multiple the OLS RMSE by 70% (see Davit et al., 2008; Nau, 2019) (3) estimate the RMSE for the ANN model; (4) determine the difference between the estimate at step 2 to the estimate at step 3. The RMSE estimate at step 3 needs to be equal to or less than the estimate at step 2 to indicate significance. Based on the procedure, the ANN model was deemed to be more efficient compared to the OLS model. In 2013, RMSE for the ANN model was .47, which was smaller than 70% of the OLS RMSE (.94 = 1.34*70%). Similarly, the RMSE for the ANN model in 2015 and 2017 was .49 and .63, respectively. These estimates were smaller than the OLS estimates multiplied by 70% (.89 = 1.27*70%; .88 = 1.25*70%, respectively). Similar results were noted for the debt-to-asset ratio across the three periods. The ANN model RMSE estimates were .44, .35, and .48 in 2013, 2015, and 2017, respectively, which were lower than the OLS RMSE estimates adjusted by to 70% (.88 = 1.25*70%; .89 = 1.27*70%; .89 = 1.27*70%, respectively).

Table 8
Summary of model fit comparison on predicted Savings-to-income ratio and debt-to-asset ratio between OLS and ANN models.

		Estimating models									Prediction model	
		2013 (n = 1048)			2015 (n = 908)			2017 (n = 959)			2015–17 prediction	
		M(Y′−Y)	RMSE	MAE (SD)	M(Y′−Y)	RMSE	MAE (SD)	M(Y′−Y)	RMSE	MAE (SD)	RMSE	MAE (SD)
Savings ratio	OLS	1.82	1.34	1.00 (.89)	4.43e−10	1.27	.98 (.80)	−1.77e−09	1.25	.98 (.77)	1.63	1.19 (1.12)
	ANN	−.08	.47	.34 (.32)	.04	.49	.35 (.34)	.12	.63	.46 (.43)	1.83	1.25 (1.33)
70% (for ANN)			.94			.89			.88		1.28	
t (for MAE)				22.59***			21.84***			18.26***		−.72
Debt ratio	OLS	−3.5e−09	1.25	.98 (.77)	−1.2e−09	1.27	.96 (.83)	2.18e−09	1.27	1.00 (.77)	3.33	2.03 (2.64)
	ANN	−.05	.44	.31 (.31)	-.02	.35	.32 (.29)	−.05	.48	.36 (.32)	1.90	1.38 (1.31)
70% (for ANN)			.88			.89			.89		2.33	
t (for MAE)				26.13***			21.93***			23.77***		3.37***

household saving, spending, and debt patterns. Variable descriptions may not have much applied meaning in other contexts. After all, a financial educator or financial service professional who is working to help a household can simply calculate the nominal value of each ratio and use estimates to guide the development and implementation of recommendations to improve a household's financial situation. There is no need to know that in any given year, say, net worth is a stable descriptor of savings and debt patterns. The ratio itself can provide insights that lead to this type of conclusion.

This is the reason that the predictive or forecasting ability of OLS and ANN modeling techniques is of such importance. What financial service professionals, educators, lenders, financial service institutions, and to some extent, policy makers, need are robust tools that can be used to forecast the financial stability of households in the future. An important question is this: which methodological approach – OLS or ANN – provides the greatest insights into future financial ratios at the household level? Several tests were conducted in this study to answer this question.

Specifically, the independent variables from the 2015 OLS and ANN models were used to forecast the savings-to-income ratio and debt-to-income ratio in 2017. As shown in the last three columns of Table 8, the OLS and ANN methodologies were similar in forecasting power for the savings-to-income ratio. The MAE t test did not show a significant difference between the two models.[3] However, the ANN model was significantly more robust when forecasting debt-to-income ratios. The ANN model showed a significant improvement in predictive power compared to the OLS model. Methodologically, this can be seen in Table 8 where the RMSE estimate was significantly different than the RMSE for the OLS model.[4]

6. Conclusion

As illustrated in this study, the variables associated with describing and forecasting a household's savings-to-income ratio and debt-to-asset ratio often vary from year to year. As shown in Tables 5 through 7, the order of influential variables changed from the savings-to-income ratio to the debt-to-asset ratio over the three time periods (i.e., 2013, 2015, and 2017). This implies that accounting for under- and un-identified dynamics between variables, which can cause compounding effects, may play an critical role in helping educators, financial service professionals, lending institutions, and policy makers better understand the dynamics that shape and shift household financial stability.

Those who have an interest in applying ratio analysis techniques at the household level have traditionally relied on parametric statistical techniques, like as OLS regressions, to make predictions about the financial stability of households. As shown in this study, these traditional tools do not always work well, primarily because financial ratios can be impacted by various under- or un-identified influential factors. This helps explain, to some extent, why lending institutions often experience unexpected credit risks. The primary purpose of this study was to describe a method, based on an artificial neural network (ANN) methodology, that can be used to improve the description and prediction of the savings-to-income ratio and the debt-to-asset ratio. It was shown that a machine learning technique does a superior job of describing the variables that have the greatest association with the savings-to-income ratio and the debt-to-asset ratio. In terms of prediction, machine learning methods appear to do a better job as a forecasting tool in relation to the debt-to-asset ratio.

As noted previously, nearly all research projects within the broad field of household finance focus on the marginal effects of specific variables in models. A marginal effect provides a useful way to interpret and explain a phenomenon. However, with conventional methodological assumptions and techniques, the marginal effect in a regression function, for example, still is not free from compounding effect issues, which tend to reduce the statistical power of the model. What typically occurs is that compounded variables are dropped out automatically through mathematical functions in the analysis. It then is difficult to test the complexity of consumer behavior. As opposed to the conventional approach, an ANN methodology can provide more meaningful insights about the influential relationships between and among independent variables when describing and predicting an outcome variable. The reason ANN models are so effective is that machine learning technologies consider under- and un-identified relationships between variables as important, rather than as random error. Research focusing on marginal effects may diminish the predictive power of variables while research using nonlinear estimations, such as ANN, appear to be more effective in handling the compounding effects of variables when making behavioral predictions.

Due to the feature of its algorithm (i.e., detecting nonlinear relationships and all possible interaction terms), Tu (1996) pointed out that ANN models outperform traditional regressions in obtaining accurate predictions. Findings from this study generally support Tu's conclusions. This indicates that an ANN methodology offers a unique way to view the assessment and prediction of financial ratios at the household level. This fits well with the literature that suggests ANN models are more powerful than conventional econometric approaches when forecasting stock markets, financial risks, credit scores, bankruptcy, and consumer choices (Gan et al., 2005; Guresen et al., 2011; Tkáč and Verner, 2016).

As opposed to machine learning methodologies, conventional regression models are analyzed with a few pre-defined independent variables. As shown in previous studies, the marginal

[3] In order to be statistically significant, the RMSE for the ANN model (i.e., 1.63) needed to be 30% lower than the RMSE for the OLS model (i.e., 1.28), which was not the case.

[4] The RMSE for the ANN model (1.90) was less than 70% of the RMSE for the OLS model (3.33 or 3.33 × .70 = 2.33). Additionally, the MAE t test result showed significant differences (t = 3.37, p < .001) between the OLS and ANN models.

effects of independent variables on financial ratios, such as the savings-to-income and debt-to-asset ratios, have been identified (e.g., DeVaney et al., 2007; Kim and Lyons, 2008; Lee and Kim, 2016; Lyons and Yilmazer, 2005; Yilmazer and DeVaney, 2005; Yuh and Hanna, 2010). However, as the findings from this study's OLS models show, relatively few variables exhibited a significant association with the savings-to-income ratio and debt-to-asset ratio over time, leading to an issue of efficiency in forecasts. Forecasting can be improved significantly if the covariance among the independent variables in a model are assumed to be intercorrelated and not necessarily linearly associated. When the rules of analysis are adjusted, the results from an ANN model can provide more insights into an outcome variable and achieve greater efficiency in predicting patterns in the future.

Results from this study can be applied outside of an academic context. In a very real sense, financial service professionals and lending institutions often need to make projections and forecasts of household stability and strength. Sometimes these forecasts are made to ensure that a household has the financial capacity to implement financial planning recommendations. In other situations, forecasts are needed to ensure that a household will have the financial stability to meet future financial obligations. Results from this study suggest that rather than focusing on one or a few variables to describe and predict household financial behavior, it may be better to assume that the variables of importance change over time. Although widely used household characteristics that are primarily descriptive (e.g., age, gender, educational level, etc.) tend to be relatively stable over time, some household characteristics are subject to more significant variations (e.g., health, seasonal economic effects, etc.). Additionally, rather than being independent factors, most household characteristics and variables are highly correlated, with variables interacting with other variables. These dynamics cannot be fully captured or assumed by currently used analytic approaches.

Findings from this study indicate that in terms of savings, net worth is an important variable that can be used to describe savings patterns. However, in terms of forecasting savings rates, education, age, race/ethnic background, debt levels, and household expenditures, in addition to net worth, tend to be the most useful variables. On the debt side, household expenditures are important when describing the solvency of a household. However, when forecasting household solvency, education and interest rates paid on loans, in addition to household expenditures, appear to be very important. However, it is important to note that while these factors are easily identified in ANN models, the real value of an ANN analysis is describing how variables interact with each other when describing and forecasting values of household financial ratios.

As with any study of this kind, the research project faced several limitations. To be most effective, ANN models require very large datasets. A machine learning technique will far outperform traditional linear models as the size of the dataset increases. In this study, however, the number of observations used in test was modest (i.e., 1048, 908, and 959 in 2013, 2015, and 2017, respectively). It is possible that the small number of observations is hiding important missing data values. Future research should focus on obtaining more observations and then dividing the sample into a training sample and a testing sample. This procedure can add validity to future study findings. Additionally, although this study attempted to include as many independent variables from the literature as possible, it is possible that a variable missing from the dataset may hold additional insights into the description and prediction of financial ratios. Future research is needed to examine this possibility.

To summarize, this study was undertaken to compare a conventional regression model to an ANN modeling approach as tools for the description and prediction of household financial ratios. Financial ratios can be used as an important indicator of personal and household financial capacity. Financial ratios are often used as objective measures of financial strength. As such, it is important to accurately describe the factors most closely associated with financial ratios. As prediction improves, it will be possible for educators, financial service professionals, lenders, and policy makers to help improve the outlook of a household's financial condition over time.

CRediT authorship contribution statement

Wookjae Heo: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Jae Min Lee:** Writing - original draft, Validation, Writing - review & editing. **Narang Park:** Writing - original draft, Writing - review & editing, Project administration. **John E. Grable:** Writing - review & editing.

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Erratum

Erratum regarding missing Declaration of Competing Interest statements in previously published articles

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Declaration of Competing Interest statements were not included in the published version of the following articles that appeared in previous issues of "Journal of Behavioral and Experimental Finance".

The appropriate Declaration/Competing Interest statements, provided by the Authors, are included below.

(1) "Does automatic bidding mechanism affect herding behavior? Evidence from online P2P lending in China" [Journal of Behavioral and Experimental Finance, 2018; 20C: 39–44] https://doi.org/10.1016/j.jbef.2018.07.001.
Declaration of competing interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

(2) "Minimizing learning in repeated real-effort tasks" [Journal of Behavioral and Experimental Finance, 2019; 22C: 239–248] https://doi.org/10.1016/j.jbef.2019.04.002.
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(3) "A technical note on the precise timing of behavioral events in economic experiments" [Journal of Behavioral and Experimental Finance, 2018; 21C: 10–14] https://doi.org/10.1016/j.jbef.2018.08.002.
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(4) "Prospect theory value and idiosyncratic volatility: Evidence from the Korean stock market" [Journal of Behavioral and Experimental Finance, 2018; 21C: 113–122] https://doi.org/10.1016/j.jbef.2018.11.006.
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(5) "Using Artificial Neural Network techniques to improve the description and prediction of household financial ratios" [Journal of Behavioral and Experimental Finance, 2020; 25C: 100273] https://doi.org/10.1016/j.jbef.2020.100273.
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(6) "The effect of experiencing a death on life insurance ownership" [Journal of Behavioral and Experimental Finance, 2019; 22C: 170–176] https://doi.org/10.1016/j.jbef.2019.03.003.
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(7) "Latent factor model for asset pricing" [Journal of Behavioral and Experimental Finance, 2020; 27C: 100353] https://doi.org/10.1016/j.jbef.2020.100353.
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