Essays on Wealth, Liquidity and Household Finance

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Abstract

In recent years, the analysis of household wealth has become a important field of study for both academics and policymakers. Consequently, in this thesis, household wealth, its determinants, and its effect on household consumption, poverty, and understanding the determinants of wealth are studied. Firstly, changes in household wealth are identified through expected and unexpected changes in house prices and disposable income. Changes in house prices and income are studied to determine if there is a relationship between consumption, investment and spending decisions. The results suggest no significant positive correlation between unexpected house price changes and household consumption in the United States. Secondly, income and asset poverty rates in the United States are studied. We define asset poverty and review how demographic and household events affect asset poverty rates. The findings suggest one in every four households did not have the financial assets to cover three months of their basic consumption needs in 2011. Black, single female headed households, and renters are more likely to be asset poor, and remain asset poor over multiple years. Finally, this thesis examines the application of modern machine learning techniques to estimate a households net wealth, and net wealth minus housing equity. The findings reported across the 1999-2017 period, suggest variables such as profit on stock, house value, and profit on business are the most important features in predicting household wealth. Secondly, the results identify alternative variables such as dividends, years left on mortgage, and interest income are also important factors in determining a households' wealth. Thus, this thesis provides new findings that further the current understanding of how household wealth affects non-durable consumption; provides evidence that current poverty rates are underestimated in the United States; and provides new variables that can be used to estimate household wealth.

1 List of Acronyms

ANN - Artificial Neural Network

AR - Auto regression

CART - Classification and Regression Trees

CES - Consumer Expenditure Survey

CPI - Consumer Prince Index

DT - Decision Tree

DF - Decision Forest

FHFA - Federal Housing Finance Agency

IRA - Individual Retirement account

LIQ - Liquidity

MAE - Mean Absolute Error

MdAPE - Median Absolute Percentage Error

NW - Net Wealth

NW-HE - Net wealth minus housing equity

OLS - Ordinary Least Squares

PSID - Panel Study of Income Dynamics

U.K. - United Kingdom

U.S. - United States of America

WLS - Weighted least squares

ZHVI - Zillow Home Value Indices

2 Introduction

Household wealth is important both for an individual, and for the overall economy as it determines how households allocate their resources to consumption, spending on durable goods, portfolio allocation and investments in human capital and education. The great financial crisis of 2008 underscored the importance of household decisions for the performance of the macro-economy. This has led to a number of new research avenues which investigate the underlying determinants and effects household wealth has on a household. This thesis attempts to better understand household wealth and its effect on household consumption, poverty, and the determinants of wealth through the lens of household decision making.

For the empirical analysis of each chapter in this thesis, the Panel Study of Income Dynamics (PSID) is utilised. From 1968-today the PSID, ran by the University of Michigan, surveys approximately 6,000 U.S. households bi-annually.[1] This rich data-set has been employed extensively within the literature due to the significant number of variables collected on household behavior and outcomes within the survey (4,000+ each year), which allows for a wide breadth of research questions to be studied by social scientists and policy makers. The PSID was chosen as the main data-set for this study due to the breadth in variables supplied, and the longitudinal nature of the panel which allows one to conduct research studies about U.S. households before and after the financial crisis, and for the use of panel data methodologies which provide more robust estimation methods compared to cross-sectional data.

The empirical analysis presented in Chapter six explores the longstanding relationship between household wealth and household consumption. This chapter

[1] Annual from 1968-1998, bi-annual 1999 on-wards, which is the main sample period of each study.

aims to develop the existing literature by combining data from the restricted data-set from the PSID and restricted data from the online real estate agent Zillow, which has not been undertaken in the previous literature. These data-sets are applied to test for the presence of the “Wealth effect”, where unanticipated changes in house prices significantly affect household consumption. The existing literature has often used pseudo-panel studies which suffer from sample bias, and frequently have small sample sizes.

The fifth empirical chapter explores the differences between asset poverty and income poverty. Asset poverty is an alternative measure of poverty compared to the commonly cited income poverty measure. The analysis compares and contrasts current income poverty rates to asset poverty and captures reasons as to why households transition into and out of asset poverty. This chapter builds on the asset poverty concepts introduced by Caner and Wolff (2004) and applies this concept to derive asset poverty levels between 1999-2017. Furthermore, we provide a new recommendation on the standard measure of asset poverty, increasing the three month asset poverty threshold to six months.

The final empirical study in this thesis, presented in Chapter Four, identifies the determinants of household wealth using three novel machine learning techniques: decision trees, decision forests, and artificial neural networks. Machine learning techniques are becoming more widely applied for financial research. However, a significant proportion of studies focus on asset price prediction, such as stocks, commodities, and house prices. In particular, the closest relevant research to this study focus on predicting house prices, which build decision tree models based on the number of rooms, lot size, and location, for example, see Fan et al. (2006). However, there has been a lack of research applying machine learning models to household finance and household decision making questions.

Consequently, we construct decision tree and decision forest wealth trees to determine which household characteristics best predict a households net-wealth and net wealth minus housing equity. Chapter Four develops on the previous literature in a number of ways. To begin with, this study is the first to employ machine learning techniques on the PSID data-set for household finance research purposes. Secondly, unlike previous machine learning papers, which primarily focus on predicting house prices and generally focus on one small sample period, we apply the machine learning techniques over a large sample period (1999-2017). This allows us to understand if the machine learning models developed are consistent across the sample period in predicting household net-wealth and net-wealth minus housing equity.

The remainder of the thesis is organised as follows. Chapter Four identifies the determinants of household wealth using machine learning techniques. Chapter Five reviews the difference between income and asset poverty rates. Chapter Six presents the study on house prices and household consumption. Chapter Seven highlights the limitations. Finally, Chapter Eight concludes.

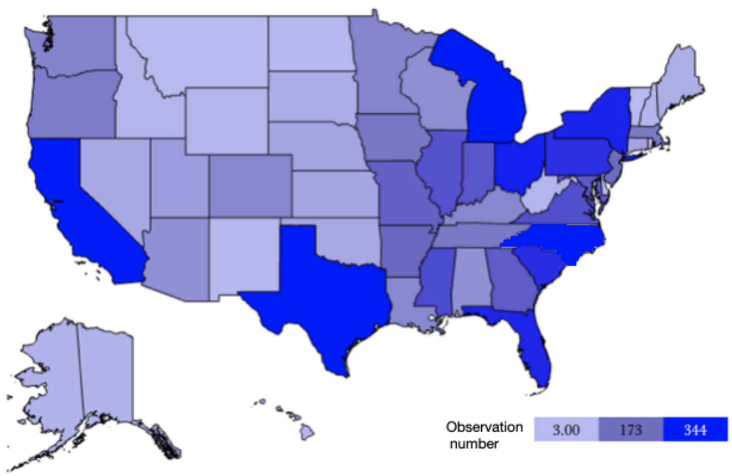
3 Panel Study of Income Dynamics and Taxsim

The primary source of data used in this study is from the Panel Study of Income Dynamics (PSID). The PSID[2] is a rich longitudinal data-set of households in the United States with information on house prices, income, wealth, and consumption variables. The PSID started collating annual information on a core sample of approximately 5,000 households in 1968. These original 5,000 households consisted of a random cross-section sample of the U.S. population with the addition of a low-income sample (which over-sampled low-income households). Since 1968, original families and their split-offs, such as children from the original core sample who may go on to form their own family, have also been tracked across time. From 1968 to 1997, the PSID was an annual survey, thereafter, waves have been biennial.

The PSID population distribution is illustrated in Figure 1. Data was taken from the 1999 wave of interviews and compared to the United States year 2000 Census Bureau's findings. On comparison, we find the PSID is representative of sampling participants from across the U.S and has similar population distributions given in the Census data. Ten states contain approximately one half of the U.S population, namely: California, Florida, Georgia, Illinois, Michigan, New York, North Carolina, Ohio, Pennsylvania, and Texas. Approximately 40% of U.S citizens live along the Atlantic (east) coast, with 16% living on the Pacific (west) coast and 12% living near the U.S Mexican border. The mid west characteristically has a lower geographic population density than the coasts, which is also represented in the PSID respondent heat map. Finally, we also include data on Hawaii and Alaska, which have several observations but less substantive than the major U.S states. This information can be found at the bottom of the heat map.

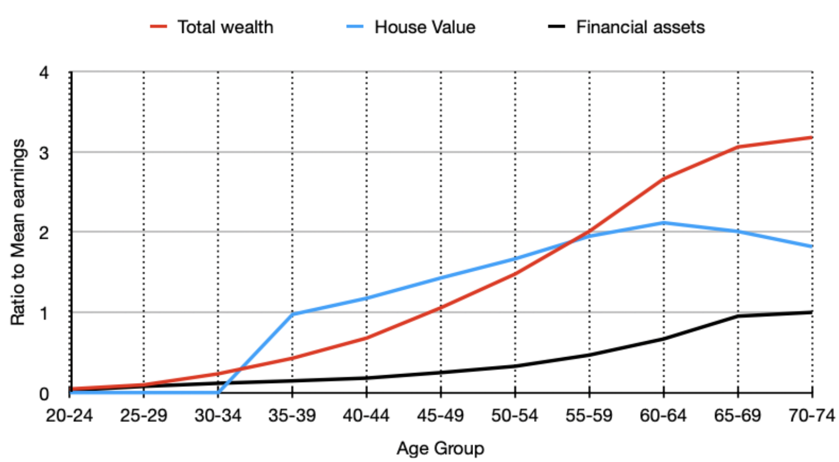
[2]Which is organised and ran by the University of Michigan.

Figure 1: Illustration of the geographic distribution of PSID survey respondents by U.S state.



Source: PSID. Where the total number of observations (households) is 6,985.

Figure 2: Five-year total income profile



From Figure 2, it is clear to see that the median household buys their property between the ages of 30 and 40. After buying a property, generally through the use of a mortgage contract, their house value is more than their total wealth, due the debt incurred taking on a mortgage contract. As households age over the life cycle, they increase financial assets ready for their retirement years. Other savings (including business interests, etc.) also increase in the later part of the life cycle, but are not included in this figure.

Wealth accumulation is often attributed to household income through savings in disposable income. Figure 3 illustrates how the PSID participant's income varies across their life cycle and by educational attainment. We notice that income across the life cycle follows the commonly seen humpback shape, with income rising as the age of the head of the household increases. Income reaches a height at age 50, and subsequently reduces at the end of their lives due to retirement decisions. Consequently, it can be easily seen that higher educational attainment increases household earnings.

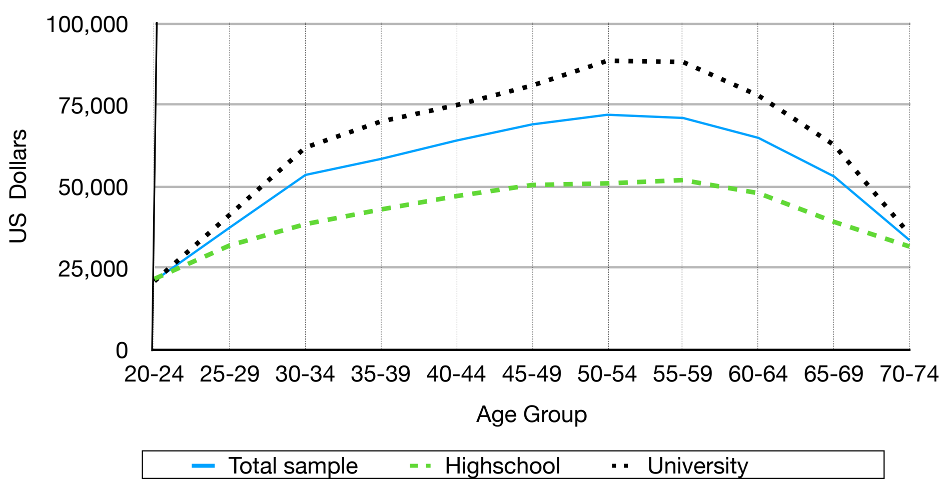


Figure 3: Income Profile

To calculate disposable income within the PSID, NBER's TAXSIM model first described by Butrica and Burkhauser (1997), and later enhanced by Kimberlin et al. (2014) is utilised. Prior to 1992, the PSID provided federal income tax estimates for each household and simulated federal income tax payments based on household responses to the survey. The simulations were based on income, filing characteristics, filing status, itemisation, and exemptions. Subsequently, the PSID did not provide any data on estimated tax liabilities for each household. Hence, to resolve this issue, the NBER's TAXSIM model was created to replicate households tax liability which combined both the PSID simulated tax program and NBER's original tax model.

Butrica and Burkhauser (1997) created the first alternative TAXSIM model that applies federal and state tax burdens to households from 1980 to 1991, and compared this to the PSID's original tax model. Their model was found to closely approximate the PSID model, with the average household income tax estimate was between 5-7.5% higher than the original PSID tax model. Since this model only applied from 1980-1991, Kimberlin et al. (2014) provided an updated model which follows the original principles prescribed by Butrica and Burkhauser. However, the authors applied the new model to more recent PSID waves. Kimberlin et al. (2014) model analyses data up to 2011.

The TAXSIM model has several assumptions. Namely, the head and the dependent spouse are a single tax filing unit, dependants (excluding the spouse) such as children, are also tax filing units, and other non-dependant family members are separate tax filing units. In total, this makes three unique tax filing units. Consequently, the summation of the within-household tax units yields the total family tax liability (Butrica and Burkhauser, 1997). Itemised deductions vary for different taxable income levels and households with and without a mortgage.

We assume all households take their itemised deductions, which will slightly over estimate federal income tax. Overestimation stems from families not claiming their eligible deductions, however, an exact amount is unknown due to lack of data. Taxable income is applied individually to the total income for a single head household, or as the summation of income where the head has a spouse. Due to the granularity of the data varying (explained below), family units other than the head and spouse may have several income and tax rates set to zero.

The PSID has different levels of income information for the head, spouse, other family units and dependants for each household. The head of the household has in-depth information on income, the spouse has less detailed information, and there is very little information for other family units and dependants. Since the granularity of the data worsens, this will add to the error of the total tax liability. We expect this to put a downward pressure on the overall tax liability as dependants and non-dependants income may be missed.

Under the assumptions provided above, and the framework built by Butrica and Burkhauser (1997), and by utilising the most recent version of the TAXSIM model provided by Kimberlin et al. (2014), we extend the model to analyse tax filings from 1999-2015. Furthermore, this will allow us to calculate the total family tax liability across the period of study which will be used to calculate the households disposable income by subtracting the total tax burden for each household from their total income. The main variables used in the TAXSIM model are outlined below in Table 1.

Source: Descriptions provided Butrica and Burkhauser (1997) and Kimberlin et al. (2014).

Next, we compare age and gender statistics to the 2010 Census Briefs from

Table 1: Sources of taxable wealth from the PSID

Tax variable	Definition
1. ID number	Identifies households across periods.
2. Year	Applies relevant tax measurements to their appropriate year.
3. State	Taxes are analysed at the state level. Local tax situations change annually. Due to the dynamic behaviour of local taxes, these are assumed to be negligible.
4. Filing status	Single head, separated spouse, or married.
5. Number of dependants	Number of children under the age of 16 in the household.
6. Number of seniors	Head and wife age and treats accordingly if they are above the retirement age.
7. Primary wages	Sum of labour, total business and farm income for the head of the household.
8.Secondary wages	Sum of labour, total business and farm income for the spouse.
9. Dividends	Dividends earned through investments, excluding property dividend income.
10. Other property	Sum of monthly rental , alimony received, trust fund, annuities minus alimony paid.
11. Pensions	The monthly sum of head and spouse pension income.
12. Social security income	Social security income for head and spouse (post 2005, data not collected prior).
13. Non-taxable transfers	Transfer income items are summed for income and unemployment variables.
14. Rent paid	Rental expense paid over x time period.
15. Property tax	Real estate tax on their current property and any other property owned.
16. Child care	Child care benefits.
17. Unemployment income	Monthly income from unemployment for head and spouse.
18. Mortgage	Summation of mortgage interest, charitable donation minus applicable deductions.
19. Capital gains (short term)	Short term capital gains or losses.
20. Capital gains (long term)	Long term capital gains or losses.

the U.S. Census Bureau.[3] We find the age of the head of the household to be approximately proportional with the Census Briefs except for younger households. PSID heads are older than the age distribution reported by the Census Bureau as the youngest age the head of the household can be is 18 years old. From the head gender category we identify that the PSID over-samples males as the head of

[3]For more information, see https://www.census.gov/prod/cen2010/briefs/c2010br-03.pdf

the household. Although 67.57% of the PSID heads are married, there is a slight imbalance of males can be seen within the PSID data-set. However, we expect this will have little impact on the models employed in this study. Interestingly, we note that 32% of households are currently renters. With such a large proportion of households having no housing equity, this provides support towards for testing NW and NW-HE independently to ensure housing equity does not drive our results in the later chapters.

PSID summary statistics

	Observations	Percentage
Head age		
<25	6,469	4.73
25-34	25,614	18.73
35-44	32,849	24.88
45-54	32,848	24.02
55-64	20,349	14.88
64-75	11,036	8.07
75+	6,578	4.81
Head race		
White	84,600	62.62
Black	25,614	30.49
Asian	2,042	1.51
Hispanic	2,497	1.85
Head gender		
Male	105,303	76.97
Female	31,449	23.03
Head education		
High school	76,412	58.03
College	41,700	31.67
Post grad	13,568	10.70
Marital status		
Married	92,432	67.57
Not-married	44,370	35.43
Tenure		
Homeowner	87,210	63.75
Renter	43,906	32.09
Mortgage		
Yes	64,480	47.13
No	72,322	52.87
Vehicle ownership		
Yes	117,046	85.50
No	19,756	14.50

Table 2: Authors calculations from the PSID data-set, waves included 1999-2017

Table 3 presents the mean wealth data and the wealth distribution across our sample period of 1999-2017. Under our two definitions of wealth, NW, and NW-HE, the mean wealth increases (for both measures) between 1999-2007; with the mean NW peaking in 2007 at \$322,060. The average NW of U.S households reduced by approximately ten percent from 2007-2009, and we note a six percent reduction in net wealth minus housing equity across the same period. The effects of the financial crisis can be seen most strongly in 2011, where NW is eighteen percent lower than the 2007 peak. Household wealth is depressed across both measures for the next decade. In 2017 the mean NW surpassed the 2007 peak, recovering to \$327,390. The data clearly shows our sample has three well defined periods, the boom period, 1999-2007, the bust, 2009-2011, and the recovery period, 2013-2017.

The bottom panel from Table 3 presents the percentile wealth of households. For both measures, the percentiles broadly follow the same pattern as the mean wealth data. With growth between 1999-2007, a decline between 2009-2011, and recovery from 2013-2017. A noticeable exception to this trend is the 10th percentile of NW-HE. Throughout each wave, their (negative) wealth steadily worsens, and only recovers slightly in 2017. This is driven partly through increasing debt levels, and furthered worsens by the 2008 financial crisis. Interestingly, the 90th percentile experience wealth reduction in the 2009 wave only for NW and NW-HE, with their mean NW wealth decreasing by 13% and 14.1% for NW-HE. In 2011, the 90th percentiles average NW and NW-HE increased by 10.3% and 6% respectively, all other percentiles wealth reduced between 2009-2011.

PSID Wealth Distributions

Wealth	Mean ($)									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
NW	175.38	199.70	213.72	261.77	322.06	289.15	271.94	281.82	329.63	327.39
NW-HE	131.36	144.28	147.26	173.60	220.11	207.11	195.41	202.42	239.03	231.77
NW	Percentiles									
10	0.00	-0.01	0.00	-0.06	-0.08	-7.00	-11.80	-10.80	-8.27	-4.80
25	4.50	5.00	6.00	6.80	6.90	3.00	2.26	2.50	4.00	4.20
50	37.00	45.60	51.18	65.00	76.80	57.80	48.98	51.00	60.70	59.50
75	139.00	169.00	188.00	239.90	285.00	235.00	225.00	230.00	261.75	257.00
90	365.00	439.60	486.00	610.40	724.50	630.00	695.40	693.00	773.50	786.00
NW-HE										
10	-1.80	-3.00	-3.95	-5.20	-6.50	-11.00	-12.80	-14.50	-15.50	-13.96
25	1.50	1.47	1.50	1.05	1.20	0.41	0.40	0.30	0.30	0.50
50	14.50	15.50	17.00	18.00	20.00	17.00	15.00	16.00	15.50	17.00
75	71.70	88.00	86.00	106.00	126.00	108.00	104.00	115.00	122.01	108.00
90	251.00	293.00	315.00	390.00	490.00	420.60	446.00	473.00	540.00	537.40

Table 3: Authors calculations from the PSID data-set. Values quoted in thousands of dollars. All values are CPI adjusted to 1999 dollars.

Table 4: Sources of wealth from the PSID

Asset type	Asset description
1. Housing equity	Home value minus outstanding mortgage
2. Net business value	Net farm and business assets
3. Current/Saving accounts	Value of current checking or saving accounts
4. Annuity/ IRA value	Value of annuity and pensions
5. Inheritance received	Value of inheritance received
6. Other home	Net value of homes other than their main dwelling
7. Other assets	Net value of other assets including bonds and insurances
8. Stock Value	Value of current stock holdings
9. Vehicle value	Net value of their vehicle
10. Students loans	Total student debt value
11. Debt	Value of other types of debt such as loans, utilities, other

Source: Descriptions provided by the PSID.

Note values are adjusted for CPI for 1999 dollars following the U.S. Bureau of Labour Statistics. We define Net wealth as the sum of asset types (1) to (9) minus asset type (10 and 11). Net wealth minus housing equity is the sum of asset types (2) to (9) minus asset type (10 and 11). Liquid wealth is the sum of asset types (3) (7) (8) and (9).

The above summary of the PSID will help inform the subsequent chapters.

4 Determinants Of Household Wealth: A Machine Learning Approach

Using household-level data from the Panel Study of Income Dynamics, we show that machine learning techniques can predict household wealth with a median absolute percentage error (MdAPE) of 15.74%. This study utilises decision trees, decision forests, and artificial neural networks, common statistical pattern recognition tools used in machine learning to predict U.S. household net wealth and net wealth minus housing equity. The findings reported across the 1999-2017 period, suggest variables such as profit on stock, house value, and profit on business are the best features in predicting household wealth. Secondly, the results identify alternative variables such as dividends, years left on mortgage, and interest income are also important factors in determining the wealth of a household. Thirdly, we forecast cross-sectional household wealth and find machine learning algorithms have substantially higher predictive power compared to a weighted least squares regression model, and can forecast future wealth with a 61% MdAPE. Finally, the findings capture life cycle behaviour within households. We believe this novel application of machine learning algorithms provides new insights into their effectiveness and applicability to household-level data.

4.1 Introduction

Wealth ownership is a key determinant in social stratification in the United States. Increased household wealth can positively influence children's educational attainment, household well-being, future income, and promote household portfolio diversification decisions (De Nardi et al., 2010; Mian et al., 2013; Piketty and Zucman, 2014). Recent studies have largely focused on the determinants of wealth inequality (De Nardi and Fella, 2017; Killewald et al., 2017; Zucman, 2019), wealth concentration (Alvaredo and Saez, 2009; Roine and Waldenström, 2009), and asset allocation of a households wealth portfolio (Addoum, 2017; Dimmock et al., 2018; Flavin and Yamashita, 2002; Poterba and Samwick, 2001).

To calculate household wealth, one can simply sum a family's assets, such as stocks, house value, savings, etc., then deduct their liabilities, such as long and short term debt obligations. The residual, hopefully positive, is the household net wealth. However, how could one estimate net wealth if you have incomplete information about a household's assets or liabilities? Do other variables exist, aside from a household's assets or liabilities, that could be useful predictors for net wealth? If so, can we reliably determine the salient variables involved in predicting household wealth across time? In this study, we explore if notable machine learning techniques can be successfully applied to the aforementioned questions; namely predicting household wealth and providing insights into the underlying relationships between easily available household information and wealth[4].

The single largest asset held in most households wealth portfolio is their house value. In 2018, 66% [5] of U.S. households owned their own home, with a further twenty-five percent of households renting their property. Wolff (2017) findings

[4] We define our Net wealth and Net-wealth minus housing equity measures in Table 4

[5] See 2017 economic federal reserve report on economic well-being.

highlight (between 2010-2016) U.S. households held approximately 30.7% of their total household wealth in their principal residence in 2010, trending down to 25.1% in 2016.[6] Alternatively, total stock holdings as percentage of wealth increased over the same period from 11.8% to 16.1%. Identifying household balance sheet trends is useful in reviewing how households allocate their wealth. However, it does not identify or measure how the economic or social characteristics of a household influence household wealth.

Conventional wealth models have extensively used either ratios, distributions, or hedonic-based regression approaches to identify correlations between household wealth and household characteristics. In particular, ratio and distribution analysis are often used for identifying changes in trends in household wealth over time, and are important in identifying the weighting of a households wealth portfolio when analysing net wealth. They are also useful for looking at how wealth varies by age, gender, and location. However, they fall short at statistically identifying the major determinants in predicting household wealth. Classical hedonic regression studies improve on ratios and distributions by allowing one to identify the correlation between economic and (some) social characteristics when reviewing their impact on household wealth. However, these models often suffer from strict estimation assumptions, and mainly focus on one small segment of the population (e.g., age, gender, education status etc). Consequently, this study suggests the use of new machine learning methodologies, such as *decision trees*, *decision forests* and *artificial neural networks* (ANN) as a new method to analyse the determinants of household wealth.

There have been several attempts to identify the different determinants of housing wealth using a variety of models, these include classical *hedonic regres-*

[6]As a percent of gross assets, data from the Survey of Consumer Finances (SCF).

sions, *random forests*, *support vector vegression models* [7], and *automated valuation models* (Nguyen, 2018). However, these models often have strict selection techniques for independent variables. This study will build on the work conducted by Fan et al. (2006), where we will initially utilise a decision tree approach which is an important non-parametric statistical pattern recognition tool. From decision trees, we look to identify if we can improve point estimations by employing decision forests, or through deep learning methods such as ANNs. Using the rich data from the Panel Study of Income Dynamics (PSID), we firstly are able to investigate the feature importance of household Net Wealth (NW) and Net Wealth minus Housing Equity (NW-HE) based on a households social and economic characteristics. Secondly, we compare and contrast each model to understand and identify the predictive power of each model, and then apply them to cross year predictions.

Machine learning techniques, such as decision trees[8], have become increasingly popular in both the academic and commercial fields. Recent applications of decision trees have been used as an approach to stock selection (Sorensen et al., 2000), and there is a growing number of papers using decision trees in predicting house prices (Fan et al., 2006; Revend, 2020). Decision trees are often applied to data mining issues as they can analyse both continuous and categorical variables to resolve classification problems and regression inconsistencies. Decision trees are also not affected as severely by missing data (a common issue in panel data sets) compared to other machine learning models such as Support Vector Regression models.

Our study differs from the previous literature in a number of ways. Firstly, we believe this paper is the first application of machine learning techniques to

[7] https://pdfs.semanticscholar.org/782d/3fdf15f5ff99d5fb6acafb61ed8e1c60fab8.pdf
[8] Also commonly referred too as classification trees or hierarchical classifiers

estimate and forecast both current and future household wealth directly. Utilising household level data from the PSID we identify that profit on stock, individual retirement account (IRA) value, and profit on business are consistently the best features for predicting household net wealth across the sample period 1999-2017. Furthermore we identify alternative variables that would not be commonly cited as good predictors of household wealth. These include, years left on current mortgage, dividend payments, and interest income. Secondly, our findings suggest the best performing decision trees, decision forests, and artificial neural network models can estimate household net wealth with a MdAPE of 24.67%, 20.99%, and 20.90% respectively. These results are significantly higher than weighted least squares (WLS) regressions. Thirdly, we find machine learning models can forecast future NW with a 61% MdAPE, however, they lose predictive power over the forecasting period (1999-2017) and perform substantially better than WLS regressions. Finally, we find net wealth is best explained by homeownership for black and female, and education and opening businesses is important for white and male headed households. Understanding the determinants of household wealth is important for policy makers, researchers, and for the wealth management sector. In particular, by selecting the top features that predict household wealth, this study brings new insights in the estimation of household wealth.

4.2 Literature Review

The measurement of household wealth, wealth accumulation, and savings behaviour have received recent interest by both policy makers and academics. Historically, countries in both Europe and America have had readily available wealth data from prominent surveys, e.g. the Survey of Consumer Finances (SCF), the Panel Study of Income Dynamics for the U.S., and Household Finance and Consumption Survey (HFCS) for European countries. The wealth data taken from surveys vary with either time series data, or panel data, which allows researchers to create and adapt experiments that work with the currently available data. However, there are a number of other countries that have only recently started collecting data, or have only partial measurements at best, e.g. South Africa, and regions such as South America, etc, see (Chatterjee et al., 2020; Torche and Spilerman, 2006)

There are currently four main ways to estimate household wealth. The first method is through aggregating household wealth, referred to as the household balance sheet. The household balance sheet captures the economic activity derived from both stocks and flows. This provides both consistent and internationally comparable estimates of aggregate household wealth (Chatterjee et al., 2020; Wolff and Marley, 1989). The U.S. household balance sheet was created in 1980s (Wolff and Marley, 1989), while other European countries were released in 2010 (Piketty and Zucman, 2014). The "flows" are measured by the difference between current income and consumption expenditures. Flows are often referred to as financial savings, and are most commonly used to analyse household saving trends. Alternatively, the "stock" measure the accumulated net wealth (i.e. the difference from one year to the next of assets less liabilities). The stock measure, which captures economic savings, provides an alternative view of household savings which incorporates both the flow measure and the changes in the value of assets and liabilities (Goh et al., 2005). Therefore, when evaluating asset price changes, the stock measure is most useful.

The second method of measuring wealth is through the use of national wealth databases. These sources often have complete records of assets and liabilities of their citizens. The use of the administrative tax records are often employed to gather data. For example, Boserup et al. (2016) employed data from the Danish Tax Agency who collect information on a households income sources, wealth components such as stocks, bonds, and house value, and their debt obligations. These data-sources are often unique to each country, as there is no standardised approach in collecting this data. Consequently, estimating household wealth is limited to the data-collection techniques administered and collated within each country.

The third method, which we utilise in this study, is looking at data on aggregate wealth from panel data surveys, such as the PSID. The USA is a particularly good country to study as surveys on household wealth have been running since the 1960s, such as the SCF and the PSID. These type of data-sources sample the population and measure household income, expenditure, wealth levels, and other household characteristics. From this, the implied wealth can be calculated. These surveys have some notable limitations. Firstly, independent variables such as house value are self-reported by the participants. Hence, bias can be introduced between a households real wealth, and their self-reported wealth. Secondly, these surveys often suffer from sample bias within the households surveyed. For example, the PSID over-samples low income households, while the SCF has a much richer data-set on high income/wealth households.

The fourth common method of measuring household wealth is using estate taxes and personal income tax. Estate duty has been commonly used to estimate wealth distributions as far back as 1908 (Mallet, 1908). Estate taxes are most frequently used for summary statistics, and allow researchers to review historical trends in wealth, where more quantitative and descriptive data-sets are unavailable (Atkinson and Harrison, 1974; Piketty and Saez, 2006). Unfortunately, estate taxes often fail to capture the demographic information and other important household level data that is needed to model the distribution of wealth. In this study, we will focus on the third method, of using aggregated wealth and household level information to estimate wealth.

4.2.1 Current literature

In this study we employ three machine learning models; decision trees, decision forests and artificial neural networks. Since we apply these models in a novel approach to predicting wealth, we first review the largest application of decision trees in household finance - house price prediction.

Historically, the main body of real estate literature has utilised hedonic regressions[9] approaches to identify the relationship between housing characteristics and its effect on housing value. This allows one to calculate the market value for each characteristic. For example, a common approach is to calculate the increase in house value if a household were to add another bedroom. Classical ordinary least squares (OLS) regressions have a number of benefits for estimating the relationships between household characteristics on house prices. These advantages mainly stem from their simplicity and ease of application to a variety of datasets, in-turn aiding comparability across studies (Herath and Maier, 2010; Liao and Wang, 2012; Selim, 2011). However, the use of hedonic regressions comes with several disadvantages. Firstly, the demand and supply functions that form the framework for hedonic regressions are empirically difficult to identify (Bartik, 1987; Rosen, 1974; Zietz et al., 2008). Secondly, housing characteristics may not be valued equally across a given distribution of house prices. In particular, the marginal value, percentage contribution, and elasticity valuations may differ across the house price distribution. Consequently, one would have to assume that

[9]Due to the volume of papers, only a brief summary will be given in this study

the preference structure of all homeowners would be identical and that the owners of low-value and high-value homes differ in only income constraints. This is highlighted in the representative agent paradigm. For example, if there is a rich household and poor household, the poor consumer does not wish to purchase an expensive house due to their income constraints and credit score. Alternatively, the rich household doesn't want to be seen to be living in a "poor man's home" as it will affect their social status. This leads to market segmentation where builders will infer that these groups prefer different valued homes with certain housing and neighbourhood characteristics. This leads to two sets of supply and demand curves due to this aforementioned market segmentation (Zietz et al., 2008).

Real estate is a heterogeneous good. House prices are derived from a variety of housing characteristics. These include geographical location, neighbourhood quality, and structural characteristics. Sirmans et al. (2005), compiled one hundred and twenty-five hedonic regression focused papers and found the main structural features analysed were lot size, square footage, number of rooms, bathrooms, bedrooms, air conditioning, fireplaces, swimming pools and garages. From these one hundred and twenty-five hedonic regression studies, there was significant parameter uncertainty in both the magnitude and direction of different housing characteristics on house prices. Interestingly, Sirmans, Macpherson, and Zietz established that only fifty-two percent of papers found a positive impact on the house price when increasing the number of bedrooms. This is indicative of high parameter uncertainty found within hedonic regressions.

With some restrictive limitations and assumptions required to use classical hedonic regressions, a new alternative methodology has started to be utilised; decision trees. Decision trees have been extensively used within several disciplines; manufacturing, astronomy, medicine, and production optimisation. They are utilised as there are several benefits upon employing them. Firstly, they are simple to understand and interpret as they can be displayed graphically and have an intuitive design (for example, see Figure 5). Secondly, they use a white box model which allows for a clearer understanding of the causal effects and processes that underlie the model. In comparison, black box models such as neural networks and gradient boosting models have a higher degree of accuracy, but do not provide estimates for features in a models predictions (Delibasic et al., 2013). Thirdly, decision trees are not significantly affected by missing data (a common issue with panel data). Finally, decision trees make no inherent assumptions about the relationships between variables (features) and do not fall victim to multicollinearity problems, unlike black box models.

Similar to other models, decision tree models have some inherent issues. Decision tree models can often suffer from over-fitting problems due to complex multilayered trees. To resolve over-fitting problems, 'pruning' techniques are employed to reduce the size of the decision tree by removing sections that provide little to no explanatory power. This improves the predictive power of the model and reduces over fitting. There are two different ways on deciding when to stop the growth of a tree: *pre-pruning* and *post-pruning*. Pre-pruning prospectively decides when to stop a decision tree following stopping rules that prevent branch growth that does not improve predictive power of the model. Common stopping criteria includes: 1) The number of observations in a node is less than a certain threshold, 2) all observations reaching anode belong to the same class, and 3) there is no rejection of the chi-square tests on the independence between a feature and the class attribute (Breiman and Friedman, 1985; Esposito et al., 1999). Post pruning methods allow the decision tree to grow even if the results are worthless and then retrospectively prune back branches to determine which branches add predictive power to the model. Common post-pruning methods include: *reduced error pruning*, *minimum error pruning*, and *critical value pruning*. For this study we will employ post-pruning techniques exclusively.[10]

Decision tree models are becoming more popular within the literature, and there is a growing number of studies utilising decision tree approaches. For example, Malliaris and Malliaris (2015) employ a C5.0 decision tree methodology to investigate financial variables that drive gold prices. Other notable studies include Delen et al. (2013) who investigated how financial ratios impacted firm performance. They employed four ML models (CHAID, C5.0, QUEST and CRT). Finally, Liu et al. (2017) attempted to forest copper prices in the short and long term and suggested decision trees should be utilised for a broad range of fields due to their readily applicable nature.

Decision forests (commonly referred to as random forests) have found to be a more optimal solution compared to decision trees. Breiman (2001) introduced random forests with great success. They have been widely adopted by several scientific fields, including; in genetic and bioinformatic studies, flood hazard modelling, and used widely in the physics sciences. Recently, decision forests have been applied to financial applications. Applications of decision forests include predicting stock prices (Khaidem et al., 2016), analysing potential insurance customers Lin et al. (2017), and have been employed for detecting financial fraud (Liu et al., 2015). Their wide applicability is due to their ability to reduce parameter instability found within decision trees due to their CART framework (Ziegler and König, 2014). In particular, we employ them in this study as they have been found to be consistent, reduce the variance found within the nodes of the decision trees while not increasing the prediction bias, and are asymptotically normal (Biau and

[10]For a comprehensive explanation on pruning methods, see Esposito et al. (1999)

Scornet, 2016).[11]

Other notable papers include, Park and Bae (2015) who reviewed four ML algorithms and tested their predictive power on data in Fairfax county, Virginia. Their results indicate that RIPPER and C4.5 algorithms were the best models for accurately predicting house prices. Selim (2009) compared the predictive performance of hedonic based regression models to artificial neural network models. The author suggested that AI models can help model house prices in Turkey. Another study conducted by Wang et al. (2014) found that support vector machine and particle swarm optimisation models were significant when applied to real estate price forecasting. There are notable issues with these studies. For example, Park and Bae only review house prices in one distinct county, Fairfax. Generalising a model for the whole U.S. could cause their results to show idiosyncrasies for the Fairfax region. Also, as the authors note they do not include different types of residential property, such as apartments, townhouses and detached houses etc. Their results could be influenced by these variables.

Unfortunately, there has been little research applying machine learning techniques for predicting household wealth. Notable wealth focused papers include Gaillin (2021), who utilises U.S. data from Zillow to construct a measure of the aggregate housing wealth between 2001-18 and applies automated valuation models (AVM). The authors suggest AVM estimates have a higher responsiveness to changing market conditions compared to traditional survey-based measures and find less volatility in AVM estimates compared to repeat-sales indices. Jean (2016) apply neural networks to determine if daytime satellite imagery of five African countries can help predict average household consumption expenditure and asset wealth. Their results indicate that satellite imagery explains 75% of the variation

[11] For more information about the pros and cons of decision forests, see Tyralis et al. (2019)

in local-level economic outcomes.

The most relevant study comparable to this article was produced by Fan et al. (2006). The authors utilised a CART decision tree model to investigate their applicability to 5,589 public resale data of flats in the Singaporean housing market. Their results indicate that homeowners of two, three and four bedroom apartments put value in the basic fundamentals of the apartment, such as floor area, age, and arrangement of the apartment. Homeowners of larger apartments had more value in the quality and finish of the apartment, indicative of having higher consumption value for their apartment. This study looks to build on the framework outlined by Fan et al. and apply this to U.S. household level data found in PSID.

4.3 Methodology

This section will provide a fundamental description on how decision trees and decision forests methodologies are structured. In particular, we will review how decision tree and decision forest models are built and note assumptions that may influence our results. This methodology adapts the decision tree framework first employed by Fan et al. (2006).

Learning algorithms typically use heuristics to investigate the possible relationships between combinations of different attribute values and classes (Fayyad and Irani, 1992). To identify and test the relationships within the data set, the sample is split into two groups; a training sample and a test sample. The decision tree algorithm starts with an internal node (root), which contains all training samples. Then the decision tree searches through the data to determine which independent variable partitions best split the training set such that each sub-sample has the largest difference in regard to the dependant variable (target variable). These partitions (or splits), are commonly referred to as branches. The branches start from the root node and continue until no further splits can be made that are statistically significant, this is known as a the terminal node (leaf). Each branch is statistically tested, with branches showing the minimum impurity/error selected and allocated to subgroups that show similar outcomes. Each subgroup may have differing explanatory power for the target feature. This recursive partitioning process allows one to find relationships and correlations between the target feature and independent variables.

Commonly used decision tree algorithms are CART (Classification and regression trees), ID3, C4.5/5.0 and CHAID (Chi-square automatic interaction detection). CHAID models are employed for categorical variables only, where CART and C4.5/5.0 can be used for both continuous and categorical variables. CART and C4.5/5.0 assess node splitting criterion using several statistical tests. These include, F-test, chi-squared tests, Gini impurity measures and reductions in variance measures. In this study we employ a CART model for three reasons. Firstly, C4.5 models often suffer from over fitting when the model is applied to data with uncommon characteristics and/or has multiple outliers. Consequently, this causes fragmentations (insignificant nodes with few samples) in the distribution process. Secondly, C4.5 (an improved version of ID 3) can construct many empty branches with zero values. These zero value branches do not assist to construct the tree or help classification, rather it makes the tree larger and more complex (For more information see Mazid et al. (2010)). Finally, by using the CART model, we will be able to compare our results with similar studies such as Fan, Ong and Koh.

4.3.1 Tree Growing

Decision trees are built through two techniques: tree growing and pruning. To grow a decision tree, tree algorithms search for the independent variable that splits the sample so that the difference in subgroups is greatest with respect to the dependent variable. The decision tree begins from the root node (d_1 node in Figure 5), and then partitions the sample until no further split provides statistically significant differences in respect to the dependant variable and the new subgroups. Since each subgroup can split into further subgroups, the decision tree can quickly form many layers (referred to as the depth of the tree), this is known as tree growth. When a subgroup can no longer split due to there being no significant difference between the subgroup and the dependant variable, this is known as a leaf node (terminal node, e.g. π_{l_4} on figure 5). The tree then stops growing branches along this path. Nodes that are not terminal nodes are referred to as internal nodes.

Figure 5 demonstrates the routing of a sample along the decision tree to a leaf node (l_4). The probability of the sample moving to the left of the node is $d_n(x)$, and to the right as $\bar{d}_n(x) = 1 - d_n(x)$. Hence, the probability of it reaching l_4 is $\mu_{l_4}(x) = d_1(x)\bar{d}_2(x)\bar{d}_5(x)$ with it's related prediction as π_{l_4}.

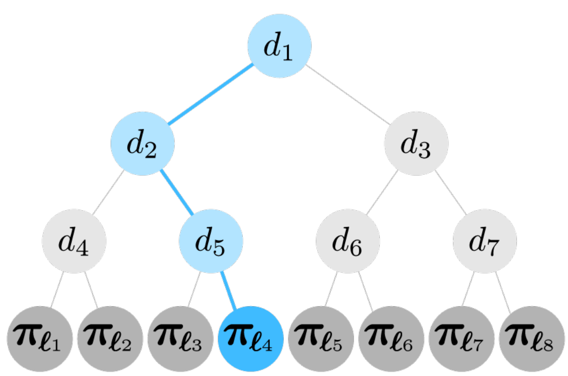


Figure 4: A grown decision tree

CART splitting can best be described as follows: an instance goes left if a *condition* is met, and goes right otherwise, where the condition is expressed as attribute ($X_i \leq$ c) for continuous attributes. For categorical or nominal attributes the *condition* is expressed as a list of values. For example, an instance goes left if a homeowner is Black, White, Asian and goes right otherwise.

Both the splitter, and the split point are automatically found by CART with the optimal split being dependant on the splitting rule chosen (such as Gini, Mean Squared Error (MSE), twoing, symmetric Gini etc). In general, binary splits are preferred to multi-way splits because they fragment the data more slowly than multi-way splits, and the repeated splits on the same attribute will eventually generate as many partitions required to improve the predictive performance of the model. For this study, as we utilise a CART method, we use an impurity-based split selection method to determine and reduce impurity found within nodes so we can choose the best node splitting decision for each node. The best splitting criterion at a node should be the split that leads to the largest reduction in impurity. In particular, we focus on the MSE measure for reducing node impurity as we are estimating regression trees where our dependant variable (wealth) is continuous. We define the within-node variance of Y as:

$$i(v) = \sum_{j \in v} [Y_j - \bar{Y}(v)]^2, \tag{1}$$

where $\bar{Y}(v)$ is the mean of Y_j within node v, and $i(v)$ represent the impurity measure of root node v.

The change in the error measure for a parent node v splitting into the left v_L and right v_R child node can be written as:

$$\Delta i(s, v) = i(v) - i(v_L) - i(v_R). \tag{2}$$

4.3.2 Tree Pruning

Early studies on decision trees did not allow for tree pruning. Rather, trees were deemed final when they had grown until a stopping condition was met. Unfortunately, this resulted in overly large trees with terminal nodes which had very few observations; the trees suffered from over-fitting. Pruning involves removing the split generating two (or more) terminal nodes and combining them together to produce the parent node, therefore reducing the size of the tree. To define the optimal tree we must review cost-complexity measure. The cost-complexity measure is defined as

$$R_\alpha(T) = R(T) + \alpha|\tilde{T}|, \tag{3}$$

where R(T) is the training sample cost of the tree, $\alpha \geq 0$ is the complexity cost of a terminal node. $|\tilde{T}|$ is the number of terminal nodes in the tree and measures the trees complexity. Hence, $\alpha|\tilde{T}|$ measures all the penalising costs related to the tree complexity (i.e. tree size). If $\alpha = 0$, then the minimum cost-complexity of the tree is at a maximum. As α progressively increases, the minimum cost-complexity of a tree reduces because the splits at the bottom of the tree reduce R(T) the least will be cut away. Consequently, progressively increasing α from zero will prune away all splits. Therefore the optimal tree is defined as the tree in the pruned sequence that achieves minimum cost on the test data (Steinberg and Colla, 2009).

We define R(T) as the misclassification rate of a tree T:

$$R(T) = \sum_{v \in T} i(v) \tag{4}$$

where i(v) represents the impurity measure of a root node v. From this we can define that $R_\alpha(T)$ is the sum of the estimated misclassification rate of the tree and the cost penalty for its complexity. The pruning process objective is to find a sub-tree $T(\alpha)$, for every value of α that satisfies:

$$R_\alpha[T(\alpha)] = \min_{T \subset T_{max}} R_\alpha(T) \tag{5}$$

where T_{max} is the fully grown tree, $T \subset T_{max}$ infers that T is a sub-tree of the grown tree T_{max}. [12]

4.3.3 Decision Forests

In addition to decision trees, we utilise decision forests (Breiman, 2001; James et al. 2013). Decision forests are robust to errors that result from the inclusion of variables that do not improve the performance when conducting feature selection. As such, they do not suffer from over-fitting issues found in decision tree methodologies. Decision forests are an ensemble learning method constructed from a large collection of de-correlated decision trees taken from the training sample. The training algorithm for decision forests apply bootstrap aggregating, commonly referred to as bagging. We define a set of inputs from a training set as $x' = [x_1, ..., x_N] \in$ X, and outputs y' $\in$ Y. Bagging selects a total of B[13] bootstrap samples randomly from the training set, and subsequently fit trees (t_b) using the Gini impurity to these samples. Once the decision forests have been trained on the training sample, the test set is used to predict values of X, by averaging the predictors from the individual regression trees using:

$$\hat{y} = \frac{1}{B} \sum_{b=1}^{B} t_b(x'), \tag{6}$$

[12] For further details about tree pruning see Fan, Ong, and Koh, 2006'; Zhang and Singer, 1999.

[13] B is a free parameter and varies according to the size and nature of the data-set. In this paper we set B = 50. B was found to optimal at 50 by using cross-validation. Increasing B did not significantly change the results reported.

Since a single decision tree can be sensitive to the noise within the training set, when averaged over a large number of trees, decision forests have increased performance due to a reduction in the potential variance.

4.3.4 Neural Networks

The third non-linear method applied is the artificial neural network. ANN methods have become a popular approach within the literature due to their applicability to predictive associations. ANNs are often applied to image, text, and voice recognition applications, and more recently to financial forecasting. Their applications stems from the concept of 'universal approximation', first described by Hornik et al. (1989). In essence, an ANN is capable of adapting to arbitrary and unknown functional forms with a varying degree of precision (Selim, 2009). We briefly describe ANNs in the following section, however, this is a well documented approach, and therefore direct the reader to the following work (Goodfellow et al. (2016)) for further reading.

Within the rapidly growing field of Deep Learning, an area of research dedicated to exploring ANNs with many parameters, there are many various ANN architectures. This study applies a simple and commonly favored *multi-layered perceptron* feed-forward neural network. These networks contain multiple layers: an input layer that contains the independent variables, the hidden layer(s) which perform non-linear operations to transform these predictors, and the output layer that aggregates the output of the hidden layers to construct a prediction. Each unit (referred to as nodes or neurons) in a layer relates to all the other units in that said layer. These connections between the layers are not all equal, as each connection (often denoted with a line) is parameterised by an independent *weight* and *bias*. Information passes in one direction, from the input, through the hidden

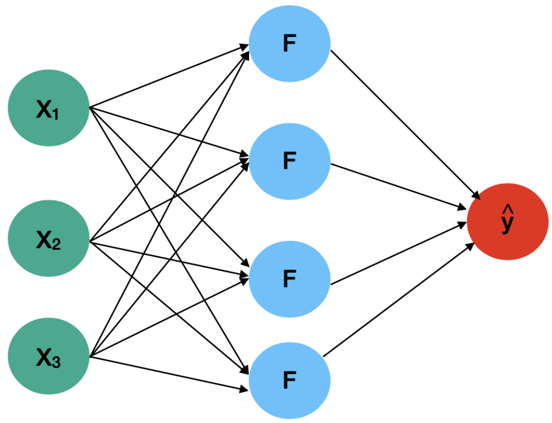


Figure 5: Neural network with one hidden layer. The green circles is the input layer, blue circles form the hidden layer, and the red circle is the output layer. Arrows from each neuron have an associated weight parameter. The hidden layer has a nonlinear activation function 'F' which transforms the input information and sends this to the output layer

layers until it reaches the output layer. Figure 6 denotes a single hidden layer ANN. The weight and bias parameters at each neuron are updated through an iterative process called *backpropagation*, where for a given cost function of the network, a gradient associated with this cost function is calculated per input sample, and sent back through the network and recalculated with respect to each neuron at each hidden layer. Using this gradient calculation, each neuron can be updated with respect to its gradient and thereby how much any given neuron update affects the overall loss of the network. This procedure and its modern applications is covered in much more detail by Goodfellow et al. (2016).

Figure 6 has three inputs, shown as circles. The input layer is often viewed as a virtual layer which doesn't form part of the hidden layers, i.e. having zero layers. There is one hidden layer in this example, however, the number of hidden layers and the number of neurons within each layer can be manipulated and selected depending on the research question and data being analysed. The hidden layer has a non-linear activation function F. Finally, there is one output layer that aggregates the information from the hidden layer and makes a regressed wealth prediction $\hat{y}$.

Due to the number of unique architectures that can be employed, and to find a successful network architecture through cross-validation, we model ANN with up to four hidden layers. We choose the number of neurons in each layer following the geometric pyramid rule first proposed by Masters (1993). In essence, the geometric pyramid rule suggests that there is no set defined criteria when selecting the number of hidden neurons. However, a good approximation for different structures is a hidden layer will have approximately $\sqrt{n * m}$ neurons where n is the number of inputs, and m is the number of outputs.

We utilise the widely cited rectified linear unit activation function (commonly referred to as ReLU)[14]. The rectifier is an activation function that assigns zero values if the input is zero or less, and the value itself if it is above zero. ReLU is defined as

$$ReLU(x) = \begin{cases} 0 & \text{if x} < 0 \\ x & otherwise, \end{cases} \tag{7}$$

which allows for faster evaluation compared to classical activation functions.[15]

ANN applicability comes with some drawbacks. Firstly, ANN are often described as a model which is hard to interpret, highly parameterized, and generally have a lack of set generalised rules with respect to the ANN design. This leads researchers to create unique design parameters that are employed in order for the ANN to produce accurate results. To further reduce the errors within the ANN

[14]Notable other activation functions include; linear activation, sigmoid, Tanh, and softmax. For more information about activation functions see Szandała (2021).

[15]For more information about ReLU and how it's been applied to other ANNs see Schmidt-Hieber et al. (2020), Gu et al. (2018), and Jarrett et al. (2009)

predict we employ early stopping regularisation which helps reduce the prediction errors in the training and validation sample. Early stopping allows one to control the model to stop generalising the model at the point of which the algorithm starts to make statistical inferences from the noise within the data. Consequently, the optimisation of the ANN are stopped when the validation sample errors begin to grow.

4.3.5 Forecasting Accuracy

To assess the predictive power of the decision trees and random forests, we utilise several statistical metrics to measure the accuracy of the forecasts. Let $\hat{W}_t$ with t *in* 1,...,N denote the predicted time series. We can subsequently measure the out-of-sample forecasting accuracy afterwards, once the true wealth W_t are known. We utilise the Mean Absolute Error (MAE) given by:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |x_t - \hat{x_t}|, \tag{8}$$

where N is the number of samples. The RMSE can also be defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} |x_t - \hat{x_t}|}. \tag{9}$$

We also utilise the standard deviation of the predictions as a measure of the uncertainty within the forecasts:

$$\sigma = \sqrt{\frac{\sum_{b=1}^{B}(t_b(x') - \hat{y})^2}{B-1}}. \tag{10}$$

Finally, to compare decision tree and decision forest models across years we utilise the Median Absolute Percentage error (MdAPE). The MdAPE orders the absolute percentage error (APE) in numerical value from smallest to largest, and uses the middle value (or the average of the middle two values if the sample size is an even number) as the median. We define the APE:

$$p_t = |\frac{y_t - \hat{y}_t}{y_t}| = |\frac{e_t}{y_t}|, \tag{11}$$

where p_t is the APE, y_t is the actual outcome value at period t (in this study this will be implied NW or NW-HE, and $\hat{y}_t$ is the forecast value derived from the decision tree or decision forest, e_t is the forecast error at period t. Hence the MdAPE can simply be defined as:

$$MdAPE = median(p_1, p_2, ..., p_n). \tag{12}$$

4.4 Data and sample selection

This study employs biannual data from the PSID, from 1999-2017. The central variables used in this paper are NW, NW-HE, and the majority of the variables found within the family file for each wave, which are tested as features.[16]

4.4.1 Wealth data

This study utilises two types of wealth information, NW and NW-HE. The PSID derives the NW and NW-HE from self-reported values. These include: implied housing equity, implied current savings, implied business value, implied debt value, implied annuity/IRA value, implied other home values, implied inheritance received, implied value of other assets, implied stock value, implied vehicle value, implied student loans. Implied wealth variables are created through a combination of variables to create a single value. For example, debt value is the summation of

[16]There are approximately 3,600 features within each wave.

a households short and long term loan values. Please see Chapter 3 for a review of the wealth data utilised from the PSID.

4.4.2 Sample Selection

To effectively grow and prune decision trees and decision forests, the models require sample selections. To prevent outliers distorting tree growth, we winsorize the maximum and minimum NW and NW-HE at the 1% level. Consequently, approximately 120 households are dropped from each wave. Secondly, NW and NW-HE are constructed through a linear combination of seven variables, namely; implied farm/business assets, implied housing equity, implied other real estate value, implied stock value, implied value of checking and saving accounts, implied other savings, and implied other debts. We must drop these variable for two reasons. Firstly, there is little research or statistical interest in regressing the components of household wealth on wealth. Secondly, if we removed for example a single variable, the decision tree would try to find a non-linear relationship with the remaining features that sum to give NW and NW-HE. In essence, the models would simply capture the remaining wealth variables that are used to calculate NW and NW-HE, and if one single wealth variable was removed, the model would simply be estimating the size of the omitted variable. As such, we remove the above variables that sum to give NW and NW-HE.[17] By removing the aforementioned wealth variables that are used to calculate NW and NW-HE, we have a true non-linear relationship. Finally, we remove NW-HE as a variable when NW is the target and vice-versa.

[17] In total, 8 wealth variables are removed when estimating NW and NW-HE.

4.5 Results

The objective of this section is to investigate and identify the determinants between household characteristics and household wealth for U.S. households. Firstly, the tree node randomly allocates the data between a training data-set, and a test data-set, where 80% of the sample is allocated to the training data-set, and 20% is allocated to the test data-set. This data is split in this manner to ensure that each model can be generalised, and to ensure its fit. [18] Decision tree and decision forest models will be run independently on NW and NW-HE, and these wealth definitions will be our target feature (dependent variables), and household characteristics will be our independent variables.

4.5.1 Feature importance

This section will compare feature importance for decision trees and decision forests. The tree-building process is estimated and a tree is built for each bi-annual wave of data (1999-2017). On average each tree has 250 internal nodes and 450 leaf nodes, with a minimum of 5 observations set within each leaf node. The leaf node represents the forecast value (regression value) of a households NW or NW-HE. In order to identify which wealth variables best explain wealth, we utilise the variables in the prior period (2 years prior) to determine the current NW and NW-HE.

The decision tree identifies how the independent variables differentiate the NW and NW-HE of households within the training set. The root node of the tree contains the entire training set. In the initial split, the tree node identifies an independent variable which is the best splitter by comparing the classified results

[18]The household wealth tree is built using the previously mentioned CART framework and ran using both python3 and the Scikit-learn python package containing libraries for machine learning classifiers.

produced by all the independent variables, because this variable leads to the largest reduction in node impurity. In other words, the first splitter can best differentiate between the categories in the target field. We report the feature importance of decision tree and decision forest models in the Appendix. For example, in 2001 the test set is firstly partitioned by 'Home Equity' when NW is the target feature, and 'Profit on Stock' when NW-HE is the target feature. The tree split on these features as their MSE reduced the node impurity by the largest amount. Such partitioning allows us to compare the effects of different independent variables on the target feature. The splitting rule determining the initial split is often viewed as the central variable of decision tree algorithms. Therefore in our 2001 example this implies that a households Home Equity (when the target feature is NW), and Profit on stock (when the target feature is NW-HE) are the most important determinants of U.S. household net wealth and net wealth minus housing equity based on a households information in the prior period.

From this initial split, the decision tree further partitions the data, node by node, until it reaches a leaf node. As the depth of the tree increases, the normalised error reduction in each node will decrease. We find an average depth of approximately 50 for each tree, with a range of between 40-55. At a certain depth, partitioning ceases when the splits no longer add value to the regression prediction, when the subset at a node has equivalent value to the target variable, or if the minimum number of observations in a leaf node is five. With this in mind, we rank the top ten features for each bi-annual PSID wave for NW and NW-HE.

Table 9 presents the ten most important lagged features for predicting NW and NW-HE for decision trees. Ten features are presented as the normalised error reduction values become increasingly small after ten. From Table 9 we can identify that IRA value is most frequently the best splitter for NW for decision trees between 2007-2017, being the most important feature in six out of ten waves. From 2001-2005 IRA value was of weak importance for predicting NW (ranking approximately the 5th best splitter). IRA value subsequently became the best splitter from 2007. Prior to 2007 profit on stocks was the most important splitter for predicting NW. This is particularly interesting as only 22% of households hold stocks, with the majority being in the top wealth quartile. From this we can infer the decision tree is capturing the differences in wealth from the stock feature. Furthermore, pre-2007 bullish stock price market is likely the reason we see profit on stock being an important explanatory variable. The PSID captures the effects of the global financial crisis in the 2009 wave. After 2008 financial crisis, we identify a reduction in the explanatory power of stocks when predicting household NW and the algorithm suggests in the post-financial crisis IRA value is the best splitter. The increase in the IRA feature importance could also be influenced by the ageing of the households over the sample period, where household income and wealth reduces and their IRA wealth will become a larger proportion of their NW.

House value is also an important splitter for NW featuring in nine of the ten waves, with it mainly being one the top three features. This follows our predictions that house value is one the most important feature in determining a households NW as many households place a large proportion of their wealth into their home. Before the financial crisis, house value was frequently found to be the second best splitter for decision tree models for NW. However, after the financial crisis the feature importance of house value dropped to the third most important feature, with profit in stocks replacing it as the second best splitter in most waves. With the significant increases in house prices over 1999-2007 period,[19] household wealth became concentrated within their housing equity. When the financial crisis struck

[19] Where house values in some areas increased by 100%

in 2008, subsequent decreases in home values, and therefore housing equity is being captured within the decision tree models. Therefore, we see a reduction in explanatory power of house value when predicting NW in future periods.

Another important splitter for NW is profit on stock which is in the top three splitters in seven out of ten waves. Profit on stock refers to the profit a household would make if it sold its current stock holdings. We believe profit on stock ranks so highly due its' ability to separate wealthy, and poor households, due to the small number of people holding stocks as previously mentioned. The PSID oversamples low income households compared to richer households. These households are less likely to hold stock-holdings compared to richer households.

Subsequent nodes for NW vary in normalised error reduction and their associated rank. Notable variables that are consistently in the top ten are: years on mortgage, interest income, current cash, other real estate and profit on business, and dividend income. Although there is no real discernible trend amongst their feature importance as they fluctuate across each wave, their consistency within the top ten features indicates the algorithm consistently finds them to be useful in predicting NW. We find that from node six onwards, the feature importance ranks vary from year to year. Often these nodes are financial variables. These include features relating to household characteristics and their expenditures, e.g. insurance costs, leisure expenses, weeks worked, industry the household works in. Due to the fluctuations in these bottom variables we do not infer economic meaning in them due to their low normalised error reduction.

Next we review the NW-HE feature importance for decision trees. We find the most frequent top node for NW-HE is IRA value, being the top ranked node in six out of ten waves. Similar to NW, household IRA value reduces node price variance most frequently across wave, and is therefore the best indicator for net wealth without housing equity. Similar to NW, we find common features, such as profit on stock values, profit on business, and other RE frequently features in the top five best splitters for NW-HE. The normalised error reduction coefficient reduced over the sample period similarly to NW. However, the average normalized error reduction for NW-HE is lower than NW, which is most likely due to lower variance within the NW-HE estimates. We do see some more interesting features in NW-HE decision trees compared to NW. These include, the size of the households vehicle deposit in 2001, the amount of money donated to charity in 2003, phone expenses in 2009, and spouse age in 2013. These variables only feature in the NW-HE feature importance ranks once. Therefore, we cannot conclude if these have much statistical significance or are artefacts of the decision tree models.

We now examine the feature importance of decision forest models. The results are reported in Table 11. The feature importance of decision forest models follow a similar pattern to the decision trees for both NW and NW-HE. IRA value is consistently in the top three features from the 2007 wave onwards. Similarly, the profit on stocks for NW-HE feature follow a similar pattern to decision tree models which is the most important splitter between 1999-2005, then subsequently becomes the second most important for most future waves.

There are a few key differences between decision tree models and decision forests. In particular, for NW, house value has a higher feature ranking within the decision forests models compared to the decision tree models (especially between 2001-2005). Secondly, the average normalised error reduction for each feature is lower for decision forests. The lower error reflects the power of the bagging process, this is further verified by the model performance, which is discussed below. As such the feature importance results for decision have a higher prediction power for household wealth under both the NW and NW-HE measures.

4.5.2 Model performance

To be able to determine the statistical significance of decision trees and decision forests, we present the Median Absolute Percentage Error (MdAPE)[20], R^2, and MAE results are reported both for the training and test data-sets, which were modelled on each dependant variable (NW and NW-HE) respectively. We first present the MdAPE for decision trees and decision forests in Table 10 and 12 respectively.

From Table 10 we note three discernible trends from the decision trees MdAPEs. Firstly, the MdAPE for the training and test data-sets reduces over the sample period, i.e. the machine learning algorithm can predict with a higher accuracy the NW and NW-HE of households in later waves.[21] This can partly be explained by the reduction in NW and NW-HE after the financial crisis, so there is less variance within the data. However, as noted in Table 4, a large majority of household wealth had been recovered from the 2007 peak in the 2015 and 2017 waves, so we find evidence that the algorithm finds it easier to predict NW and NW-HE over time. Secondly, NW-HE decision tree models have lower MdAPE on average compared with NW models. This is most likely due to the lower variance in the NW-HE wealth data. However, we find on average a 2% increase in explanatory power within the NW models compared to NW-HE models. Finally, as expected, the MdAPE for the training sets for both NW and NW-HE decision tree models is lower (i.e. better) and have significantly higher explanatory power as seen in the R^2 statistics. Figure 7 presents an illustration of the yearly MdAPE for both decision tree and decision forest models.

[20] As previously mentioned, MdAPE is a preferred over MAPE as it is more resistant measure to outliers.

[21] The lowest MdAPE for NW in the 2001 wave at 25.21%, and when NW-HE is the target feature the best MdAPE was in 2013 at 24.07%.

Evaluating the MdAPE of the decision forest we find evidence of much higher explanatory power in the decision forest models compared to decision trees, with R^2 increasing by 14% for NW, and by 13% for NW-HE.[22] This supports the benefits previously mentioned that decision forests improve model accuracy without increasing the bias in the predictions. Secondly, we see a similar trend of increasing performance of the decision forest models over the sample period, evidenced in the decreasing MdAPEs. Interestingly, both NW and NW-HE models MdAPEs decrease at a faster rate compared to decision tree models after the 2007 wave. The best model for predicting NW-HE was found in the 2015 wave at 15.74%. We infer from this that 50% of the algorithms NW-HE predictions had an error less than 15.74% and 50% had a NW-HE prediction higher than this. There is no clear evidence as to why the 2015 NW-HE model has the lowest MdAPE compared to other PSID waves.

[22]We also note that decision forests have 26% better MdAPE compared to decision trees.

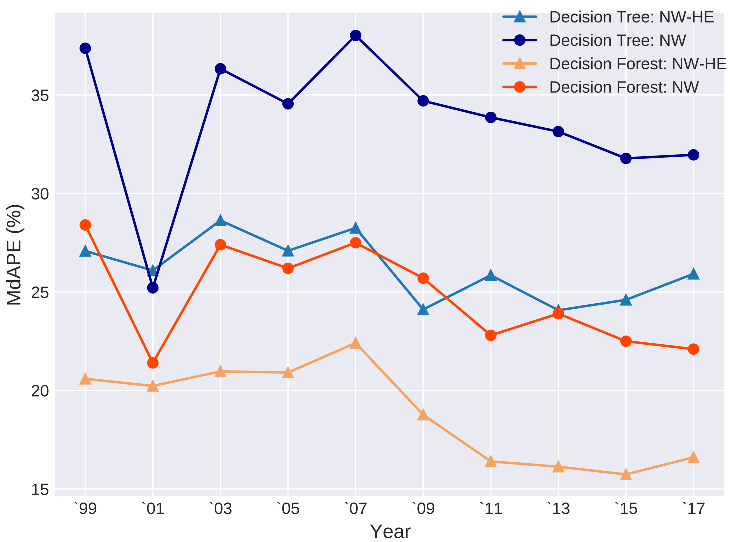


Figure 6: MdAPE for both Decision Trees and Decision Forests across the sample period. All results are from test splits using 5-fold cross validation.

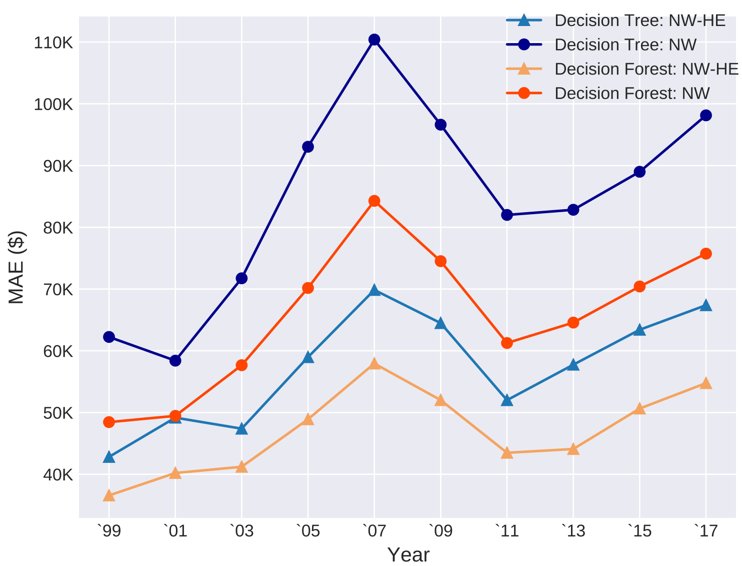


Figure 7: MAE for both Decision Trees and Decision Forests across the sample period. All results are from test splits using 5-fold cross validation.

Decision Tree Results

Year	NW-HE		NW	
	Train	Test	Train	Test
2001	19.12 (0.79)	26.09 (0.56)	17.63 (0.82)	25.21 (0.65)
2003	19.96 (0.79)	28.63 (0.52)	24.86 (0.80)	36.33 (0.58)
2005	19.46 (0.80)	27.09 (0.57)	23.51 (0.82)	34.55 (0.57)
2007	19.52 (0.78)	28.25 (0.55)	25.19 (0.81)	38.02 (0.56)
2009	17.75 (0.75)	24.11 (0.52)	24.33 (0.78)	34.70 (0.55)
2011	17.57 (0.82)	25.85 (0.66)	23.70 (0.83)	33.86 (0.65)
2013	17.03 (0.81)	24.07 (0.62)	23.17 (0.81)	33.14 (0.64)
2015	17.40 (0.82)	24.60 (0.60)	22.13 (0.82)	31.78 (0.62)
2017	17.77 (0.80)	25.92 (0.56)	21.58 (0.81)	31.96 (0.64)
Avg	18.40 (0.80)	26.07 (0.58)	22.99 (0.81)	33.28 (0.60)
WLS Avg	-	1,110	-	1,421

Table 5: MdAPE results for Decision Tree models using 5-fold cross validation. Best performing parameters discovered via grid search. R^2 values are reported in brackets. WLS is the average weighted least squares regression.

Decision Forest Results

Year	NW-HE		NW	
	Train	Test	Train	Test
2001	7.10 (0.96)	20.23 (0.70)	07.5 (0.96)	21.4 (0.74)
2003	7.79 (0.96)	20.97 (0.69)	10.0 (0.96)	27.4 (0.72)
2005	7.64 (0.96)	20.91 (0.72)	09.3 (0.96)	26.2 (0.73)
2007	8.01 (0.96)	22.41 (0.68)	10.1 (0.96)	27.5 (0.72)
2009	6.82 (0.95)	18.77 (0.67)	09.5 (0.96)	25.7 (0.69)
2011	6.23 (0.97)	16.40 (0.76)	08.5 (0.97)	22.8 (0.78)
2013	6.05 (0.96)	16.13 (0.74)	08.8 (0.96)	23.9 (0.76)
2015	5.94 (0.96)	15.74 (0.73)	08.0 (0.96)	22.5 (0.75)
2017	6.40 (0.96)	16.61 (0.71)	08.1 (0.96)	22.1 (0.74)
Avg	6.89 (0.96)	18.69 (0.71)	8.07 (0.96)	24.38 (0.74)
WLS Avg	-	1,110	-	1,421

Table 6: MdAPE for Decision Forest models using 5-fold cross validation. Best performing parameters discovered via grid search.

From Table 12 and 14 we see the MAE results for NW and NW-HE for decision trees and decision forests. Firstly, we identify the average MAE for decision

Artificial Neural Network Results

Year	NW-HE (MdAPE)	NW (MdAPE)
2001	18.80	20.90
2003	19.91	25.54
2005	21.73	26.00
2007	21.99	26.58
2009	19.06	25.92
2011	17.58	24.44
2013	17.10	23.83
2015	15.55	22.20
2017	17.79	21.18
Avg	18.83	24.06
WLS Avg	1,110	1,421

Table 7: MdAPE for Neural Network models using 5-fold cross validation. Best performing hyper-parameters discovered via grid search. Average weighted Least squares reported.

forests compared to decision trees improves the predictive power by approximately $13,500. This is to be expected as the MdAPE for each wave of decision forests were found to be lower compared to decision trees. Secondly, we note the largest MAE for NW in 2007 wave for both decision trees and decision forest models at $107,195 and $86,381 respectively. This highlights the difficulty of estimating NW at the height of the asset price bubble. We suspect this is primarily due to the variance found within the algorithms when household wealth was at its peak in 2007. Although the size of the MAE may appear large on first inspection, this is driven mainly by the higher net wealth households where we find much larger variances for households wealth levels. Figure 8 presents the MAE for both decision tree and decision forest models.

The MAE for the training sets (for both NW and NW-HE) is lower than the test data-set (results not reported). This is to be expected, as 80% of the data is used to train the model, whereas 20% is used for on the test data-set. Secondly, we note the MAE trends upwards across the sample period for both NW and NW-HE across both decision tree and decision forest models. This increase in MAE could be attributed to the recovery of household wealth after the great financial crisis. However, as our coefficient of determination stay relatively constant across for both decision tree and decision forest models over the sample period, the increases seen in the MAE do not concern us as the MdAPE reduces over the same period. These results highlight promise for statistical pattern recognition techniques such as decision trees and decision forests as they can produce reasonable estimates when predicting household wealth.

To apply ANNs to our research question, we make a feature selection based on the feature importance's calculated by the decision tree and decision forest models. It is both impractical and unwise to utilise over 3,000 input neurons, as most neurons have little to no explanatory power of NW and NW-HE. Unlike decision trees and decision forests which can handle a large number of input features (as they simply won't be used due to stipulations set by the tree growing algorithm e.g. by setting tree depth and minimum number of observations), ANNs work most effectively with fewer neurons which speeds up prediction times, and this results in more reasonable predictions.[23] Hence, we average the feature rankings of the top 50 features for both decision trees and decision forests and employ these 50 variables as the input variables. The ANNs results are reported for NW and NW-HE in Table 7.

We utilise the ANN as a performance measure to decision tree and decision forest estimations. The results indicate that ANNs have the highest predictive power compared to decision trees and decision forests, with the best performing ANN model featuring in 2015 with a MdAPE of 15.55%. Similar to decision trees and decision forests, the deep learning algorithm has better predictive power for

[23]For robustness we utilise the same feature inputs used in decision trees and decision forests

NW-HE compared to NW, with the average difference being 3%. Furthermore, we note a similar trend across the sample period, where ANN models have better predictive power for later years; 2011 on-wards. Interestingly, the ANNs model do not significantly improve estimates compared to decision forests. This is captured in the average MdAPE reported, where ANNs are 0.01% and 0.29% more accurate compared to the average decision forests MdAPE for NW-HE and NW respectively. Due to the ANN architecture, we are unable to discern feature rankings. We conclude that due to the marginal difference between average MdAPE performance between decision forests and ANNs, decision forests are a more appropriate model for this research question as they allow one to see both feature rankings and model performance compared to ANNs.

The bottom panel of Table 7 presents the average weighted least squares regressions across the sample period. The best performing WLS model for both NW and NW-HE is 827% in year 2005, and 1,012% in 2003 respectively. These high MdAPE are consistent with our expectations that linear regressions are unable to accurately estimate a model for household wealth due to the high dimensions of the data, and the non-linear nature of our research question.[24] The above four model results highlight that machine learning models significantly outperform classical WLS regression estimates.

4.5.3 Cross year predictions

In this section, we apply the aforementioned machine learning models to forecast household NW and NW-HE in future sample periods. In particular, we address the following questions;

1. How effective are machine learning models when forecasting future house-

[24]Polynomial regressions were also employed with similar results.

hold wealth?

2. Do machine learning models improve forecasting household wealth compared to classical regressions?

Firstly, we make a strict sample selection from the PSID data-set. We drop households who change family composition (i.e. when family members move into or out of the defined family unit). The family is also dropped if they get married or divorced. These sample selections allows us to track the head of the household across years and follow family units that do not experience significant life events that could affect their NW and NW-HE, e.g. due to divorce, or birth of a child etc. This reduces our sample size to 2,846 households.[25]

A decision tree model, decision forest model, and artificial neural network model are trained on data from the 1999 sample period. We also utilise the standard least squares regression model to capture how classical regressions would perform. This allows us to calculate analytical estimates and avoid sophisticated optimisation and computation which allows for greater comparison. The machine learning models and regression model are then applied to the out-of-sample household level data in future sample periods to test the aforementioned questions. The results are reported in Table 8.

The top panel presents the cross year MdAPE predictions for decision trees.[26] There is a significant increase in the cross sectional MdAPE for both NW and NW-HE compared to in-year sample estimates for decision tree models. In particular, the average cross sectional MdAPE for decision tree models across the sample period is approximately 50% and 82% higher for NW and NW-HE respectively, compared to same year estimates previously estimated. [27] As expected, the best

[25]Similar to previous models, we winsorize data at the 1% level.

[26]The decisions trees are constructed under the same architecture as previously noted.

[27]See Table 5 and 6 for in same year estimates of NW and NW-HE decision tree models. We also note this is an imperfect comparison due to different sized data-sets used.

performing cross sectional estimates for the 1999 model is for the year 2001 with a MdAPE of 74.3% and 96% for NW and NW-HE respectively. The highest increase in MdAPE for both NW and NW-HE is between the 2007-2009 year, which is most likely due to the financial crisis. Interestingly, unlike the same year predictions, cross-year estimates for NW predictions are better than NW-HE. We believe this is most likely due to the new sample selection where stable households are only followed across the sample period.

The second panel presents the MdAPE cross year predictions for decision forest models. We note similar trends between decision trees and decision forests, where NW is predicted more accurately compared to NW-HE across each wave. Cross sectional decision forests NW predictions are more accurate compared to decision tree models. However, from 2005 onwards, decision forests do not capture NW-HE predictions as well as decision tree results. This increase in error most likely stems from the bagging process, where decision forests are averaged across 50 decision trees. Due to smaller sample sizes in the cross year predictions, this leads to higher errors in the decision trees, which on average skew the NW-HE predictions up to a maximum of 158.65% in 2017. On average, the average cross sectional MdAPE for decision forest models across the sample period is approximately 51% and 105% higher for NW and NW-HE respectively, compared to single-year estimates.

4.5.4 Household characteristics and life events

In this section, we reduce the PSID data-set to 20 variables which contain information about household characteristics (for example, their religion, health status and marital status) and life events they could experience (such as losing a home, opening a business or becoming married etc). Household wealth is predicted across the sample period, and the households are controlled by different demographics.

Cross Year Predictions

	Year									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
Decision Tree										
NW	-	74.27	74.55	79.98	81.69	87.46	91.85	90.41	91.05	90.99
NW-HE	-	95.97	96.93	100.65	102.76	113.09	107.94	117.13	115.58	114.85
Decision Forest										
NW	-	61.41	65.13	70.17	72.72	78.92	79.60	81.31	86.58	85.25
NW-HE	-	93.51	91.58	105.60	125.99	131.73	127.87	130.47	153.36	158.65

Table 8: Cross year prediction from the PSID data-set. Results reported are 5-fold cross validated MdAPE. MdAPE values are quoted in percentages.

Due to the significant amount of decision forests generated, we present the results from 2007-2013, however, results have been generated across the entire sample period.

The results below are presented using Shap value plots, which provide an in-depth view of a decision forest. Each Shap graph contains the entire variable list included within each model. In particular, each figure illustrates the feature importance, where the most important feature for explaining household wealth is found at the top of the graph, and features are ranked in a descending order of importance. Secondly, they highlight the value of a feature, where red dots indicate a high feature value, and blue dot indicates a blue score. For example, high educational attainment, e.g. postgraduate, would be indicated with a red dot, and high-school level education would be indicated with a blue dot. Thirdly, the impact is shown on the x-axis, which shows whether the effect of a value is associated with a higher or lower prediction. Finally, the correlation of the observation with wealth is shown. Observations on the right of the zero impact score indicate a positive association with Net Wealth or Net Wealth minus housing equity, and if the observation is on the left of zero impact score, it has a negative correlation with household wealth. Each dot represents a leaf node of a decision forest, which contains five households.

Figures 9 and 10 present white and black household net wealth predictions. Buying or losing a home has the highest feature importance for black households compared to having a new child and educational attainment are consistently the most important splitters for white households. As expected, losing a home indicated with a red observations has a strong negative association with NW for both races, and buying a home indicated with red observations has a strong positive increase for household wealth. Interestingly, having a child is consistently the top observation for white household. We can potentially infer that households who are having a child may have done either some financial planning to support their child or have higher prior wealth to be able to support their children prior to birth. Furthermore, the Decision Forest models suggest that higher educational attainment indicated by the red observations have a significant positive association with net wealth for white households compared to black, indicating white households education has a larger impact on their wealth compared to black households.

Figures 11-14 show the model results for white and black, male and female headed households. For both races, higher educational attainment is an important feature for male headed households compared to female headed households where homeownership is more important. The results show little predictive power for the bottom features, such as inheritance, religion, and marriage for female headed households, this is due to their being lower observations for the models to generalise across. Similar to the previous results, children are important for white male and female headed households. From Figure 14 across the 2009-2013 waves, we note that households who have higher numbers of total children have a negative impact on net wealth compared to having fewer children, which follows expectations due to the high cost of supporting a child. The feature rankings across the sample period are relatively stable showing household wealth doesn't significantly change across the financial crisis.

Next we attempt to capture life-cycle effects through varying the age of the household within the model. We control for young (18-39), mature (40-64), and retired households (65+), the results are reported for both races in Figures 15-20. The decision forest models highlights some clear life cycle behaviour across the trees grown. For example, young households having a child and buying a home is the most important feature for white and black household respectively. However, for mature households and elderly households, educational attainment is the most important feature for their net wealth. This indicates that gaining high educational attainment at the beginning of your lifetime does not translate into high net wealth in your earlier years, however, with presumed further job progression, and a higher likelihood of higher disposable income and job prospects in the future, higher educational attainment clearly pays off for households. Furthermore, we see for elderly households, higher health status indicates a positive impact on net wealth, which would align with expectations based on the U.S. healthcare system. However, health status does not feature highly for mature households. Indicating the models clearly identify life-cycle behaviours when presented with different strata of the PSID data-set.

To further understand if our models can not only infer correlations between household characteristics and life events, but to help further our understanding of how these events can cause changes in household wealth, the wealth change of the household between two sample periods is calculated, and the results for white and black households are presented in Figure 21 and 22. The results indicate that losing a home and closing a business are important feature for having a negative impact on black household wealth. In comparison, white households are best explained with opening businesses which have a positive impact on their net wealth.

To identify if our results are driven by housing wealth, we run the models on NW-HE for black and white households, the results are presented in Figures 33 and 34. Closing a business and losing a home are the two joint most important features for explaining black household NW-HE across the sample period. There are no clear discernible trends within the feature ranking list for white households which can be established. We can see the financial crisis having a large negative impact on black households compared to white, as the models find features that are associated with wealth destruction such as losing a home and closing a business, compared to wealth creation features, such as educational attainment and opening businesses which were more highly ranked for white households.

Finally, we present the model performance in Figure 35. The normalised MdAPE for net wealth predictions is higher compared to changes in wealth due to the larger net wealth value being estimated. We note the error reduces across the sample period indicating higher model performance, but this is likely due to the reduction in household wealth due to the financial crisis. Their is an uptick in error in the 2017 wave, which is likely due to increases in both net wealth and changes in net wealth. Furthermore, we see there is more volatility in the predictions for black households compared to white. This most likely stems from there being fewer observations, and larger changes in household wealth in black households due to a larger proportion of black households being poor. In panel B we note the explanatory power of the models, as expected, models built with all households in the test and train data-sets have the highest explanatory power reaching 73% in 2009 due to the larger sample sizes and low net wealth values, however, explanatory power is only marginally lower for white households compared to the whole sample models. Overall, with such a limited set of variables to derive net wealth from, we believe these models have performed above expectations and showed relatively stable model performance across 9-waves of data compared to other studies who utilise one year of study Fan et al. (2006).

4.5.5 Robustness tests

We have performed a number of robustness checks to identify if the results presented in this paper are artefacts of our decision tree and decision forest model specifications. Firstly, the initial setup winsorized the data at 1% in each tail. This resulted in approximately one-hundred and twenty observations being dropped from each wave. To ensure our results are robust we tested both decision trees and decision forests with no cuts, and cuts at the five percent level. When no cuts were made, we found the decision trees split unevenly due to high wealth households. In particular, businesses were the most important feature for each wave. The algorithms identified businesses to be the best splitter for NW and NW-HE as a small number of individuals had made large sums of wealth through their personal business ventures. Since this paper wants to generate models that can predict the NW and NW-HE of the average household, we believe having no cuts in the model would invalidate the overall model. Finally, we tested with five percent cuts, and found the model errors increased slightly due to the reduction in the training data samples. As such, we believe our suggested 1% cuts are sufficient and robust.

Secondly, we tested with varying levels of K fold cross validations. In particular, we present five fold cross validation. We tested two, four and ten folds and found that five fold cross validation produced the most meaningful estimations based on our sample sizes. Two fold cross validation produced insignificant results due to the lack of training samples needed by the algorithm to build NW and NW-HE models. For ten folds we found no significant changes in the out of sample prediction error. However, we found estimation times for decisions forests increased significantly for ten folds. As such, for future studies, we believe five fold cross validation is acceptable if using similar sized[28] data-sets.

Thirdly, we varied the number of bootstrap samples for the decision forest models between 30 and 200. We found 50 to be sufficient in providing adequate reduction in variance when predicting NW and NW-HE. Increasing the number of bootstraps past 50 further increased the computational power and time needed to calculate. As such we believe fifty is sufficient for this paper. Fourthly, our setup also made the minimum number of observations in each leaf node at five. We tested varying levels of minimum split-size and found that when this was reduced to two or three, the decision trees suffered from over-fitting. Increasing the minimum split-size much further than five also stopped the tree growing to its full potential and reduced the precision and the predictive performance of the decision tree models. We tested the decision trees and forests when the eight wealth variables were re-added to the training and test data-sets. As expected, the models were able to find a perfect relationship between NW and NW-HE and the removed variables.

Finally, to check the architecture of the artificial neural networks, we varied both the number of hidden layers, and the number of neurons in each layer. Furthermore, since our reported estimations of household wealth include approximately 3,000 input variables when predicting the ANN, to identify if our results

[28]Both in terms of the number of features and observations. Different data-sets may require differing number of folds.

were driven by the large number of input variable, we restricted the number of initial neurons in the input to the top 50 variables identified by decision tree and decision forest models. The results indicated that a large proportion of variation in household wealth can be identified by reducing the sample size to the top 50 features, however, we did not identify a drop in the overall model performance (through an increase in the MdAPE). Hence, to build the best performing ANN and decision trees and decision forest models, we suggest preserving the data-sets in their raw format, which allows the algorithms to learn the relationships amongst each input feature.

4.6 Conclusion

This paper builds decision tree, decision forest, and artificial neural network models to examine the feature importance of variables when predicting household NW and NW-HE. In particular, we examine which independent household variables have the highest explanatory power in predicting household net wealth and net wealth minus housing equity. We utilise decision tree and decision forest algorithms to perform these regressions which partition the data, node by node, until they arrive at a leaf node. Furthermore, we employ ANN models to test if deep learning algorithms can outperform decision trees and decision forests models. Finally, we test the notion that machine learning models provide more accurate estimates compared to traditional WLS models and measure the performance difference between each model.

Utilising the rich household level data from the Panel Study of Income Dynamics, we examine bi-annual data from 1999-2017. We show that decision trees found significant determinants of household net wealth and net wealth minus housing equity. Namely, profit on stock, IRA value, profit on business, house value, and other real estate were found to be significant determinants for NW. Similarly, profit on stock, IRA value, profit on business, and other real estate were found to be significant for NW-HE. Interestingly, we find variables such as the number of years left on a mortgage, dividend income, and interest income are consistently found to be useful splitters for predicted NW and NW-HE.

Our results indicate that decision forests provide more consistent and significant estimates for household wealth, and have approximately 24% higher predictive power compared to decision trees. In particular, our decision forest model had a MdAPE of 15.74%, and the best decision tree model had a MdAPE of 24.07%. ANN models yielded the highest performance wealth predictions with a MdAPE of 15.55%. However, since they do not allow for feature rankings to be calculated and only slightly marginal MdAPE gains, we support decision forest models to be applied to similar research questions. We believe these novel results highlight the applicability of machine learning models to financial, and household level data.

The decision tree approach has notable advantages over classical hedonic based regression methods. Decision tree make no strict assumptions based on data distributions, and the most significant variable can be determined with ease at each level of the tree, which allows for more user friendly interpretation. We believe decision trees and decision forests offer an alternative method in measuring wealth compared to classical hedonic regressions in measuring household wealth. However, there are flaws to decision trees and decision forests. For example, decision trees only identify the single most important splitter at a node, therefore, other independent variables cannot be analysed as only one can reviewed at each node (Fan, Ong and Koh). Secondly, decision trees often suffer from over-fitting problems due to small sample sizes, which limit their applications to larger and more established data-sets. Finally, there is currently few papers utilising decision tree and decision forest methodologies and applying them to financial applications. Although this body of literature is growing every year, there are still only a few papers to compare and contrast our results to.

The use of decision tree, decision forest and artificial neural network algorithms in this study opens up a new set of research questions and are applicable to both policy makers and commercial interests. Firstly, applying feature rankings and decision tree models to topics such as predicting when a household will apply for a mortgage based on their current financial position, or, determining if a household will default in any one period. Secondly, for asset management, being able to predict current and future wealth and knowing the main determinants of wealth creation and loss could help policy makers determine the effects of policies on a households finances. These questions require the improvement and development of machine learning techniques to predict future household wealth, and household dynamics. It can be difficult to find sufficient financial data sources to apply machine learning algorithms to. However, this is equally true for more classically based statistical techniques.

4.7 Appendix

Lagged Feature Importance for NW and NW-HE

Year	NW	Error Reduction	NW-HE	Error Reduction
2001	1. Home equity	0.563	1. Profit on stock	0.459
	2. Profit on stock	0.189	2. IRA value	0.311
	3. Profit on business	0.076	3. Other RE	0.122
	4. Other RE	0.061	4. Profit on business	0.144
	5. IRA value	0.059	5. Current cash	0.040
	6. Pension value	0.018	6. Bond value	0.030
	7. Accuracy of stock	0.017	7. Stock Val >5k	0.021
	8. Current cash	0.014	8. Vehicle deposit	0.011
	9. No. of pensions	0.011	9. Food expense	0.010
	10. Total income	0.010	10. Accuracy farm	0.009
2003	1. Profit on stock	0.400	1. IRA value	0.435
	2. House value	0.191	2. Other RE	0.141
	3. Other RE	0.117	3. Profit on stock	0.112
	4. IRA value	0.085	4. Profit on business	0.061
	5. Profit on Business	0.076	5. Accuracy housing	0.041
	6. Home insurance	0.030	6. Stock Val >25k	0.024
	7. Current cash	0.025	7. Head wage rate	0.020
	8. Volunteering time	0.020	8. Dividend Inc	0.018
	9. Industry sector	0.018	9. Charity donation	0.011
	10. Savings other	0.017	10. Current cash	0.014
2005	1. Profit on stock	0.232	1. Profit on stock	0.298
	2. House value	0.231	2. Other RE	0.119
	3. Other RE	0.150	3. Profit on business	0.101
	4. Profit on business	0.091	4. IRA value	0.087
	5. IRA value	0.051	5. Bond value	0.053
	6. Interest Income	0.029	6. Interest Inc	0.022
	7. Current cash	0.015	7. Taxable Inc	0.015
	8. Mortgage value	0.014	8. Div Inc spouse	0.012
	9. Saving accuracy	0.011	9. Transfer Inc	0.011
	10. Years on Mort	0.008	10. Div Inc Head	0.009

Year	NW	Error Reduction	NW-HE	Error Reduction
2007	1. IRA value	0.234	1. IRA value	0.293
	2. House value	0.194	2. Other RE	0.194
	3. Other RE	0.010	3. Profit on stock	0.085
	4. Profit on Business	0.050	4. Profit on business	0.073
	5. Asset income	0.048	5. Interest Inc	0.043
	6. Years on Mort	0.045	6. Current cash	0.022
	7. Profit on Stock	0.031	7. Accuracy house	0.019
	8. Dividend Inc	0.017	8. Stock Val >50k	0.014
	9. Leisure Expense	0.015	9. Utility cost	0.013
	10. Interest Income	0.014	10. Taxable Inc	0.011
2009	1. IRA Value	0.305	1. Profit on stock	0.283
	2. Other RE	0.132	2. Other RE	0.213
	3. House Value	0.111	3. Profit on business	0.138
	4. Profit on Business	0.090	4. IRA value	0.095
	5. Profit on Stock	0.083	5. Accuracy house	0.078
	6. Interest income	0.030	6. Interest Inc	0.043
	7. Mortgage debt	0.017	7. Stock Val >50k	0.021
	8. Total income	0.015	8. Bond value	0.019
	9. Home sale price	0.012	9. Current cash	0.015
	10. Weeks worked	0.011	10. Phone expense	0.013
2011	1. IRA value	0.390	1. IRA value	0.411
	2. Profit on stock	0.123	2. Profit on stock	0.168
	3. House value	0.107	3. Profit on business	0.124
	4. Profit on business	0.092	4. Other RE	0.101
	5. Other RE	0.053	5. Current cash	0.031
	6. Interest income	0.031	6. Dividend Head	0.020
	7. Dividend Inc	0.017	7. Bond value	0.014
	8. Current cash	0.014	8. Accuracy wealth	0.012
	9. Years on Mort	0.013	9. Accuracy house	0.012
	10. Mortgage cost	0.011	10. Dividend Inc	0.010
2013	1. IRA value	0.381	1. IRA value	0.396
	2. Profit on Stock	0.142	2. Profit on stock	0.148
	3. House value	0.101	3. Profit on business	0.114
	4. Profit on business	0.055	4. Other RE	0.059
	5. Other RE	0.041	5. Current cash	0.028
	6. Dividend Inc	0.029	6. Stock Val >50k	0.022
	7. Current cash	0.019	7. Interest income	0.021
	8. Insurance cost	0.015	8. Accuracy wealth	0.013
	9. Years on Mort	0.013	9. Interest income	0.012
	10. Interest income	0.013	10. Spouse age	0.012

Year	NW	Error Reduction	NW-HE	Error Reduction
2015	1. IRA value	0.412	1. IRA value	0.419
	2. Profit on stock	0.112	2. Profit on stocks	0.223
	3. House value	0.125	3. Profit on business	0.093
	4. Other RE	0.055	4. Other RE	0.044
	5. Profit on Business	0.048	5. Total income	0.019
	6. Property tax	0.023	6. Interest Inc	0.018
	7. Interest Inc	0.021	7. Current cash	0.017
	8. Current cash	0.014	8. Wealth accuracy	0.015
	9. Transfer Inc	0.012	9. Dividend Inc	0.013
	10. Other RE debt	0.011	10. Stock Val >50k	0.013
2017	1. IRA value	0.385	1. IRA value	0.307
	2. House value	0.146	2. Profit on stock	0.144
	3. Profit on stock	0.130	3. Profit on business	0.097
	4. Profit on Business	0.049	4. Other RE	0.053
	5. Other RE	0.040	5. Dividend Inc	0.047
	6. Years on Mort	0.031	6. Wealth accuracy	0.022
	7. Dividend Inc	0.025	7. House accuracy	0.014
	8. Food expense	0.020	8. Profit stocks >50k	0.013
	9. Other stock	0.015	9. House value	0.013
	10. Current cash	0.011	10. Stock Val >50k	0.012

Table 9: PSID decision tree feature ranks derived from authors calculations. The follow notations have been used in the table, RE refers to real estate, Inc infers income, cost refers to household expense, Mort refers to mortgages, Stock Val >xk refers to the households stock holdings above a certain $ value, industry sector refers to the industry the household head works within, value refers to the $ amount the household owns in that category, Profit on x variable refers to the profit a household would make if they liquidated their current holdings of that variable.

Year	MAE	MdAPE	R^2	Avg Depth	Avg Leaves
2001	59,152 / 49,821	27.47 / 27.43	0.61 / 0.51	41 / 34	411 / 405
2003	68,428 / 49,897	37.68 / 28.54	0.54 / 0.53	40 / 34	419 / 457
2005	98,147 / 60,810	36.28 / 28.70	0.52 / 0.55	41 / 33	428 / 431
2007	111,408 / 70,900	34.54 / 28.73	0.51 / 0.52	38 / 38	454 / 451
2009	95,281 / 70,457	33.25 / 26.54	0.51 / 0.55	39 / 37	472 / 480
2011	85,424 / 51,421	37.44 / 24.43	0.54 / 0.65	52 / 51	504 / 511
2013	85,520 / 58,790	34.82 / 25.40	0.57 / 0.58	54 / 55	529 / 511
2015	86,421 / 65,591	32.59 / 24.20	0.60 / 0.55	52 / 53	510 / 523
2017	99,228 / 68,552	31.90 / 25.41	0.59 / 0.60	51 / 55	529 / 554

Table 10: Full results on Test splits for Decision Tree Model. Left and right values in each column correspond to NW and NW-HE, respectively.

Year	NW	Error Reduction	NW-HE	Error Reduction
2001	1. Home equity	0.506	1. Profit on stock	0.249
	2. Profit on stock	0.115	2. IRA value	0.166
	3. IRA value	0.088	3. Profit on business	0.099
	4. Profit on business	0.085	4. Other RE	0.090
	5. Other RE	0.051	5. Current cash	0.018
	6. Current cash	0.013	6. Bond value	0.014
	7. Bond value	0.008	7. Stock Val >50k	0.013
	8. Insurance cost	0.007	8. Accuracy home	0.012
	9. House value	0.007	9. Stock Val >25k	0.008
	10. Vehicle deposit	0.006	10. Stock holding	0.007
2003	1. House value	0.284	1. Profit on stock	0.182
	2. Other RE	0.138	2. IRA value	0.167
	3. IRA value	0.114	3. Other RE	0.142
	4. Profit on stock	0.097	4. Profit on business	0.076
	5. Profit on Business	0.064	5. Wealth accuracy	0.035
	6. Dividend Inc	0.030	6. Current cash	0.016
	7. Current cash	0.023	7. Bond value	0.013
	8. Total income	0.021	8. Total income	0.012
	9. Interest Inc	0.011	9. Dividend head	0.009
	10. Income spouse	0.010	10. Income head	0.006
2005	1. House value	0.272	1. Profit on stock	0.242
	2. IRA value	0.241	2. Other RE	0.156
	3. Other RE	0.129	3. Profit on business	0.106
	4. Profit on stock	0.068	4. IRA value	0.092
	5. Profit on business	0.064	5. Bond value	0.022
	6. Interest Income	0.017	6. Dividends head	0.015
	7. Dividend Inc	0.015	7. Wealth accuracy	0.013
	8. Years on Mort	0.013	8. Stock Val >25k	0.013
	9. Current cash	0.012	9. Current cash	0.012
	10. Interest Inc head	0.008	10. Interest income	0.007

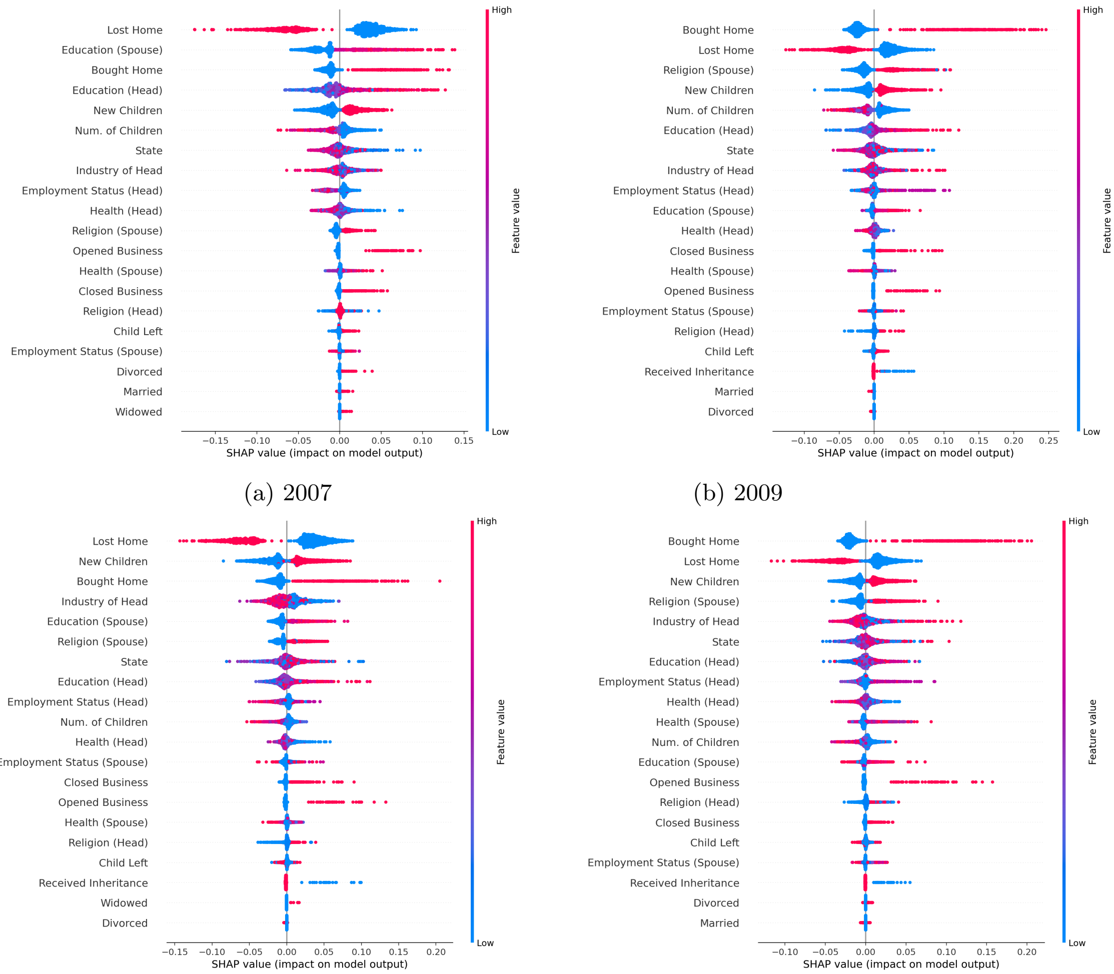
Year	NW	Error Reduction	NW-HE	Error Reduction
2007	1. IRA value	0.301	1. IRA value	0.195
	2. House value	0.172	2. Other RE	0.165
	3. Other RE	0.130	3. Profit on stock	0.103
	4. Profit on stock	0.112	4. Profit on business	0.076
	5. Profit on business	0.037	5. Wealth accuarcy	0.028
	6. Asset income	0.030	6. Dividend income	0.024
	7. Dividend Inc	0.022	7. Interest income	0.021
	8. Years on Mort	0.012	8. Current cash	0.015
	9. Current cash	0.011	9. Dividend head	0.010
	10. House tax	0.009	10. Asset income	0.009
2009	1. IRA Value	0.177	1. Profit on stock	0.222
	2. Other RE	0.167	2. Other RE	0.132
	3. House Value	0.161	3. Profit on business	0.110
	4. Profit on stock	0.143	4. IRA value	0.065
	5. Profit on business	0.067	5. Accuracy wealth	0.035
	6. Interest income	0.034	6. Dividends head	0.018
	7. Current cash	0.028	7. Current cash	0.018
	8. Dividend Inc	0.019	8. Interest income	0.012
	9. Bond value	0.015	9. Bond value	0.012
	10. Years on Mort	0.010	10. Stock Val >50k	0.007
2011	1. IRA value	0.414	1. IRA value	0.351
	2. Profit on stock	0.119	2. Profit on stock	0.129
	3. Profit on business	0.119	3. Other RE	0.097
	4. House value	0.092	4. Profit on business	0.095
	5. Other RE	0.054	5. Current cash	0.017
	6. Dividend Inc	0.023	6. Dividend Head	0.014
	7. Current cash	0.018	7. Accuracy wealth	0.012
	8. Interest Inc	0.011	8. Interest income	0.009
	9. Years on Mort	0.009	9. Bond value	0.007
	10. Div Inc Head	0.008	10. Taxable income	0.006
2013	1. IRA value	0.416	1. Profit on stock	0.228
	2. Profit on stock	0.133	2. IRA value	0.213
	3. House value	0.075	3. Profit on business	0.110
	4. Profit on business	0.075	4. Other RE	0.040
	5. Other RE	0.033	5. Wealth accuracy	0.025
	6. Current cash	0.030	6. Current cash	0.023
	7. Value of interest	0.021	7. Stock Val >50k	0.014
	8. Interest Inc	0.019	8. Interest head	0.012
	9. Dividend Inc	0.015	9. Interest income	0.008
	10. Years on Mort	0.014	10. Dividend head	0.008

Year	NW	Error Reduction	NW-HE	Error Reduction
2015	1. IRA value	0.439	1. IRA value	0.326
	2. Profit on stock	0.195	2. Profit on stocks	0.179
	3. House value	0.098	3. Other RE	0.066
	4. Profit on business	0.075	4. Profit on business	0.064
	5. Other RE	0.036	5. Current cash	0.022
	6. Current cash	0.017	6. Accuracy wealth	0.015
	7. Property tax	0.009	7. Dividends Inc	0.010
	8. Dividend Inc	0.008	8. Bond value	0.007
	9. Years on Mort	0.006	9. Total income	0.006
	10. Student loans	0.006	10. Div value >50k	0.006
2017	1. IRA value	0.443	1. IRA value	0.334
	2. Profit on stock	0.169	2. Profit on stock	0.125
	3. House value	0.121	3. Profit on business	0.080
	4. Profit on Business	0.037	4. Other RE	0.047
	5. Other RE	0.027	5. Wealth accuracy	0.029
	6. Current cash	0.017	6. Current cash	0.018
	7. Dividend Inc	0.014	7. Dividend income	0.018
	8. Rental Income	0.011	8. Business >50k	0.010
	9. Rental value	0.010	9. Pension >50k	0.006
	10. Years on Mort	0.010	10. Stock Val >50k	0.006

Table 11: PSID decision tree feature ranks derived from authors calculations. The follow notations have been used in the table, RE refers to real estate, Inc infers income, cost refers to household expense, Mort refers to mortgages, Stock Val >xk refers to the households stock holdings above a certain $ value, industry sector refers to the industry the household head works within, value refers to the $ amount the household owns in that category, Profit on x variable refers to the profit a household would make if they liquidated their current holdings of that variable.

Year	MAE	MdAPE	R^2
1999	48,451 / 36,578	28.02 / 20.64	0.73 / 0.69
2001	49,462 / 40,208	20.99 / 20.04	0.74 / 0.69
2003	57,663 / 41,214	27.08 / 20.51	0.71 / 0.68
2005	70,175 / 48,910	25.55 / 20.71	0.73 / 0.71
2007	84,285 / 57,941	27.70 / 21.88	0.71 / 0.68
2009	74,516 / 52,017	25.27 / 18.74	0.68 / 0.65
2011	61,260 / 43,480	22.89 / 16.53	0.76 / 0.74
2013	64,567 / 44,095	24.64 / 16.46	0.75 / 0.72
2015	70,416 / 50,648	22.22 / 16.66	0.74 / 0.72
2017	75,733 / 54,764	22.68 / 16.97	0.72 / 0.70

Table 12: Full results on Test splits for Decision Forest Model. Left and right values in each column correspond to NW and NW-HE, respectively.



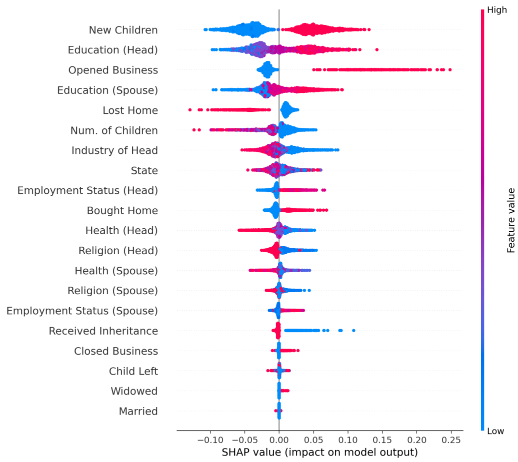
(a) 2007

(b) 2009

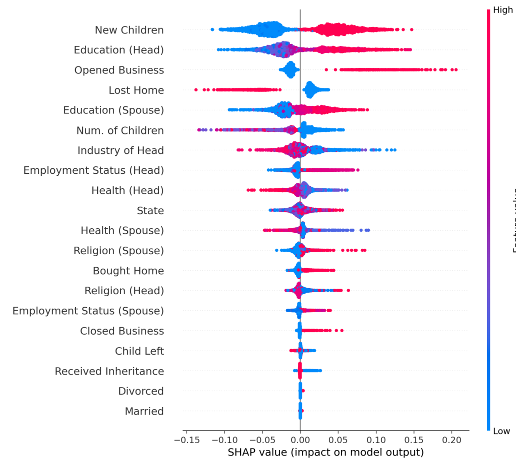
(c) 2011

(d) 2013

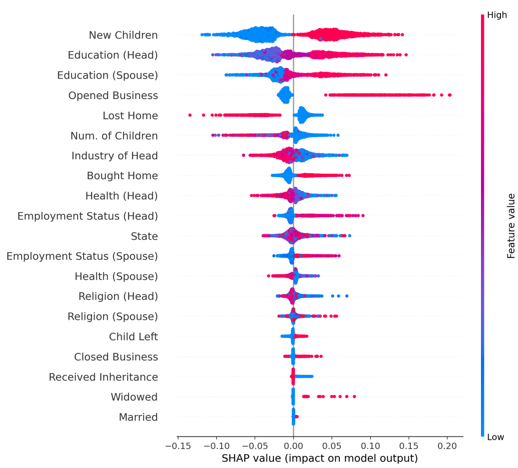
Figure 8: Net Wealth Black Households



(a) 2007



(b) 2009



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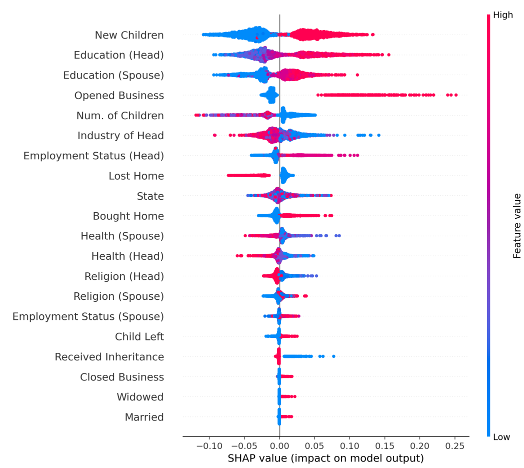
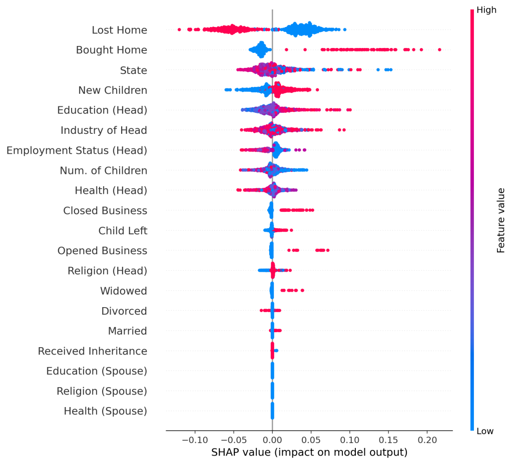
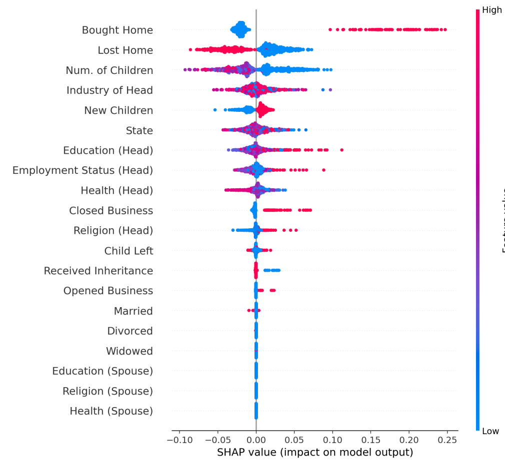


(d) 2013

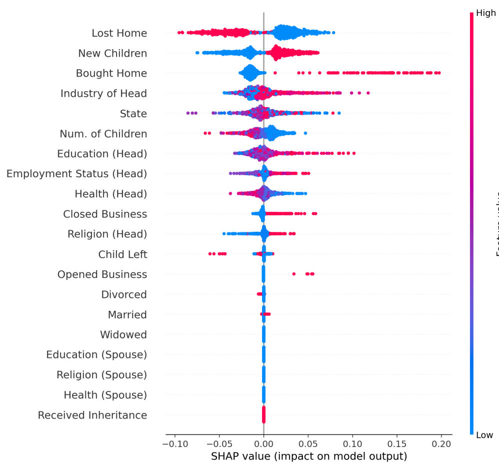
Figure 9: Net Wealth White Households



(a) 2007



(b) 2009



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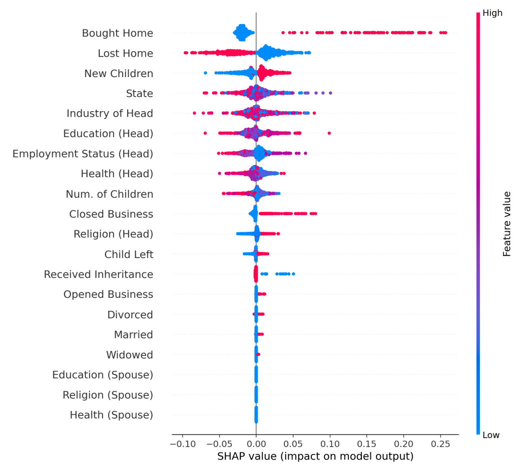
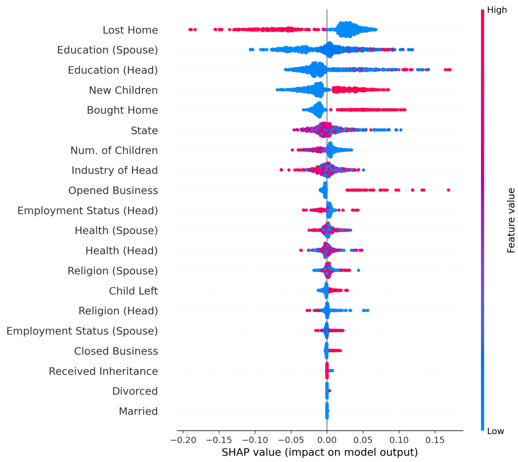
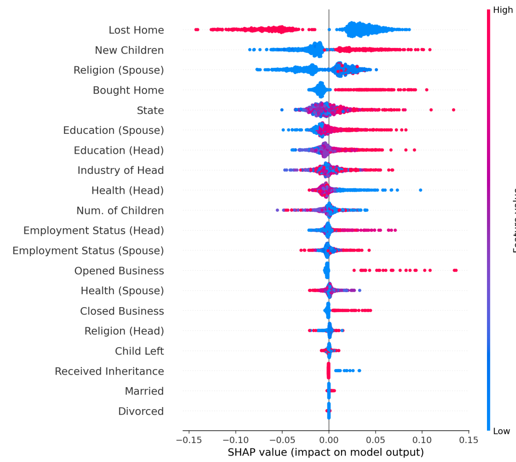


(d) 2013

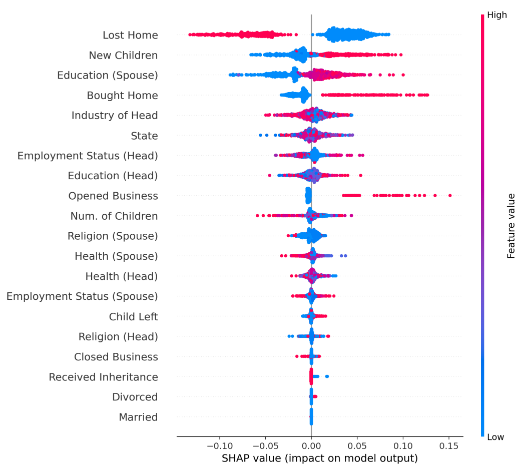
Figure 10: Black Female Headed Households



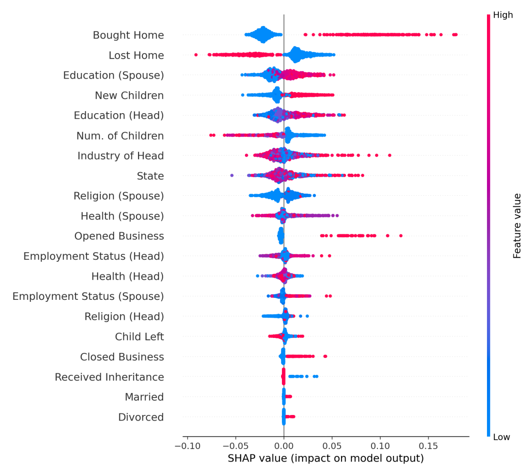
(a) 2007



(b) 2009

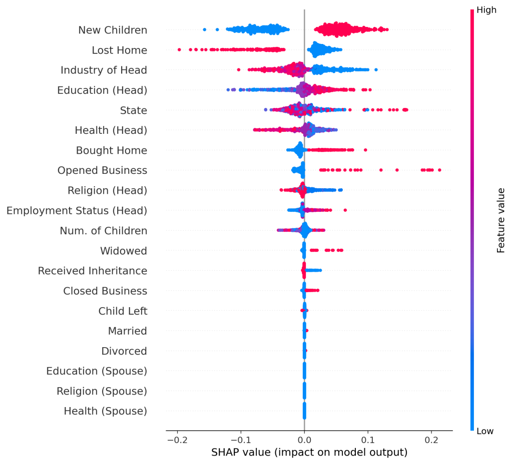


(c) 2011

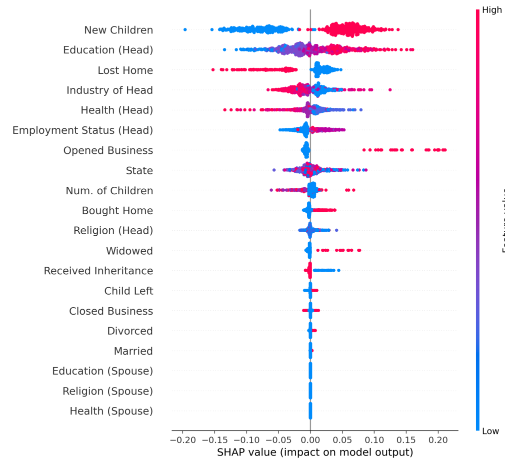


(d) 2013

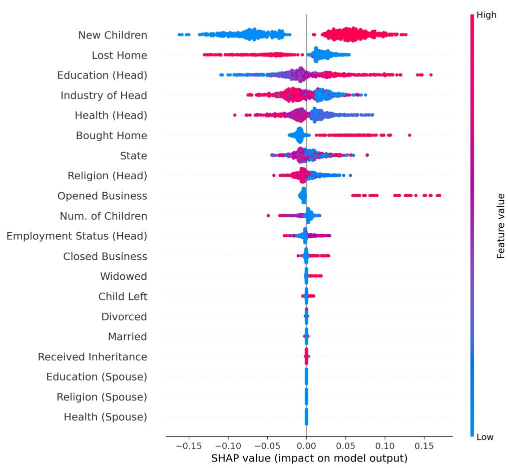
Figure 11: Black Male Headed Households



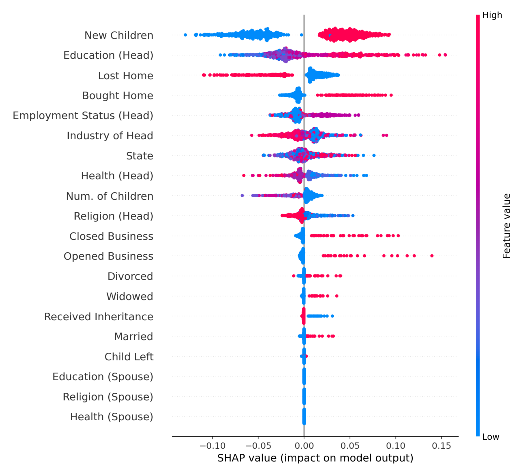
(a) 2007



(b) 2009

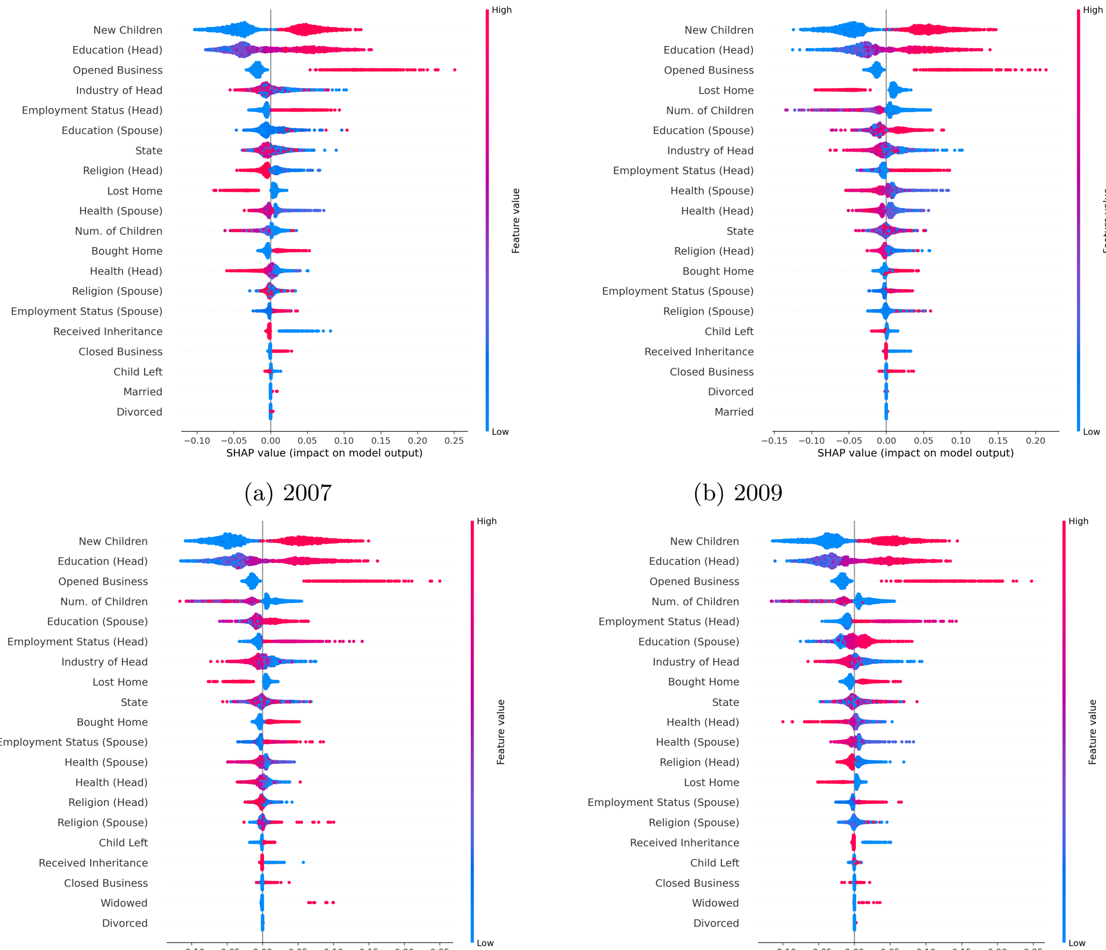


(c) 2011



(d) 2013

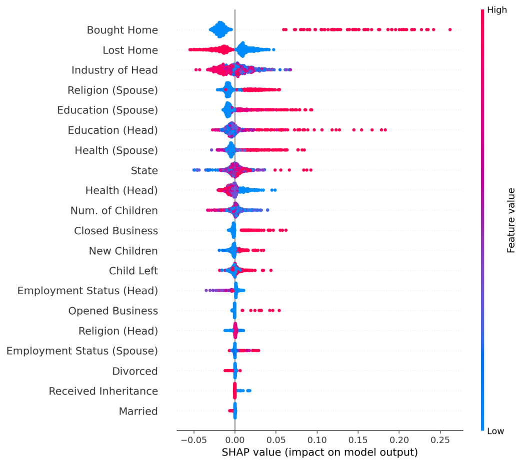
Figure 12: White Female Headed Households



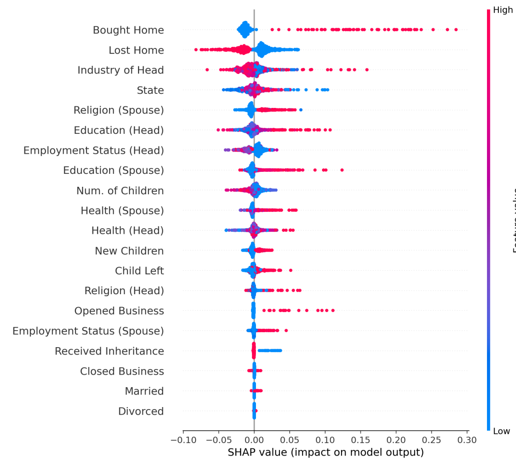
(a) 2007 (b) 2009

(c) 2011 (d) 2013

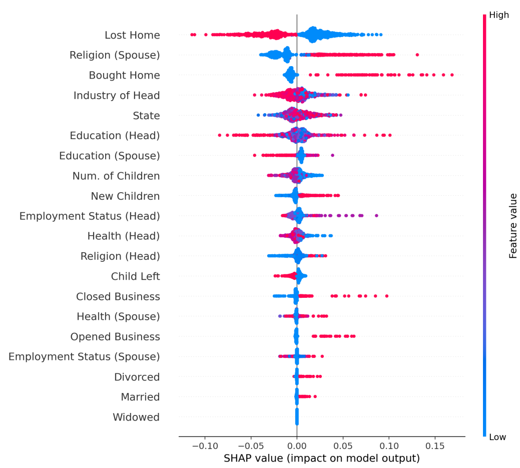
Figure 13: White Male Headed Households



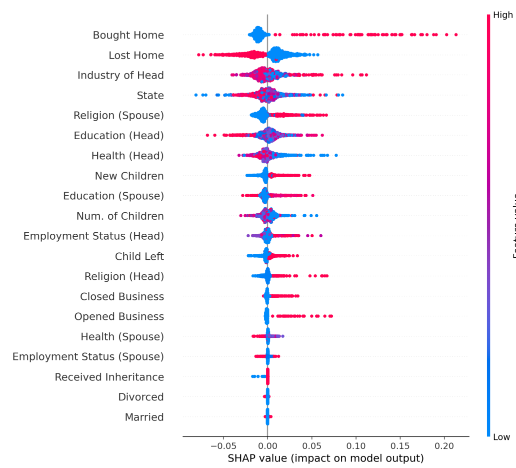
(a) 2007



(b) 2009

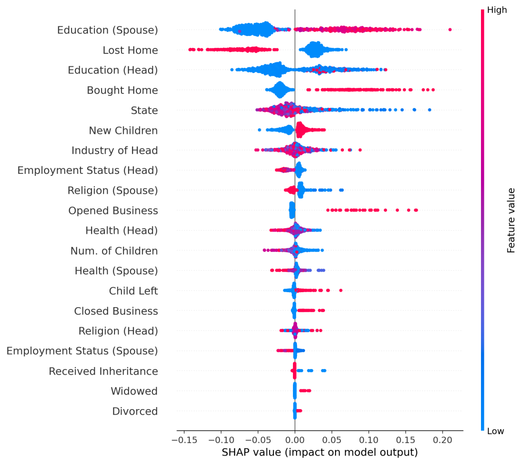


(c) 2011

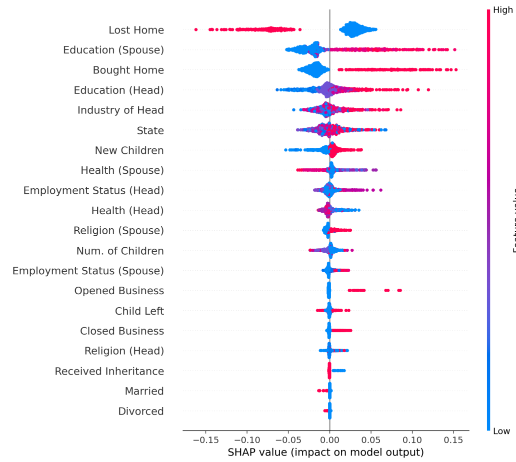


(d) 2013

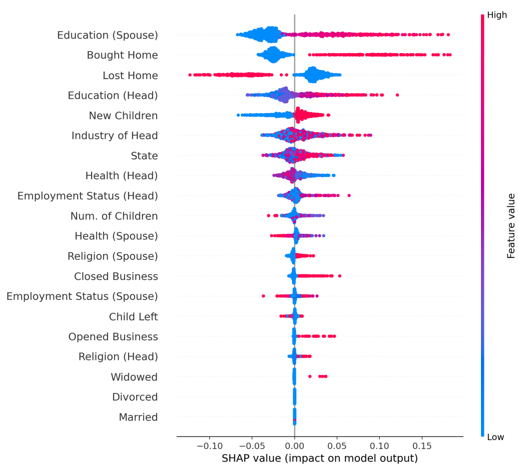
Figure 14: Black Young Households



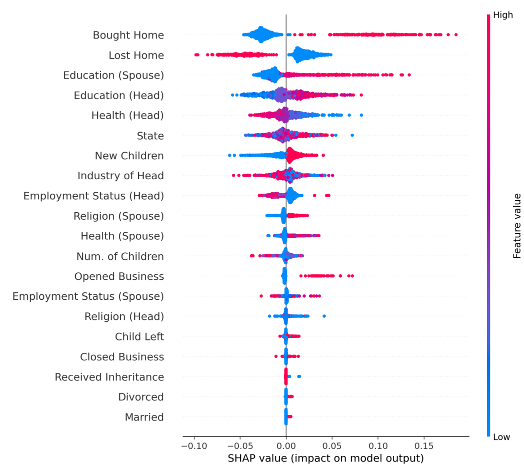
(a) 2007



(b) 2009

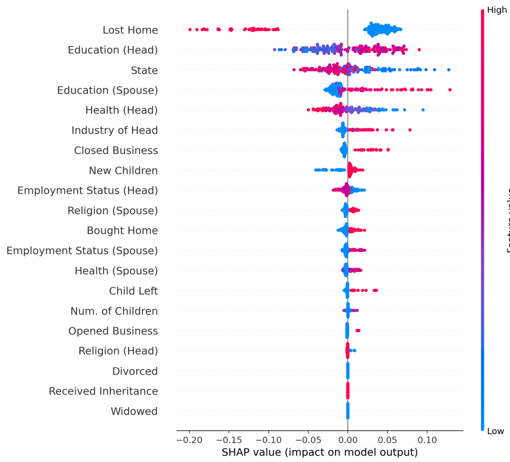


(c) 2011



(d) 2013

Figure 15: Black Mature Households



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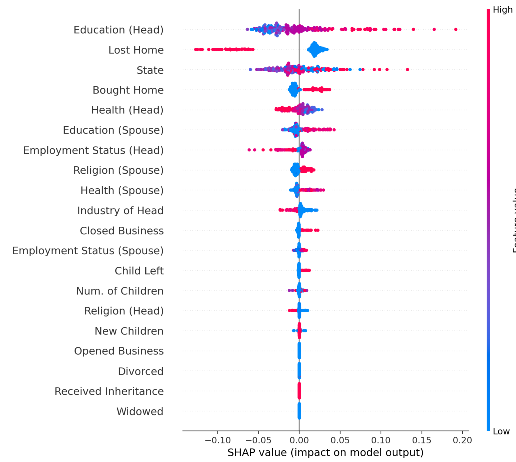
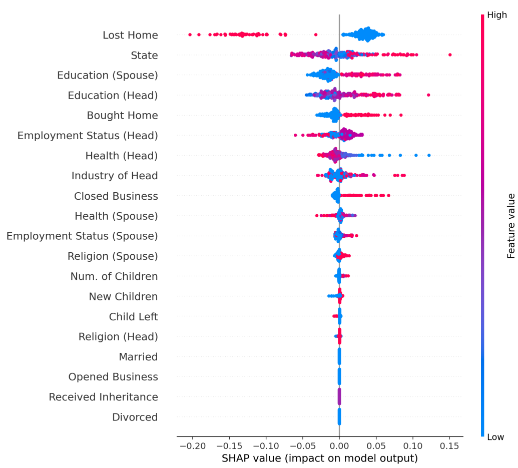
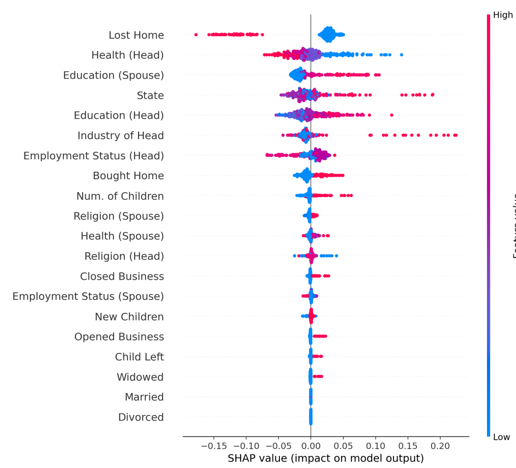


(b) 2009

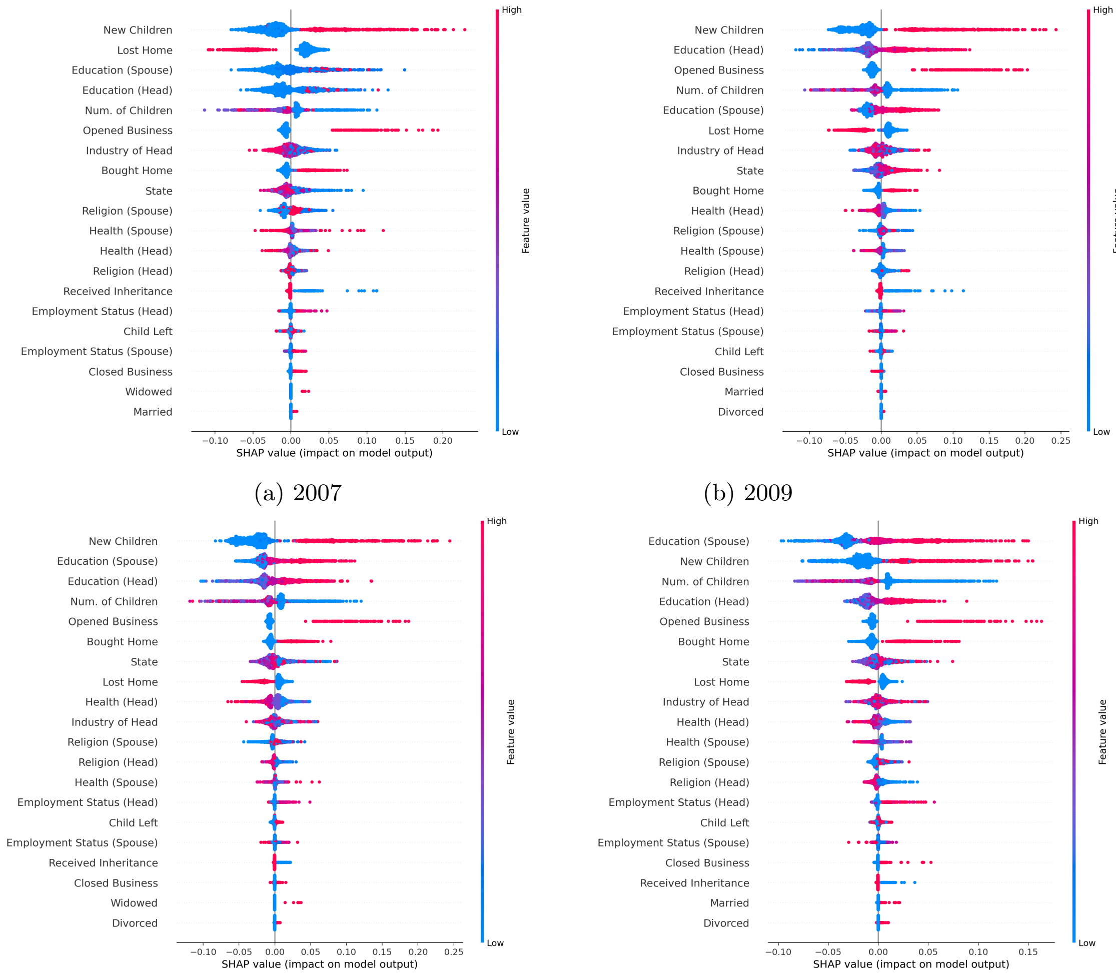


(c) 2011



(d) 2013

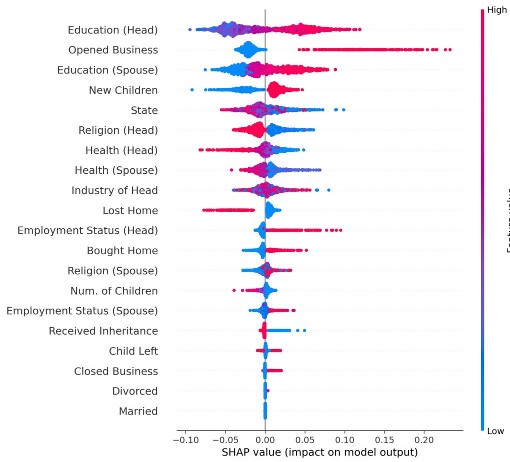
Figure 16: Black Elderly Households



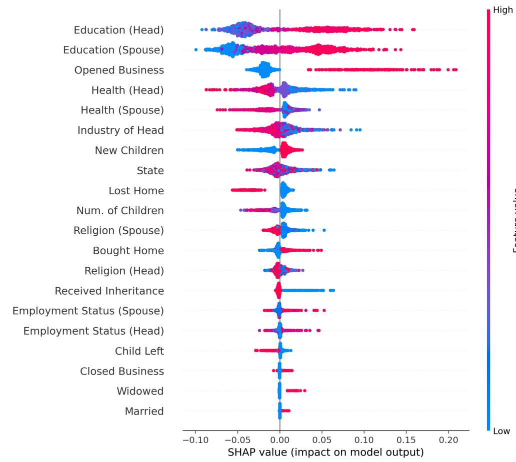
(a) 2007 (b) 2009

(c) 2011 (d) 2013

Figure 17: White Young Households



(a) 2007



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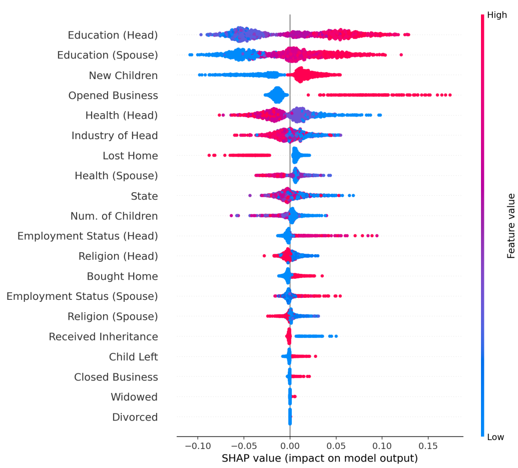

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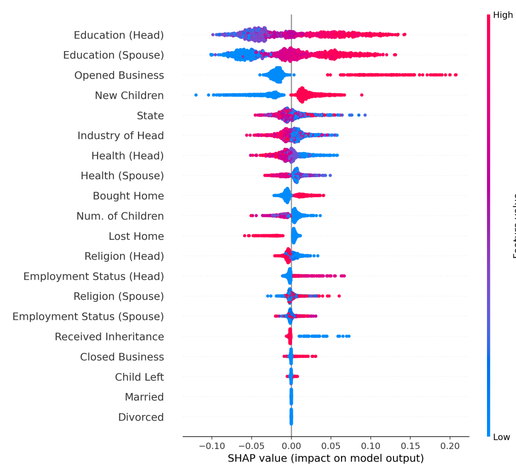
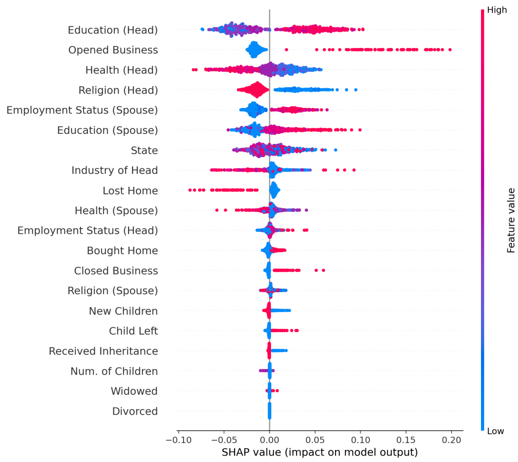
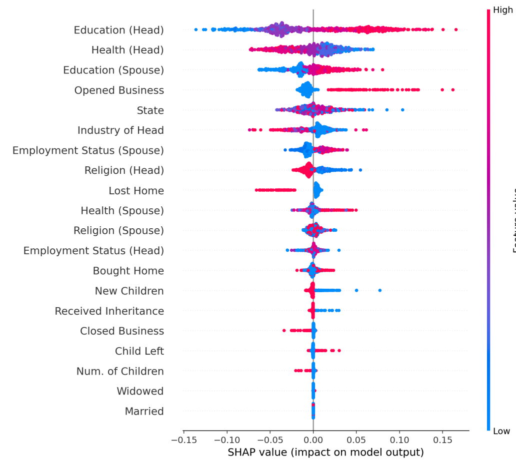


(d) 2013

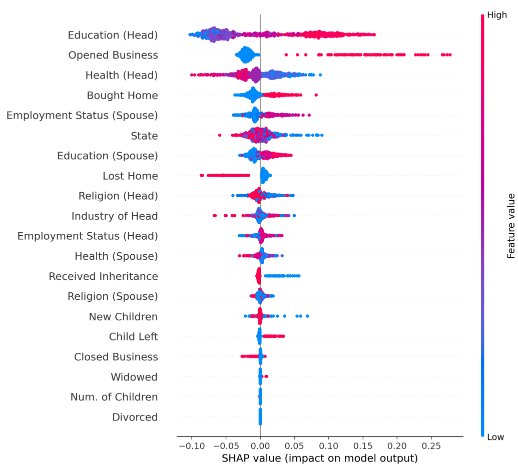
Figure 18: White Mature Households



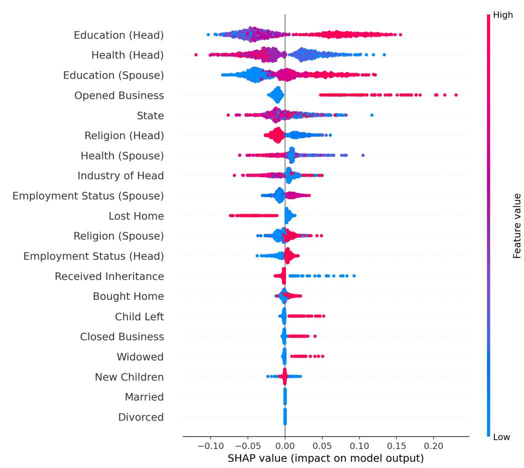
(a) 2007



(b) 2009

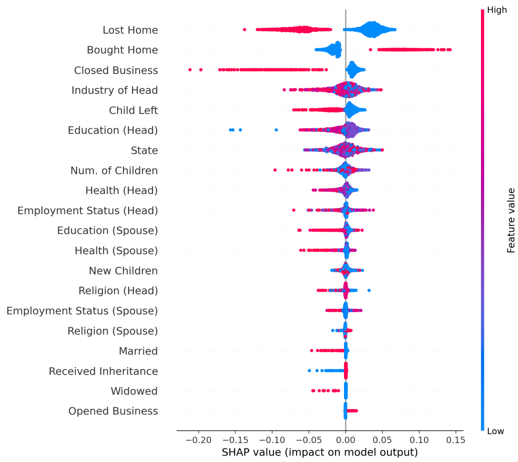


(c) 2011

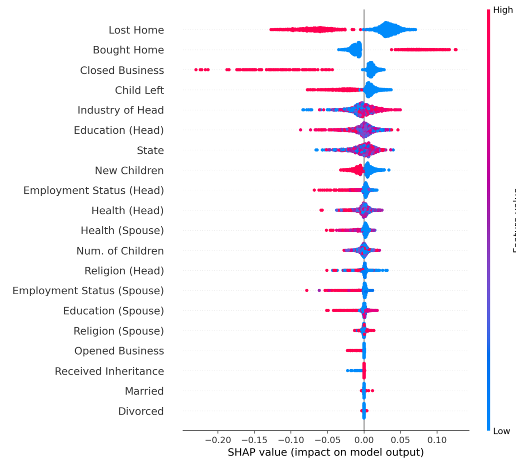


(d) 2013

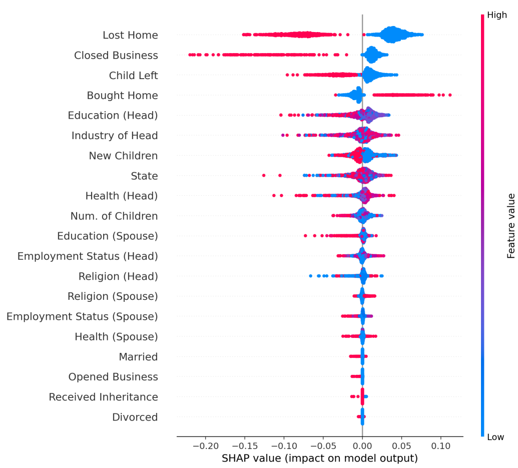
Figure 19: White Elderly Households



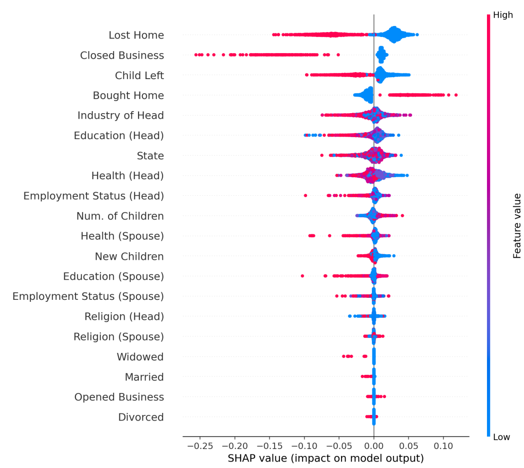
(a) 2007



(b) 2009

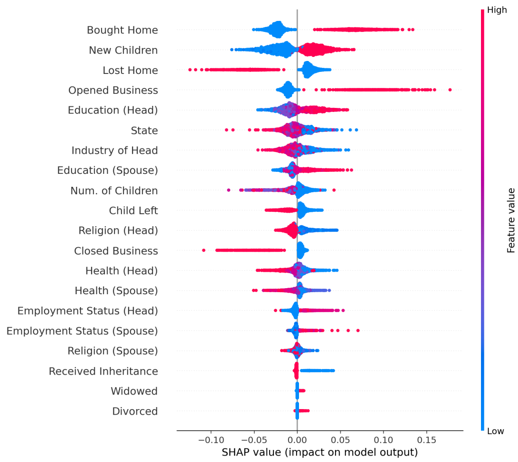


(c) 2011

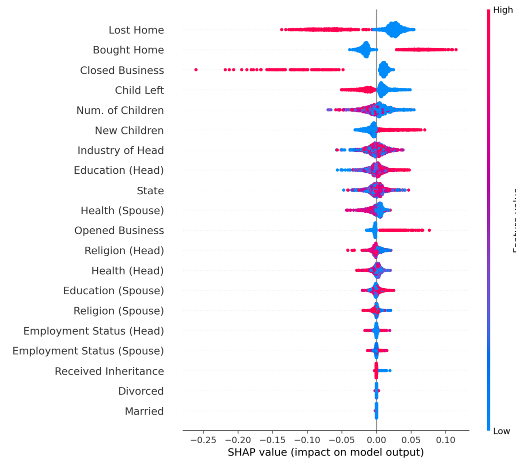


(d) 2013

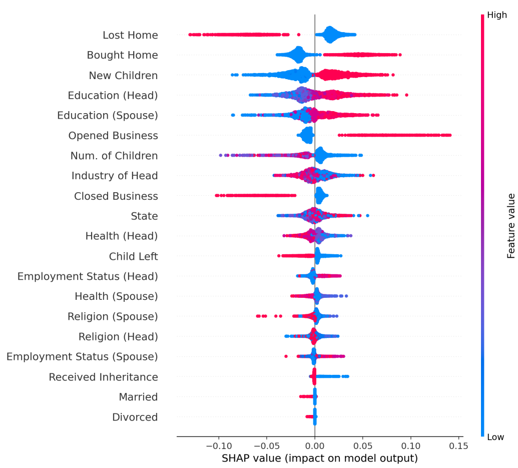
Figure 20: Change in Black Household Net Wealth



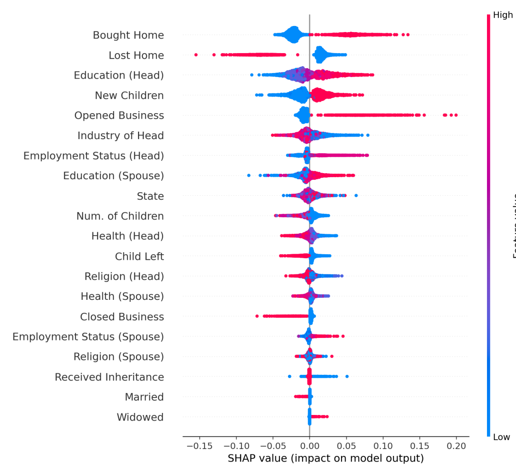
(a) 2007



(b) 2009

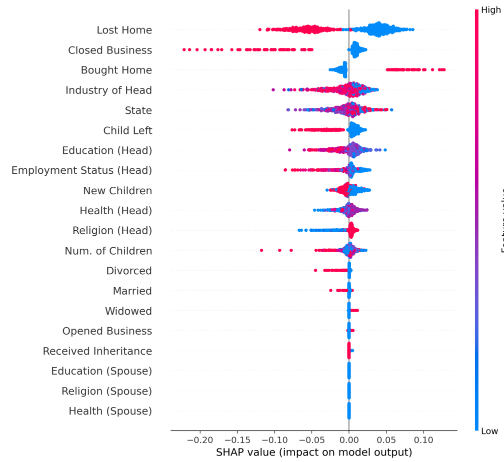


(c) 2011

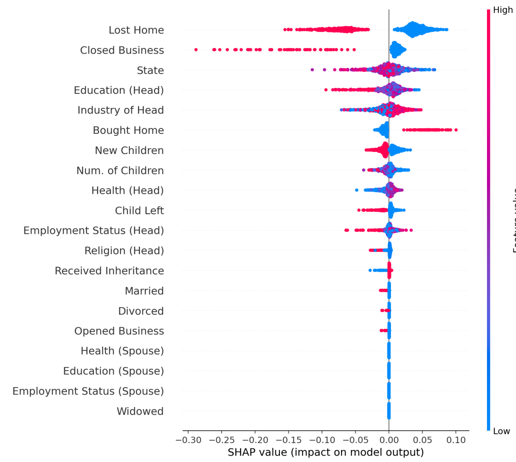


(d) 2013

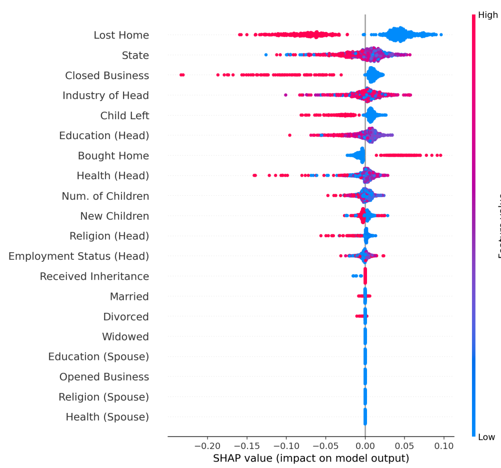
Figure 21: Change in White Household Net Wealth



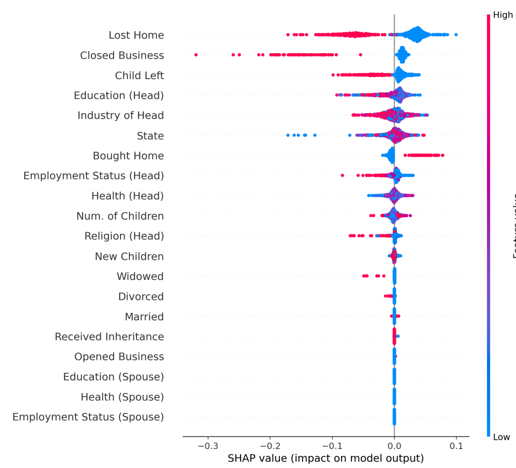
(a) 2007



(b) 2009

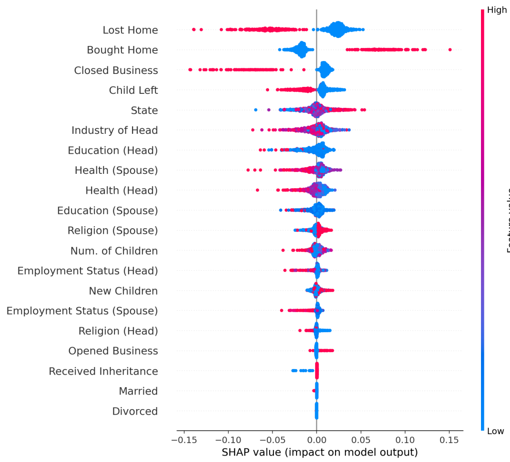


(c) 2011

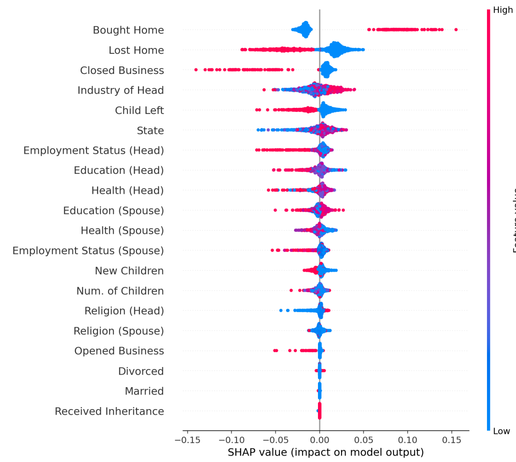


(d) 2013

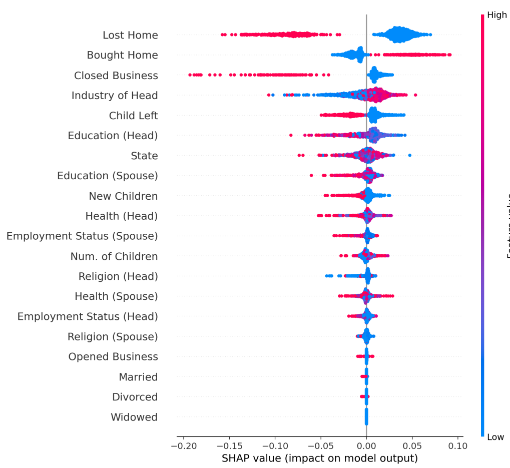
Figure 22: Change in Black Female Household Net Wealth



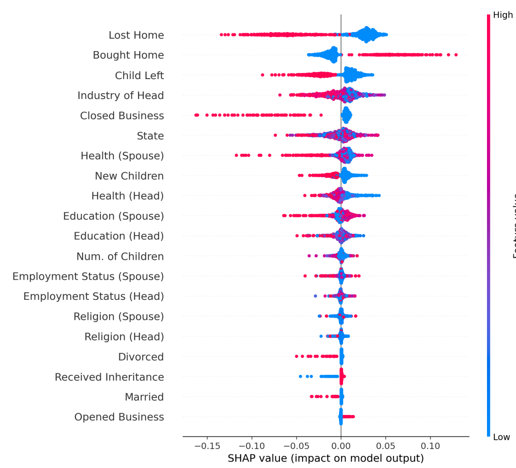
(a) 2007



(b) 2009

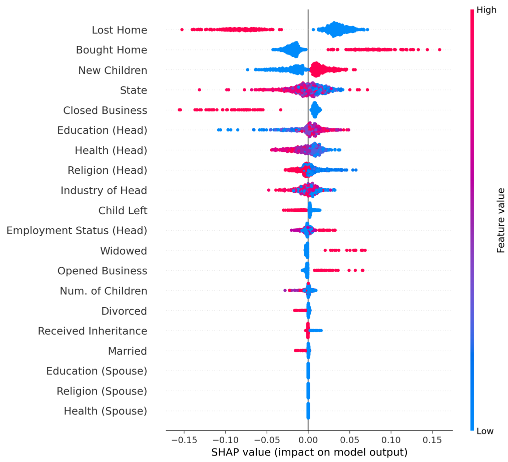


(c) 2011

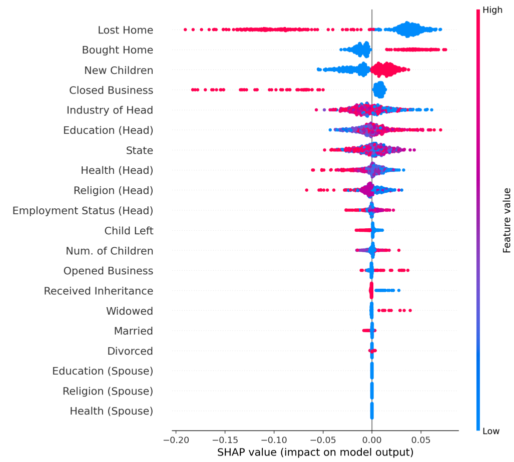


(d) 2013

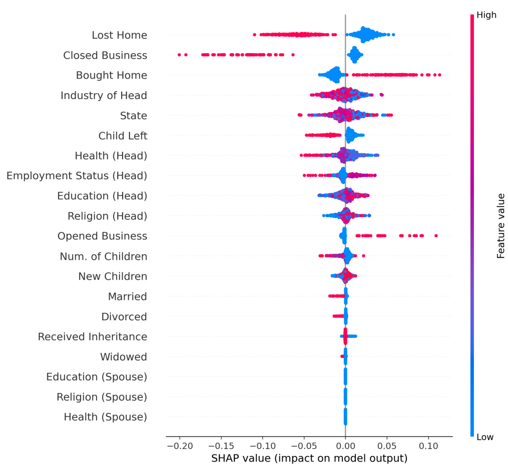
Figure 23: Change in Black Male Household Net Wealth



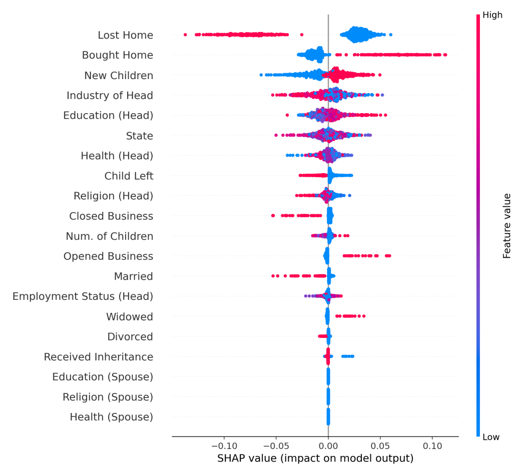
(a) 2007



(b) 2009

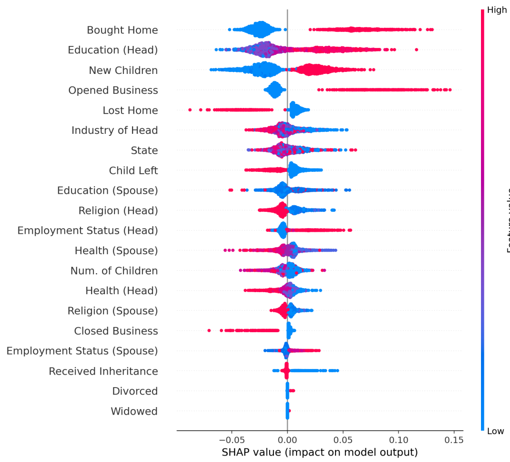


(c) 2011

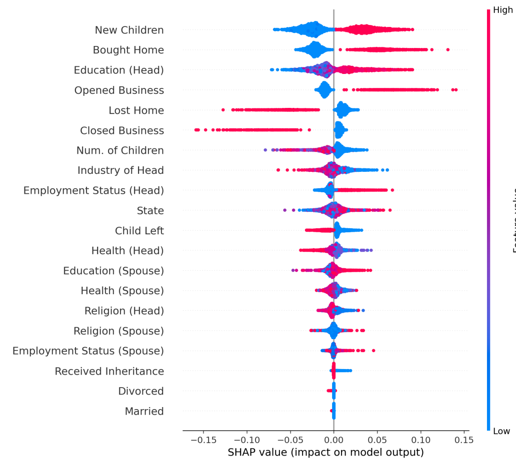


(d) 2013

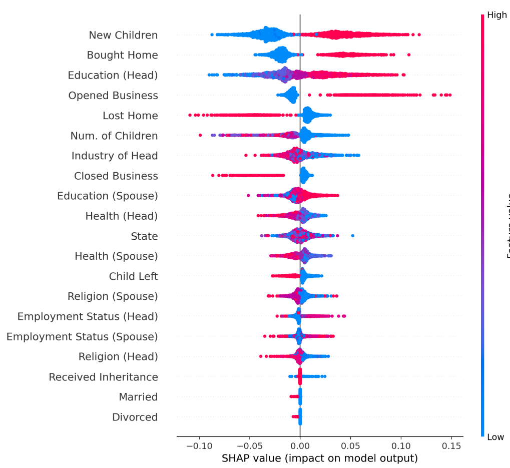
Figure 24: Change in White Female Household Net Wealth



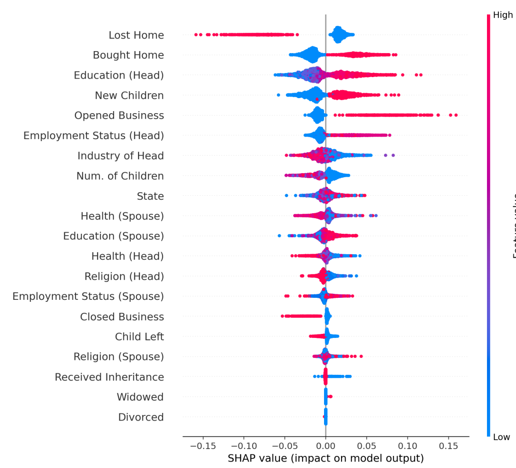
(a) 2007



(b) 2009

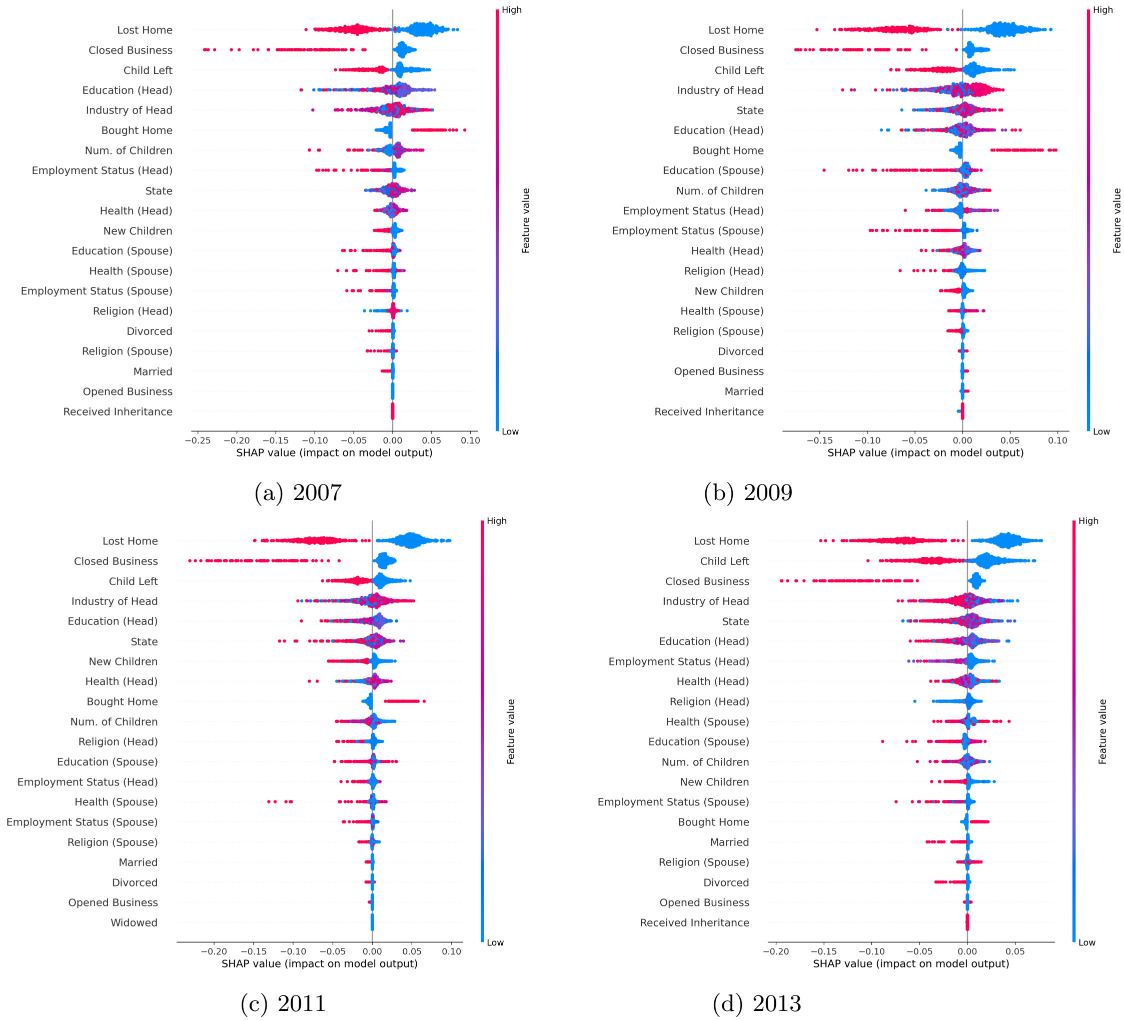


(c) 2011



(d) 2013

Figure 25: Change in White Male Household Net Wealth



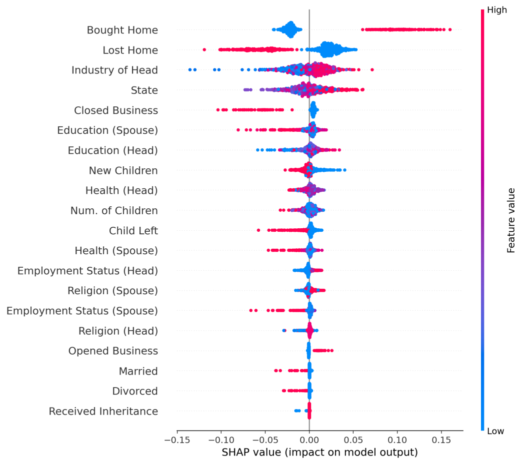
(a) 2007

(b) 2009

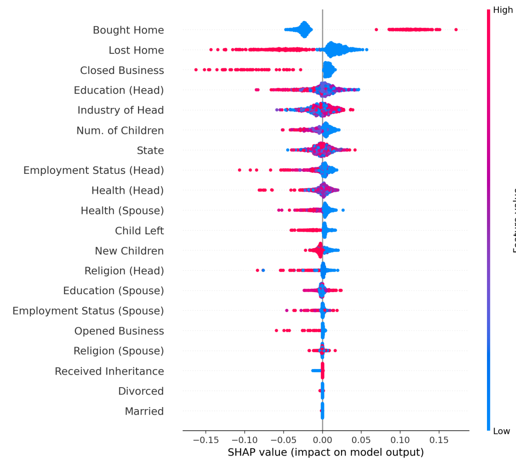
(c) 2011

(d) 2013

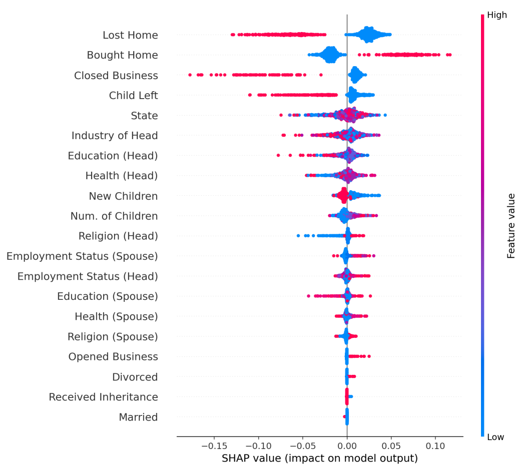
Figure 26: Change in Black Young Household Net Wealth



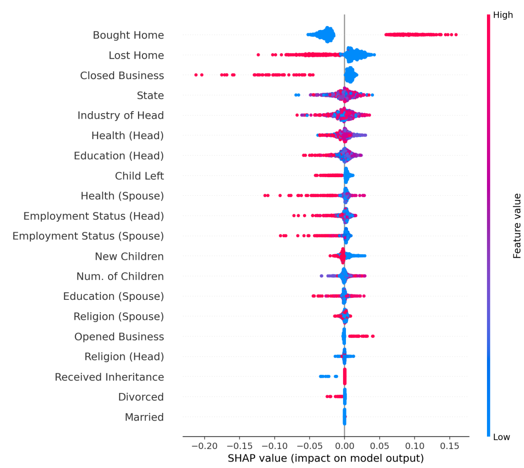
(a) 2007



(b) 2009

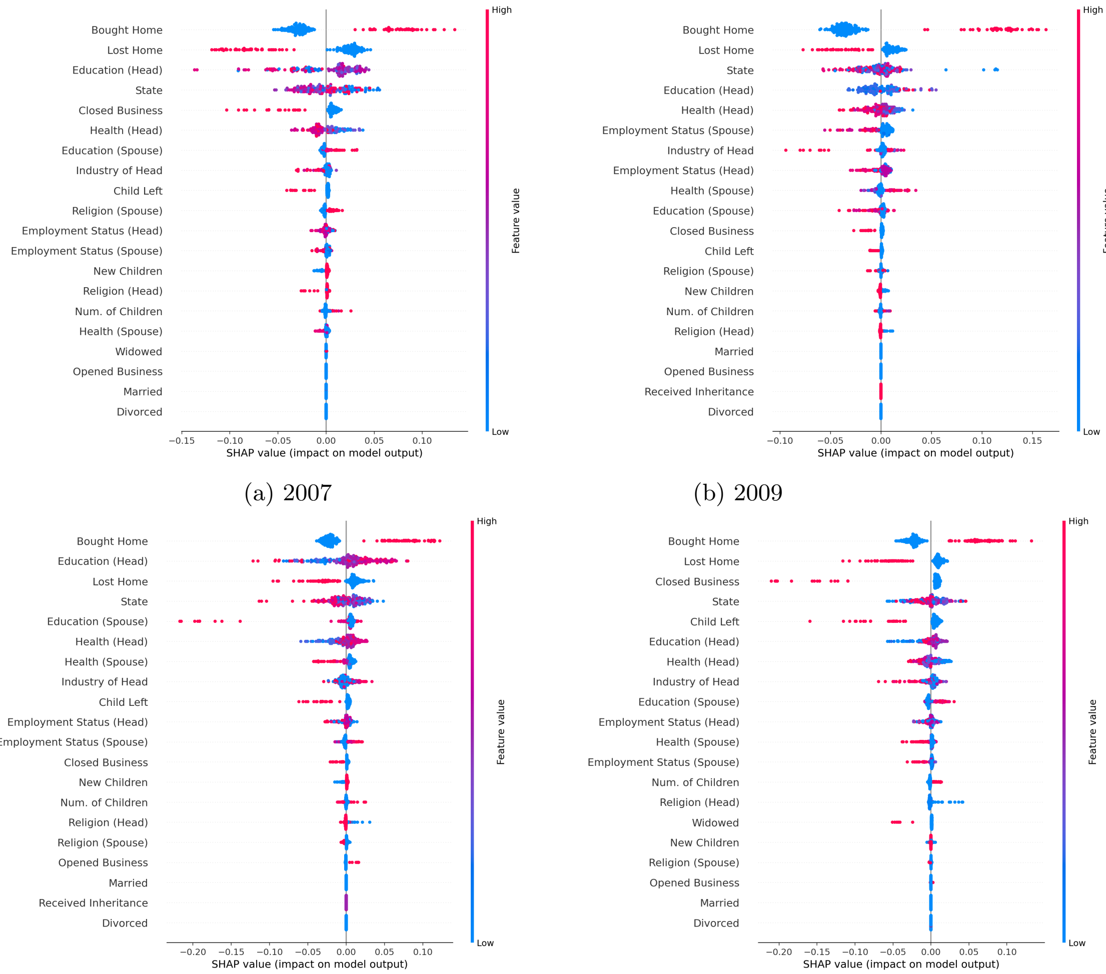


(c) 2011



(d) 2013

Figure 27: Change in Black Mature Household Net Wealth



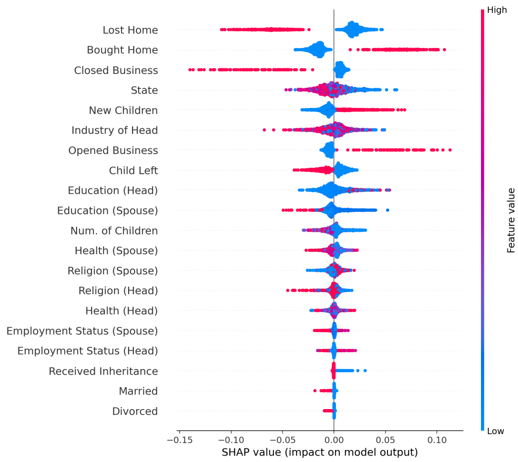
(a) 2007

(b) 2009

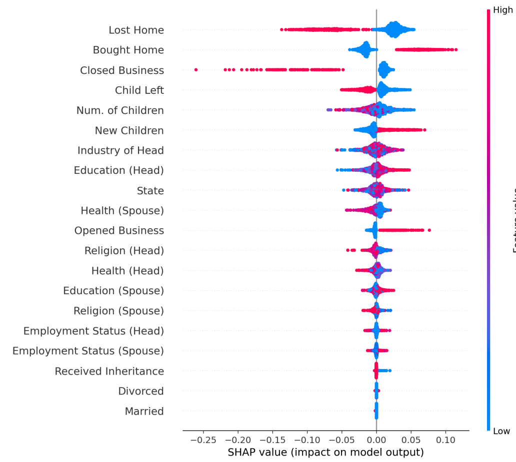
(c) 2011

(d) 2013

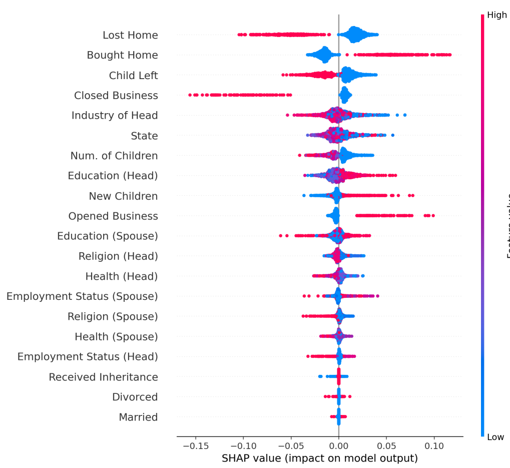
Figure 28: Change in Black Elderly Household Net Wealth



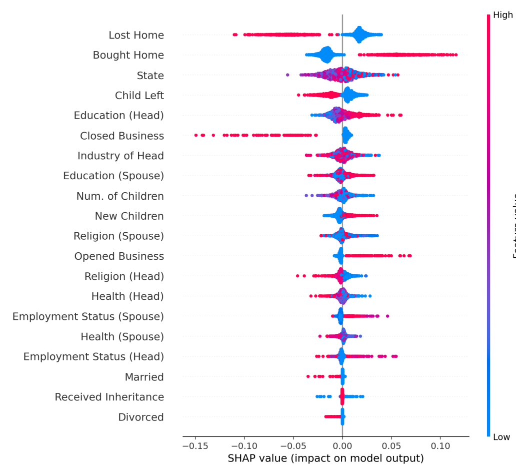
(a) 2007



(b) 2009

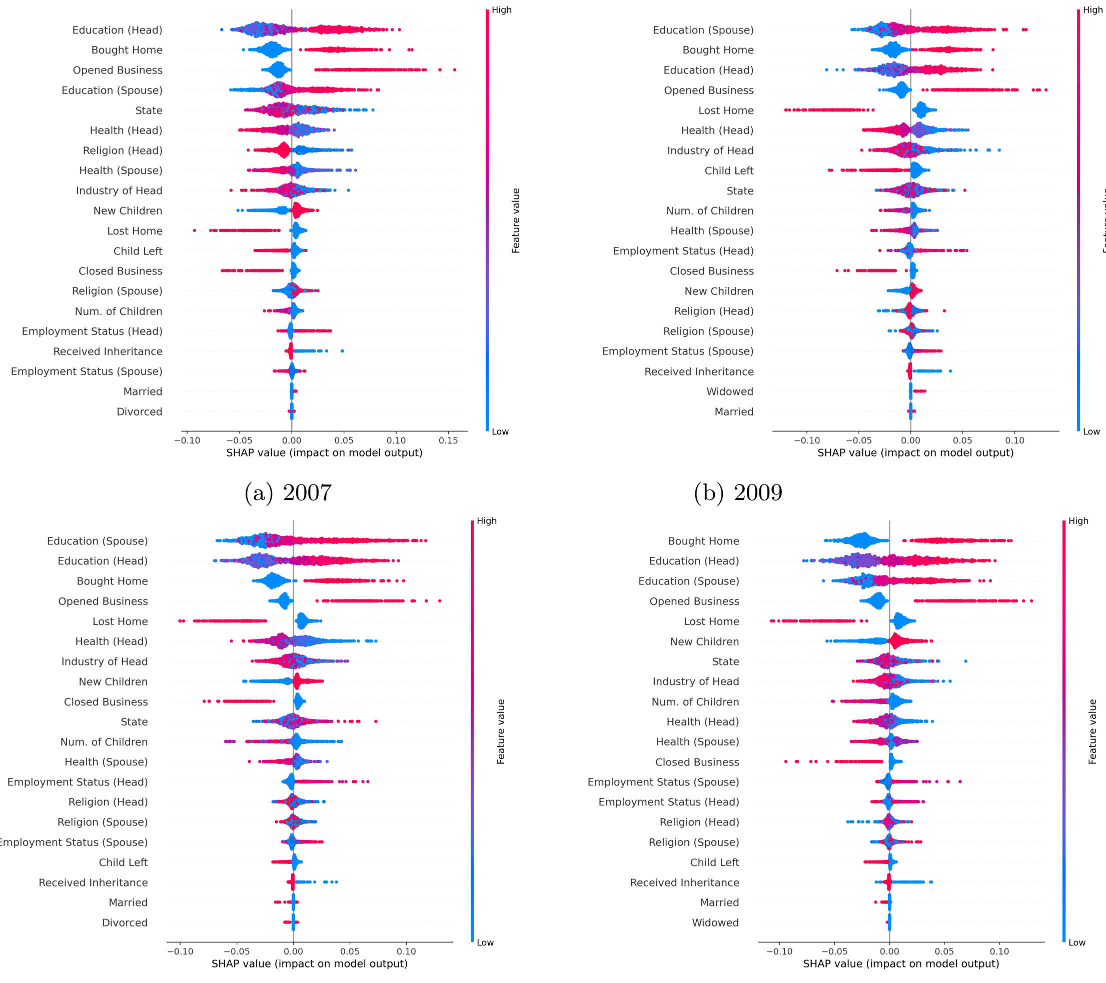


(c) 2011



(d) 2013

Figure 29: Change in White Young Household Net Wealth



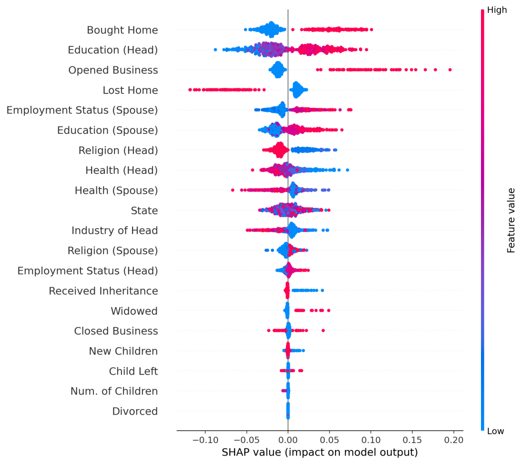
(a) 2007

(b) 2009

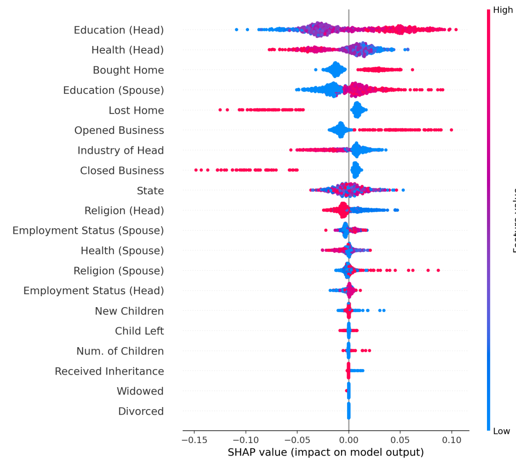
(c) 2011

(d) 2013

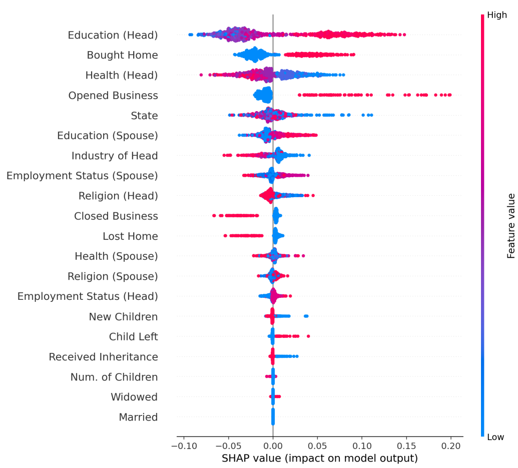
Figure 30: Change in White Mature Household Net Wealth



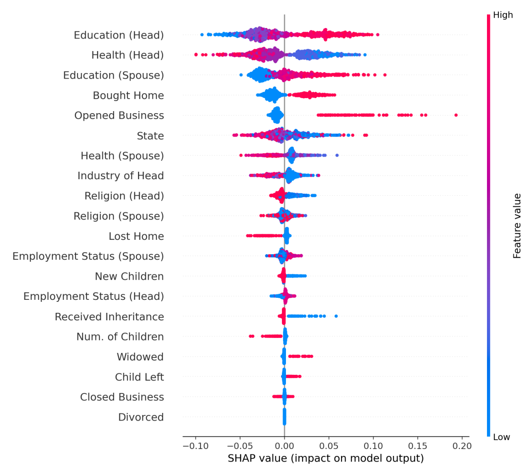
(a) 2007



(b) 2009

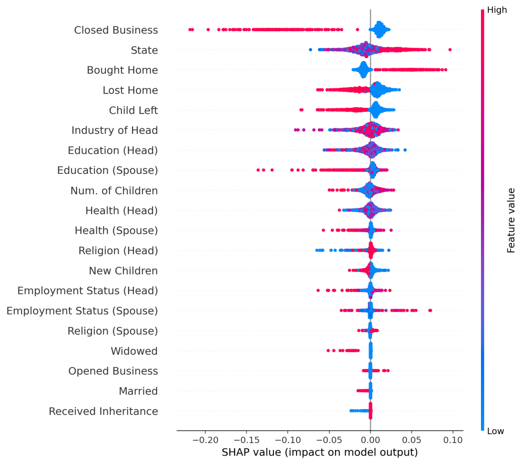


(c) 2011

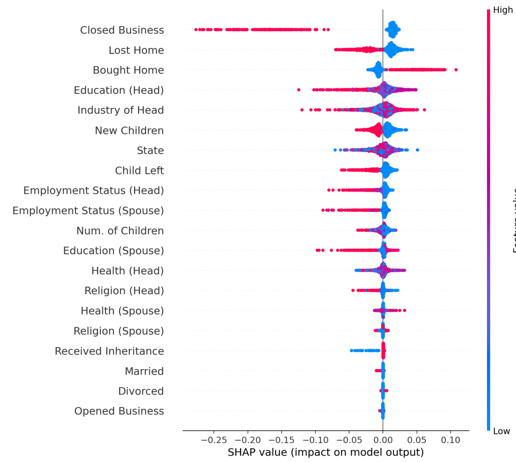


(d) 2013

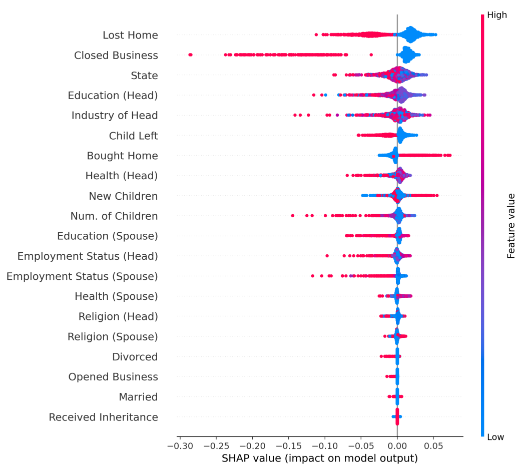
Figure 31: Change in White Elderly Household Net Wealth



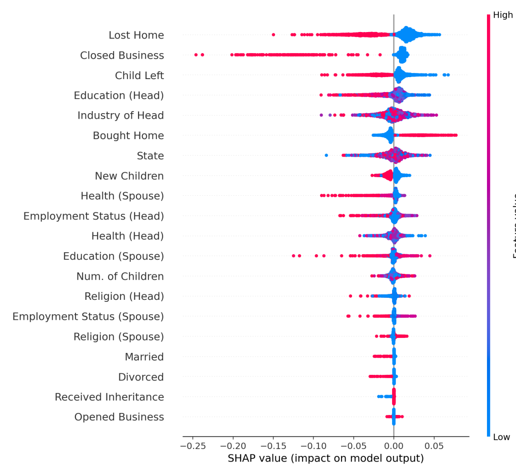
(a) 2007



(b) 2009

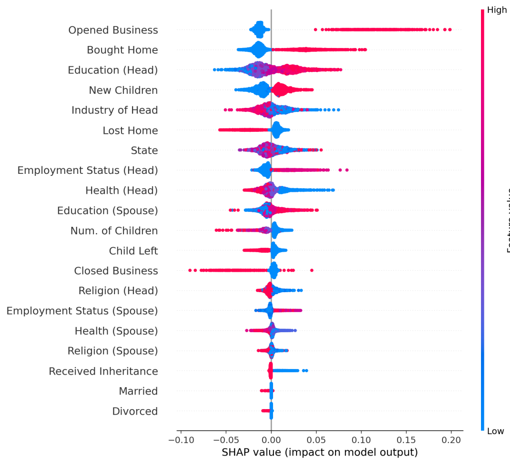


(c) 2011

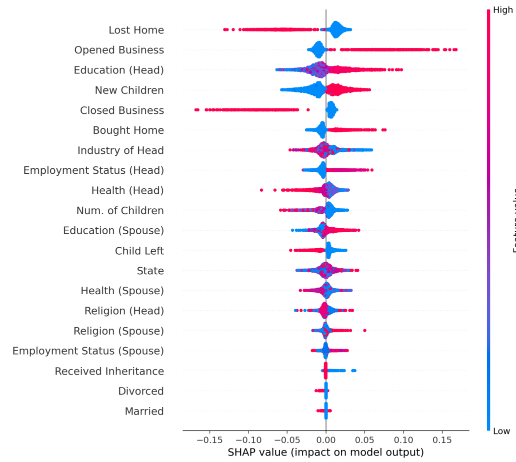


(d) 2013

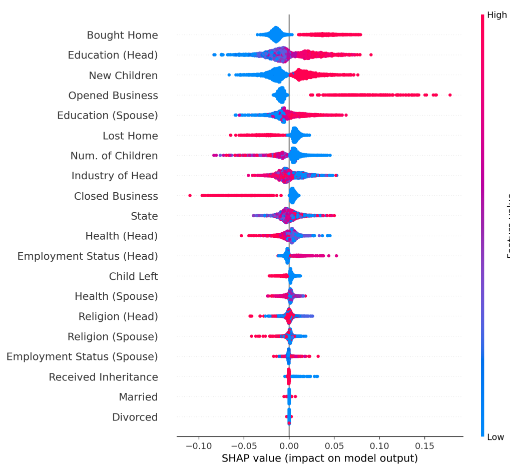
Figure 32: Black NW-HE



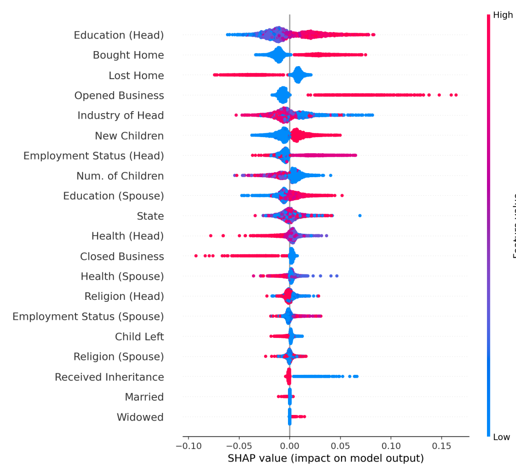
(a) 2007



(b) 2009

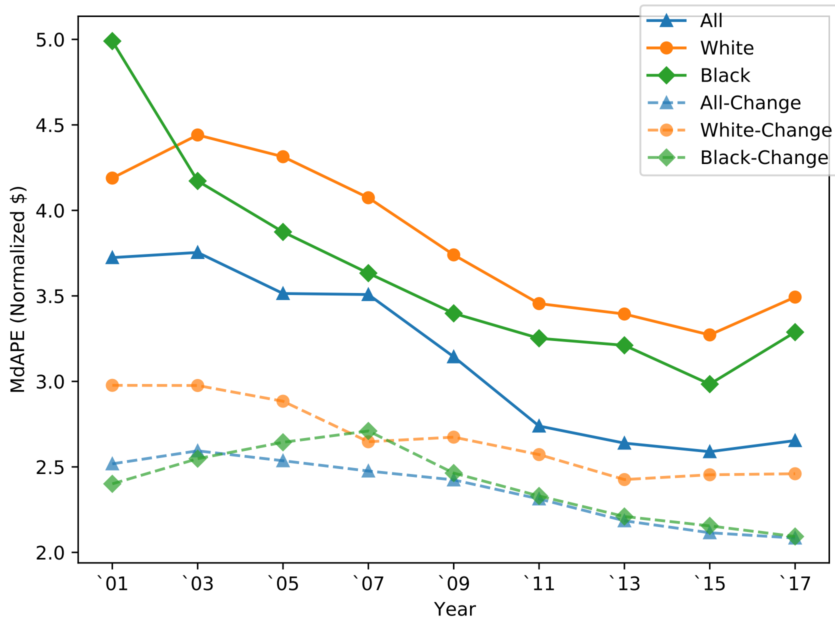


(c) 2011

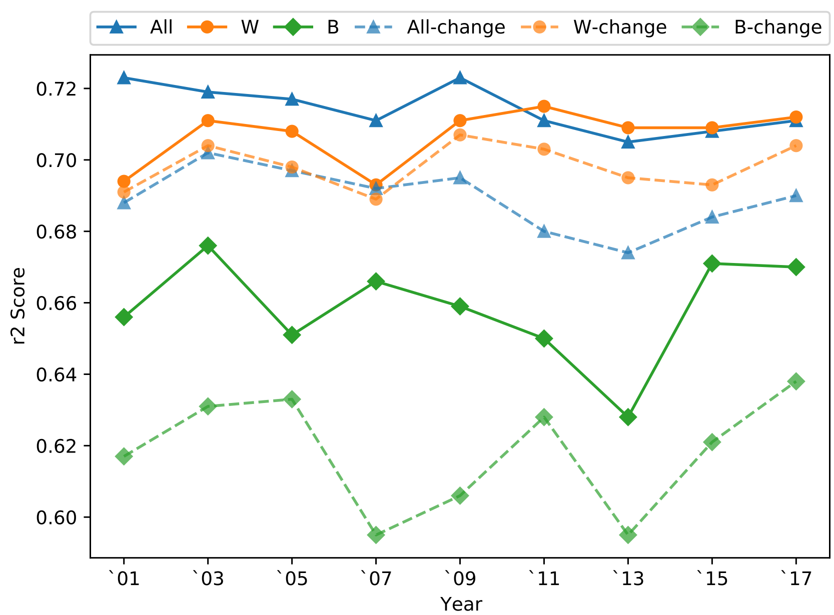


(d) 2013

Figure 33: White NW-HE



(a) MdAPE entire sample period



(b) Explanatory power

Figure 34: Model performance

5 U.S. Income Poverty and Asset Poverty

This study introduces a measure of asset poverty and examines how U.S. asset poverty changed before and after the global financial crisis. Utilising data from the Panel Study of Income Dynamics, we find that asset poverty rates have increased from 1999-2017. In particular, our findings suggest that asset poverty rates reached 28.14% in 2011, where one in every four households did not have the financial assets to cover three months of their basic consumption needs. The results indicate that black, unmarried females, and renters are most likely to be asset-poor compared to white, married couples, and homeowners. Current U.S. Government poverty rates calculated through household income are found to be approximately 9% less than asset poverty rates.

5.1 Introduction

The United States (U.S.) declared a "War on Poverty" in January 1964. As a result of President Johnson's declaration, the office of Economic Opportunity started measuring and quantifying the dynamic changes in U.S. household poverty. This has led policymakers to design and create a wide range of poverty focused policies which has had mixed success. A common way to measure poverty is to compare if an individual or households' current resources can meet their basic subsistence needs. If they cannot meet their basic needs, they are defined to be poor. Currently, the main estimation technique used to measure a households basic needs centres on household income (referred to as income poverty). However, many scholars do not support income as a suitable measure for a poverty threshold. In particular, some scholars suggest that poverty is not simply due to a lack of income, rather a lack of financial assets (Caner and Wolff, 2004). By using income as a measure of poverty, the U.S. could actually be understating the true rate of poverty. Asset-based policies, which were originally designed to improve and encourage individuals and families to increase their wealth portfolios, were first proposed in the early 1990s as an alternative method to reduce poverty compared to standard income-focused policies (Carney and Gale, 2001; Sherraden, 1991). In this study we look to measure, identify, and quantify recent trends in U.S. asset poverty rates for individuals and households.

Asset-based policies propose that an individual's, household's, and community's well-being is derived from assets, enabling one to pursue their life goals. Financial assets, and especially liquid assets, allows households to have a financial safety net in times of financial uncertainty. Financial instability often stems from health issues, unemployment, and unexpected life or economic events such as divorce, deaths, and financial depressions. Without a substantial financial cushion to fall back upon, poor households can soon fall into a spiral of debt, unemployment and are unable to relocate/re-educate themselves to adapt and remain competitive in the job market. Conversely, rich households have the financial means to diversify their wealth portfolios in downturns to avoid significant losses. Furthermore, they are able to relocate themselves to more prosperous regions of employment and have the ability to re-educate themselves so they can re-enter the job market quickly. Consequently, identifying and determining the underlying causes of asset poverty will help both policy makers and academics to reduce household poverty (Sherraden et al., 2011).

A widely cited feature of asset inequality is homeownership. Piketty and Zucman (2014), suggest that the late twentieth-century surge in wealth-to-income ratios in Western economies is primarily due to the increasing housing wealth. The importance of housing is more evident for poor U.S. households, which, according to Mian and Sufi (2015), hold \$4 of housing equity for every \$1 of other assets.[29] Consequently, many homeowners who are highly leveraged or credit-constrained, are more vulnerable to house price changes. Homeowners who have a un-diversified wealth portfolio, with a significant exposure to their housing wealth are exposed to unexpected changes in labour markets, financial crises, or if their health worsens and they are unable to earn labour income.

This study contributes and expands on the current literature in several ways. Firstly, we extend and apply Caner and Wolff (2004) methodology to new data from the Panel Study of Income Dynamics (PSID data-set) from 1999-2017. This sample period will allow us to review how the financial crisis affected U.S. households and in particular, look at how asset-poor households were affected by an unanticipated economic shock. Secondly, we provide insights into which individ-

[29]The median U.S. household held 37.4% of their total wealth in housing wealth between 2001-2010 (Cooper and Dynan, 2016; Wolff, 2016)

uals and households are likely to move into, and move out of, asset poverty and determine which events cause these transitions. Finally, we propose an alternative measure of 'basic needs' used within the asset poverty measurement, which stems from the increased time it takes households to gain employment into current labour markets.

5.2 Current literature

Assets can be divided into personal and social assets and further subdivided into tangible and intangible assets (Sherraden, 1991). Intangible assets, such as human capital, cultural capital, and informal social capital, are often hard to quantify and measure their associated impact on households (Nam and Kwon, 2008). As such, a large proportion of asset poverty studies focus on physical capital and, in particular, the current wealth of an individual or household. To determine if a household is poor, net income has been the most frequently used indicator (Chaudry and Wimer, 2016; Dormekpor, 2015; Meyer and Mittag, 2019). However, income is volatile. In the event of crises, such as poor health, redundancy, or financial crises, labour income can quickly cease, and a household may be reliant on their current wealth to maintain their current consumption.

Asset poverty studies often utilise three measures of wealth, namely, net wealth, net wealth minus housing equity, and liquid assets. These wealth measures are subsequently used to identify households who fall below a minimum level, referred to as the poverty line or poverty threshold (Caner and Wolff, 2004). Unexpected events such as a global pandemic, financial crisis, loss of health, or labour market changes can often lead to depressed expected household income. Households often utilise wealth, rather than income, in times of crisis so they can perform consumption smoothing across their lifetime (Browning et al., 2013). Younger households react less strongly to income shocks as they have a longer time horizon in order to accumulate assets compared to elderly households. Wealth levels vary unevenly for different age groups, races, educational attainment, and if an individual is a homeowner or renter (Wolff, 2016). Consequently, some individuals and households have fewer or (greater) resources to utilise when an unexpected change occurs in their life.

This papers builds on the financial resilience of U.S. households. Baker and Yannelis (2017) found underprepared households will cut down their consumption and change spending allocations in the event of an unexpected costly life event, such as death, divorce, or loss of work. Furthermore, Agarwal et al. (2016), furthers this work and notes poorer U.S. households will utilise more expensive financing to cover regular consumption, for example, utilising pay-day loans with high interest rates. Therefore, financial resilience can be summarised within three categories, financial resources, social and community resources, and personal resources (there social and personal resources, see O'Neill and Xiao, 2006). This study will focus on the financial resources and in particular their liquid wealth due to the inability of poorer households to readily convert illiquid assets into wealth.

Wealth inequality has been prevalent throughout the United States. Racial wealth inequality, in particular, has been severe for several decades. A recent study conducted by Burd-Sharps and Rasch (2015), suggests that wealth loss sustained due to the 2008 financial crisis, was higher for black households compared to white households. Furthermore, they forecast that the ratio of white to black wealth will continue to increase and reach the ratio of to 4.5 to 1 by 2031. Shapiro et al. (2013) suggest that racial wealth inequality stems from differences in a) inheritance, with black households less likely to receive inheritance, b) college education, the children of high income households are 45% more likely to attend college and therefore earn higher future income, c) marriage, with black households not significantly benefiting from marriage compared to white households who gain approximately $75,000 over their lifetime, and d) homeownership, being the largest difference between racial groups as black households are much less likely to own a home compared to white individuals or households.

A vibrant discussion in asset-based policy is focused on policy developments aimed towards supporting children. It is widely known that children from poorer households have stunted developmental outcomes. Shanks (2007) employed the PSID data-set and found that similar to differences in household income, higher inter-generational wealth levels can influence both mathematics scores and reduce behaviour problems depending on the race of the child. In addition, Conley (1999) found that higher parental wealth is a predictor of short and long term academic achievements for children. The author found racial disparities were also primarily due to parental wealth, rather than differences in household income. Additionally, children are able to understand and articulate long-term saving goals using 'child development accounts' to save for university (Elliott III, 2009; Sherraden et al., 2007).

This paper is most closely related to Caner and Wolff (2004) and Haveman and Wolff (2004). Caner and Wolff used the PSID data-set to analyse the dynamics and determinants of asset poverty rates in U.S. households between 1984-1999. The authors suggest that asset poverty rates did not decline during the long expansionary period in the 1980s and 90s. This study looks to further improve on Caner and Wolff's methodology by reviewing if asset poverty rates are linked to households who are behind on their mortgage, if they restructured their mortgage, or have had a mortgage foreclosed. Secondly, this study examines how asset poor households responded to the 2008 financial crisis, and estimates which events are likely to cause a household to move in and out of asset poverty. Finally, we examine the development of asset poverty rates across the financial crisis, and over the sample period of 1999-2017.

5.2.1 U.S. poverty policies

The U.S. government has implemented several assistance programmes over the last few decades. We will focus on two types: means-tested programmes, and social insurance led policies. Means-tested programs directly try to assist households who have low income or few assets. On the other hand, social insurance programmes provide support to the wider populace, and are intended to support people who are at risk of disability, unemployment, or are unable to work. Social insurance programmes don't directly aim to support low income households, however, their wide ranging programmes significantly impact a large proportion of the U.S., and therefore poverty rates.

Means-tested programmes generally focus on low income and low asset households. For example, Supplemental Security Income program, provides monthly cash payments to individuals or couples who are elderly, disabled, have limited income, or have limited assets. The majority of recipients (80% (Daly and Burkhauser, 2003)) are disabled. Individuals (couples) who have less than $2,000 ($3,000) in their current accounts, land, property, and other financial resources are eligible to apply. Supplemental Security Income help over eight million recipients yearly, however, its effectiveness has often been questioned (see Duggan et al. (2015)). Other notable asset-based policies include: the home mortgage interest deduction; tax deferments on retirement accounts; and college saving plans etc. Each policy has been designed to help assist households to accumulate wealth by allowing them to save part of their income through different savings schemes.

Asset-poor households often do not participate in existing asset-based mechanisms (McKernan and Sherraden, 2008). Low-income individuals and households are less likely to own a home, to create saving and investment accounts, do not contribute to their pension pots, and are less likely to receive advanced education, where most U.S. asset-based policies are targeted. Unfortunately, the poorest individuals and households have little to no tax incentives to participate in these schemes compared to richer households. For example, Sinai and Gyourko (2004), suggest that government subsidies for owner-occupied housing through mortgage deductions support high wealth households and landlords compared to poor households. Furthermore, the largest tax subsidies went to households in states like California, where house price growth of high-value homes have appreciated most quickly, leading to higher tax subsidies. Consequently, this led to a further lack of participation from more deprived households who do not take advantage of these tax benefits as they cannot afford high value homes.

Social programs generally insure against the risk of disability, old age, and unemployment. Often, these policies require contributions in the form of tax payments from labour income, or through the employer. This often leads to poorer households, who may spend large periods of time outside the workforce, and therefore they do not pay regular income tax, are unable to meet the minimum threshold to gain access to these programs. Notable social programs include the old-age Social Security program, which provides monthly payments to those who have regularly paid through their labour income. The program provides for both the individual insured, and their associated family, including spouse, and under-18 children. The Unemployment Insurance program provides financial assistance to individuals who are unemployed, who were involuntary discharged, and who have adequate pre-unemployment and earnings histories. These fixed payments cover a short time period, generally six months, but these can be extended in crises.

5.3 Asset poor and asset rich definitions

There have been several suggestions on how to define asset poverty.[30] There is no general acceptance, as we require a set of assumptions to be able to define asset poverty. However, to allow for comparability with other studies and to clearly define a baseline threshold of poverty, this study utilises the definition first suggested by Oliver and Shapiro (1990) and later expanded by Haveman and Wolff (2005).

A household or person is asset poor if their access to wealth-type resources is insufficient to enable them to meet their basic needs for a limited period of time.

We define wealth using three measures. Namely, net wealth (NW), which is the current value of all an individual's or households asset value minus any outstanding debt.[31] The second measure of wealth is net wealth minus housing equity (NW-HE). This measure is similar to net wealth, except the housing equity component is removed. The net wealth minus housing equity measure is employed because housing equity is an unlikely source of income if a household was looking to generate immediate funds to cover a temporary shortfall in income. Finally, the third measure of wealth is liquid wealth (LIQ). Liquid wealth is the most restrictive wealth measure as it only contains current accounts and easily accessible assets.[32] Further information about which components are included for each wealth measure can be found in Table 4 (see Appendix).

To define a limited time of economic hardship, we utilise Caner and Wolff

[30]For example, Kim and Kim (2013) highlight several studies which define their own measure of asset poverty

[31]Vehicle and pension wealth are not included. Vehicles are often a necessity for poor households to maintain access to their place of work. Pensions are deemed to be long term investment vehicles that cannot be drawn down readily for immediate consumption.

[32]These measures are utilised to allow comparability with Caner and Wolff (2004).

(2004) definition that a household is considered to be asset-poor if their asset value is unable to cover their consumption needs for a period of three months.[33] A recent study published by the U.S. Bureau of Labor Statistics[34] suggest the average number of weeks of unemployment in the U.S. peaked in 2011 at forty weeks. Hence, to ensure our results are not manipulated by the three months of consumption assumption, we test asset-poverty rates to see if households can cover their basic needs for three, six, and nine months.[35]

To calculate the basic needs of a household, data from the Consumer Expenditure Survey (CES) is used. Household consumption thresholds (which are CPI adjusted) are set by the CES each year for reference households. Reference households vary by their size (number of adults and children) and age. Since we define the threshold of asset poverty as an individual or household not having the resources to cover *three* months of consumption, we take 25% of the yearly CES poverty threshold value to define the poverty line for an individual or household being asset poor. If a household is below (above) the poverty line, their current assets will not (will) cover their basic needs for a three month period. For example, a sample of poverty thresholds for 1999, 2007, and 2015 are \$4,224, \$5,247, and \$6,009 respectively for a two adult and two children household. The poverty thresholds cover a range of different family sizes with different thresholds dependant on the age of the household and the number of adults and children in the family. References poverty thresholds for families and individuals of other ages (e.g., pensioners) and sizes (e.g., two adults and three children) are matched with

[33]The authors note that this is the average duration of unemployment of U.S. households between 1984-1999. Azpitarte (2008) also employed this three month rule of 'limited' time to UK and Spanish data. The authors suggest their asset poverty rates were not significantly different for UK or Spain were the average unemployed duration was eight months.

[34]See the unusual duration of unemployment, FRED economic data (2018) for more information

[35]Results for six and nine months are reported in the robustness section

the PSID family unit sizes.[36]

To estimate asset poverty, we utilise the headcount index P_0 to estimate the share of households that fall under the poverty threshold. We define the headcount index as:

$$P_0 = \frac{1}{\sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i (V_i < PL_i), \tag{13}$$

where w_i is the weight assigned to each household, V_i is the wealth for each household, which is either net wealth, net wealth minus housing equity, or liquidity. PL_i is the poverty line and n is the sample size. The expression $(V_i < PL_i)$ takes the value one, if the value of the mean household wealth is below the poverty line (i.e they are asset poor), and zero otherwise (see Haveman and Wolff (2005).

To calculate the probability of a household being in two consecutive PSID waves, we employ the conditional probability, defined as:

$$P(Wpoor_{t_2} | Wpoor_{t_1}) = \frac{Wpoor_{t_2} \cap Wpoor_{t_1}}{P(Wpoor_{t_1})}, \tag{14}$$

where $Wpoor$ is the wealth of a household who is either net wealth poor, or net wealth minus housing equity poor. t_2 refers to the second PSID wave tested, and t_1 is the first wave tested. The household is known to be NW poor or NW-HE poor in the first period.

Finally, we utilise probit models to examine which life events explain transitions into and out of asset poverty thresholds across different time periods. To estimate two probit models with the first model determining how households transitioning into asset poverty, and the second probit model for transitions out of asset poverty. We define T_{in} as a dummy variable which is 1 if a households transitions

[36]Using the CES determination of poverty threshold will allow for greater comparison between this study and current poverty threshold values.

from being non-asset poor in year t and subsequently they fall below the asset poverty threshold in year $t+2$. Similarly, households who are below the asset poverty threshold (i.e. who are asset poor) in year t and move above the asset poverty threshold in year $t+2$ are defined as T_{out}. Therefore we can generalise both probit regressions as:

$$PR(T=1|X) = PR(T=1|x_1, x_2, ..., x_k), \tag{15}$$

where X denotes a full set of explanatory variables $x_1, x_2, ..., x_k$ which is a vector of the explanatory variables. T is estimated twice, once for T_{in} and estimated independently for T_{out}. Consequently, we can rewrite equation 3 as:

$$PR(T=1|X) = F(\beta_0 + \beta_1 x_1 + ... + \beta_k x_k) = F(\beta_0 + X\beta), \tag{16}$$

where F is a function of the explanatory variables (i.e. life events such as receiving inheritance, having a child, losing a home, and divorcing), and β is the set of coefficients of the indicator variables X. The data used within this chapter is described within Chapter 3. Summary statistics are provided in Table 13.

5.4 U.S. Asset poverty rates: 1999-2017

In this section, we will firstly review asset poverty rates and wealth distributions for the U.S. Then, we will analyse the characteristics of households who are defined to be asset-poor. Additionally, we will compare calculated asset poverty rates with the U.S. Census Bureau published statistics on income poverty. Then we will examine which events are likely to cause a household to move into asset-poverty, and which events cause households to move out of asset poverty. Finally, we will review if asset poverty rates indicate which households may struggle to meet their mortgage payments.

5.4.1 Wealth distribution

Table 14 presents the households mean wealth and the wealth distribution across our sample period of 1999-2017. Under our three definitions of wealth, net wealth (NW), net wealth minus housing equity (NW-HE), and liquidity (LIQ), the mean households wealth increase for all three measures across our sample period; with NW reaching a maximum in 2007 at $322,060. Mean net wealth and liquid assets of U.S. households reduced by approximately ten percent from 2007-2009, and we find a six percent reduction in NW-HE across the same period. The effects of the financial crisis can be seen most acutely in 2011, where NW is eighteen percent lower than the 2007 peak. Household wealth is depressed for all three wealth measures for the next eight years. In 2017, the mean household wealth surpasses the 2007 maximum, and the mean NW recovers to $327,390. The data clearly shows between 1999-2017 there are three well defined periods, 'the expansionary period', 1999-2007, 'the depression', 2009-2011, and 'the recovery period', 2013-2017.

The bottom panel from Table 14 presents the quantile wealth of households. For all three wealth measures, household wealth broadly follows the same pattern as noted for the mean wealth data, growing during the expansionary period, significant losses during the depression period, and a rebound during the recovery period. A noticeable exception to the trend is the 10th percentile of NW-HE. Throughout each wave, NW-HE wealth, which is negative, indicating the household is indebted, steadily worsens through increasing levels of debt caused by the financial crisis. These households had the largest absolute percentage wealth decrease compared to the other percentiles. Finally, another notable observation is the liquidity of households in the 10th and 25th percentile groups. These household groups have no liquid assets across the sample period. This highlights the worrying lack of liquid assets held by a significant proportion of the U.S., especially when compared to the 90th percentile

5.4.2 U.S. asset poverty rates 1999-2017

We now estimate the U.S. asset poverty rates across the sample period utilising equation 12 (see Table 15). As expected, and consistent with the literature (Caner and Wolff, 2004), our calculations show that net wealth yields the lowest asset poverty rates, as NW is least stringent measure of household wealth. Net wealth poverty rates are at their lowest in 2005 at 21.5%, and reach a maximum in 2011 at 28.14%. Our results indicate that after the financial crisis, one in every four households could not sustain themselves for more than three-months with existing resources, and not in the event of another shock.

Net wealth minus housing equity asset poverty rates follow a similar trend to NW. However, they are slightly less volatile in comparison to NW. NW-HE asset poverty rates range between 30% and 36%. The reduction in asset poverty volatility is indicate that house prices played a significant role in wealth decumulation in the bust period (between 2009 and 2011). Another noteworthy observation is the growth in poverty rates in the expansionary period of 1999-2007. Asset poverty rates over this period increased from 30.89% to 31.80%. However, across the same period NW asset poverty decreased. This most likely indicates that homeowners benefited from a rise in house prices during the expansionary period, and the increase in asset poverty rate in the NW-HE measure stems from renters not benefiting from house price appreciation.

The highest rate of asset poverty is noted within the liquidity measure. Similar to NW, liquidity asset poverty rates reduces in the expansionary stage, and poverty rates increase after the financial crisis in the depression period. In particular, the liquidity poverty rate measure is approximately twice the size of NW asset poverty rates. These high asset poverty rates (ranging between 41 to 49%) are indicative of the highly restrictive assumptions imposed on defining the liquidity measures. This restrictive definition of household wealth was similarly seen in Table 14, where the 25th percentile of U.S. households have no liquid savings to access in times of financial distress.

Overall we see that asset poverty rates have risen for each wealth measure. In total, our calculations show that the percentage change in asset poverty rates increased by 3.15% for net wealth, 4.58% for net wealth minus housing equity, and 1.12% for the liquidity measure across our sample period. The fragility of the financial health of U.S. households was at its height in 2011, where 28.14% of individuals or households did not have the financial means to meet their basic needs for a three month period. Finally, Table 16 contains the percentage change in asset poverty rates over a number of sample time periods and Figure 11 illustrates asset poverty rates across the sample period.

5.4.3 Decomposition of U.S. asset-poor households

In this section, we determine which individuals or households are asset-poor within the PSID data-set, and we look at the general characteristics of asset-poor households. Table 17 presents our results and illustrates the poverty rates for each panel. In the first panel, we partition the households by age. We observe that the age of the household has a differential impact on asset-poverty rates. For example, in 1999, young households were five times more likely to be asset-poor (based on net wealth) compared to a family aged between 55 and 64. This, of course, is

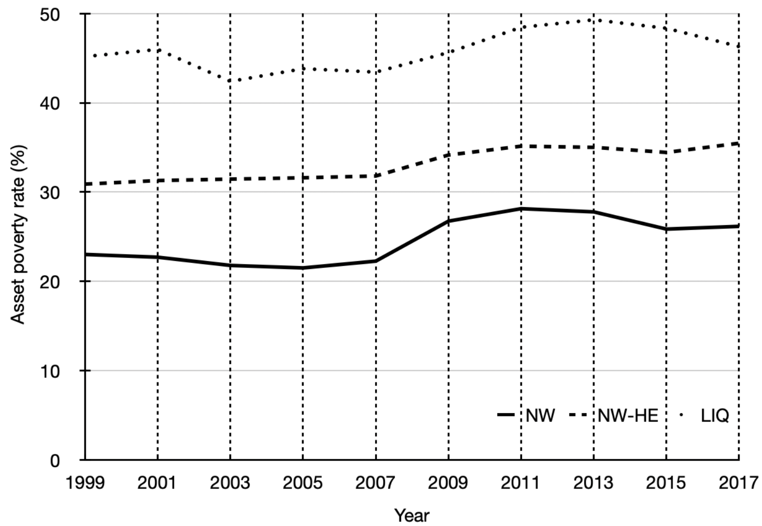


Figure 35: Asset Poverty rates for NW, NW-HE, LIQ. Rates calculated from the PSID.

linked to the life cycle of households income and wealth patterns.[37]

From table 17, the top panel highlights asset poverty rates as a function of the head of the household's age. Across the sample period we note a few discernible trends. Firstly, between 1999-2007 asset poverty rates for NW were either slowly trending upwards, or were relatively stable for households for the age groups under 55 years old. Secondly, every age group, except for households under the age of 25, had an increase in NW asset poverty rates when the financial crisis occurred (seen in the 2009 wave). Age groups 25-34, 35-44, 45-54, and 55-64 experienced an increase in asset poverty rates of approximately 4 to 8% due to the financial crisis (2007-2011). Across the sample period, we see asset poverty rates for NW increased by 5.41%, 11.55%, 10.42%, and 8.06% respectively for these age group.[38]. Households under the age of 25 saw a decrease in asset poverty rates for NW and

[37]Figure 9 illustrates the life cycle of disposable income of the PSID data-set.
[38]Similar asset poverty rates are seen for NW-HE

NW-HE. This indicates young households (< 25) were shielded from the collapse in asset prices as most young households lack the financial means to own property and have small stock holdings. Thirdly, we note the highest and lowest rates of asset poverty were in the young (under 25) and elderly (65+) households. For example from 1999-2017 asset poverty in young and elderly households changed by 1.44% and -0.74% respectively.[39]

The second panel from Table 17 highlights how asset poverty rates vary with the educational attainment of the head of the household. The results highlight that there is a higher proportion of asset-poor, high school educated households, in comparison to college and postgraduate educated families. There was an increase in asset poverty rates across all educational groups. Postgraduates have the highest increase in poverty rates across the sample period of 8.9% for the NW-HE measure. This is most likely due to the smaller sample size of postgraduates, compared to high school and college-educated households. Interestingly, we note the financial crisis impacted high school educated households more than college and postgraduate educated households. NW-HE poverty rates increased by 8.29% for high school educated households between 2007-2009, where it increased by 4.26% and 2.83% for college and postgraduate educated households respectively. We previously noted that college educated households earn, on average, a higher income and they are able to convert their higher disposable income into wealth through increased saving, this is why postgraduate educated individuals have the lowest asset poverty rates in our sample.

The third panel of Table 17 features the poverty rate for the race of the head of the household. The results suggest that there is a significant difference between white and black asset poverty rates. A black household is more than twice as

[39]The elderly age group was the only sample to have asset poverty rates decrease over the sample period.

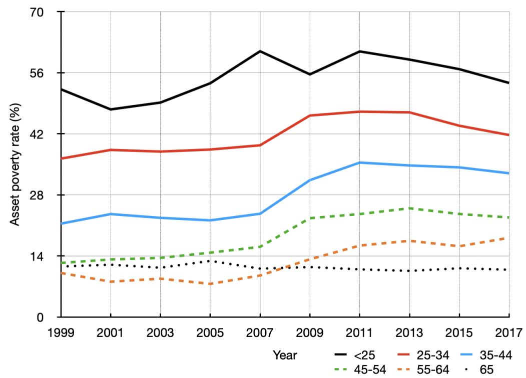
likely to be asset poor compared to a white household for both net wealth and net wealth minus housing equity for most waves. The financial crisis increased asset poverty rates for every ethnicity, with an increase of approximately 4% in poverty rates.

The fourth panel contains poverty rate differences for renters and homeowners. We see a significant increase in asset poverty for renters compared to homeowners. Renter's NW-HE poverty rate is approximately two to three times the size of homeowners across the sample period. The spillover effects of the financial crisis drives NW asset poverty rates for homeowners, where homeowners poverty rates increased by 4.61% from 2007-2009, due to the decreases in house prices. Interestingly, we note a significant difference between NW and NW-HE poverty rates in the homeowner panel across the sample period. For example, in 2005 only 4.72% of homeowners could not meet their basic needs for 3-months through their NW. When housing equity is not included in the wealth calculation, this increases by 4.18 times to 19.71% of homeowners who could not afford to meet their basic needs for 3-months. This large difference in poverty rates symbolises the amount of leverage (through mortgages) households took by investing a significant proportion of their wealth into housing. In general, the divergence in poverty rates between NW and NW-HE for homeowners is approximately two to four times larger for homeowners across the sample period. After the crisis, this spread reduces due to the fall in house prices.

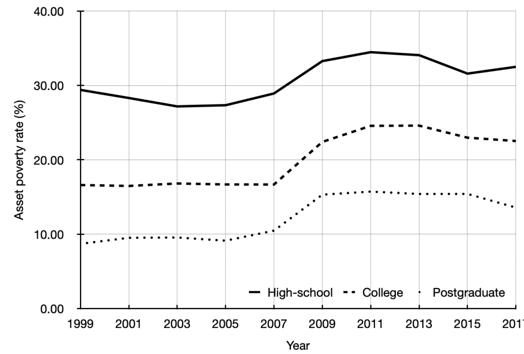
The fifth panel measures the difference in poverty rates for married and single households. Similar to tenure, the married status of a household yields a large differential impact on poverty rates. Married households are half as likely to be asset-poor compared to single households. We note over the sample period, married household's poverty rates increased by 6.93%. Conversely, unmarried household asset poverty rates, although higher, reduces over the sample period by 2.5% for net wealth.[40]

The final panel in Table 17 illustrates asset poverty rates for different family compositions. Three noticeable patterns emerge from the data. Firstly, married households (age 18-64) experienced increasing asset poverty across each wave for the whole sample period. Secondly, and consistent with Caner and Wolff (2004), single, female (age18-64) households experience very high levels of asset poverty. This stems from the cost of child care / reduced income earned by single female households who provide child care. These households often suffer from stunted job opportunities and this causes single females with children to be more likely not to maintain their basic needs for a 3-month period of time. Finally, this effect also transfers to elderly females (65+) where asset poverty rates are four times higher than that of elderly married couples.

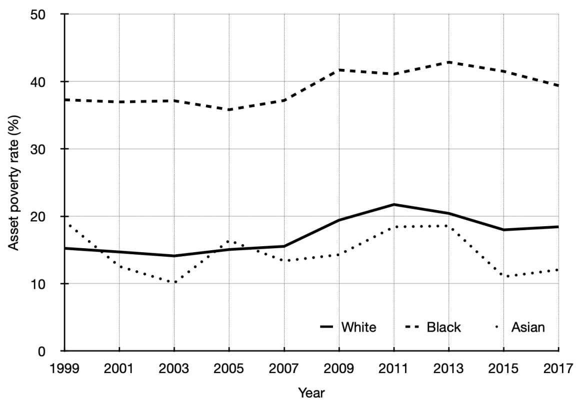
[40]Similar (smaller) results can be seen with NW-HE.



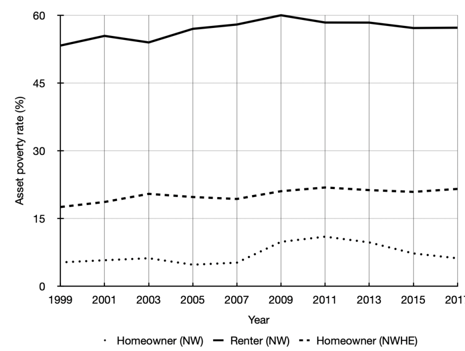
(a) Age



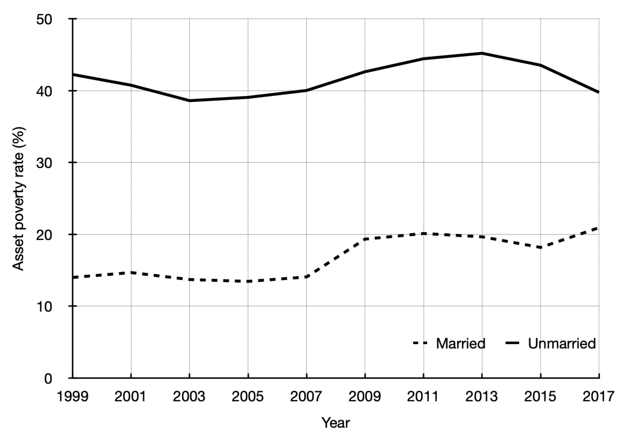
(b) Education



(c) Race of head



(d) Tenure



(e) Marriage

Figure 36: Decomposed poverty rates

5.4.4 Mortgage payments, mortgage foreclosures, mortgage restructuring

An additional three questions asked by the PSID from 2011-2017 were about a households current mortgage contract. In particular, they asked if a) they had fallen behind with their mortgage contract, b) they had restructured their mortgage contract, and c) they were currently undergoing foreclosure proceedings. Households who are in financial distress and cannot service their mortgage for any of the above reasons would likely be asset-poor in theory. The number of households considered to be NW asset poor, and experiencing one of the above three criteria can be found in Table 18.

As expected, households experiencing foreclosure on their house, due to falling behind on their mortgage payments, have the highest rate of asset poverty at 50% in 2011. Interestingly, one would expect the asset poverty rate for closure households to be higher, as the literature suggests households often try to keep their home even if they are underwater. We can imply from this that some households are tactically foreclosing on their property, a common practice seen after the financial crisis.

5.4.5 Comparison of U.S. official poverty statistics with asset poverty

It is important to consider how asset poverty rates differ from official income poverty rate statistics. Table 19 presents our calculated asset poverty rates for NW and NW-HE against historical poverty tables provided by the Census Bureau.[41] For all panels in Table 19, except for elderly males, our calculations highlight that asset poverty rates are higher than official U.S. statistics. Elderly males (65+)

[41] Official historical results can be found here (https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-people.html). Note official statistics are reported for individuals.

NW asset poverty rates trend approximately 0.5-1.5% lower than official rates, and their NW-HE is approximately 5% higher than official rates for all survey years.

The majority of NW and NW-HE asset poverty rates follow the previously discussed pattern, of expansionary period (reducing poverty rates), depression period (increased rates), and recovery period (reducing poverty rates). However, the official rates show a larger poverty rate for the recovery period (2013-2017) compared to our calculations. For example, asset poverty rates for male individuals from 1999-2017 increased by 3.28%, official income poverty rates increased by 0.6%. These patterns are mirrored across several of the panels, including data on all individuals, age categories (18-64, female 65+), and white and black poverty rate statistics.

The most substantial difference in poverty rates between official and calculated is for single female headed households between the ages of 18-64. Our calculated poverty rates indicate that single female headed households are three to four times higher than official income rates across the sample period. In particular, we identify that female households were particularly hard hit after the financial crisis (2007-2009) with an increase of 13.5% for net wealth asset poverty rates, and in comparison, official statistics only rose by 2% for the same period.

Consistent with the literature and with government statistics, we note that black households have significantly higher poverty rates for both calculated asset poverty rates, and official income poverty rates.[42] From our calculations, black households were approximately twice as likely to be asset or income poor compared to white families. Similar to our decomposition results in Table 18, Asian household's results are very volatile in the PSID data-set sample, and their poverty

[42]See Brunn-Bevel (2015); Haveman and Wolff (2005); Hirschl and Rank (2010)

rates fluctuate above and below official statistics, with no clear discernible trend.

5.4.6 Probit tests on household characteristics

In order to determine the effect each independent variable has on asset poverty, we estimate a probit model for net-wealth and net wealth minus housing equity. Similar to Caner and Wolff (2004), we model the independent variables as dummies, and we leave out age group (55-64), black households, renters, single males, college educated, and married female headed households to prevent multicollinearity. The dependant variable is NW and NW-HE, where each household takes the value of zero if they do not fall below the poverty threshold, and are one if they do. The results are reported in Table 20. We provide estimates for 2001, 2009, and 2017 waves. Finally, marginal effects are reported.

The estimates suggest that relative to renters, homeowners are much less likely to be asset-poor. In particular, in 1999 homeowners are 9% less likely to be asset poor according to the NW measure, and 4% less likely to be asset poor for the NW-HE measure. We find these results consistent across the other waves of the data surveyed. Secondly, we find evidence that race is also an important factor in determining asset poverty. White households are less likely to be asset poor compared to black households across all waves (except for the NW 2017 measure which was insignificant, but still had a negative coefficient).

Our third observation is that relative to married headed females, single females, and elderly married households are much more likely to be asset poor. This is to be expected as both noted previously, married and elderly households had much higher asset-poverty rates compared to other family compositions of age and structure. The results suggest that married households are 9.1% more likely to experience asset poverty, and elderly female are 6% more likely to be asset poor for the NW measure in the 2001 period. We yield similar results for the 2011 and 2017 periods.

Interestingly we also note that relative to 55-64 year olds, most age groups had increased asset poverty rates. This provides support to our previous findings that as a household ages, they are less likely to be asset poor. Furthermore, elderly (65+) households were also more likely to be asset poor compared to the control group for 2001 and 2009. We can infer from this that as households reached retirement, they were not likely to be able to escape asset poverty as they have reduced earning potential. We find a marginal effect of between 3-7% for households younger households being asset poor compared to the 55-64 year old group.

5.4.7 Probability and duration of being asset poor

In this section we identify the conditional probability of a household being asset poor in two consecutive PSID waves and determine the probability of different subgroups remaining in asset poverty over two periods. Secondly, we evaluate the duration of asset poverty across the sample period, and various sub-periods.

To determine the conditional probability of a household being asset poor over two consecutive waves, we first track the head of the household over each wave. The household must be asset poor for each wave with respect to either NW or NW-HE. Secondly, we determine the probability of certain types of households remaining asset poor over two consecutive periods, with the aforementioned assumptions. The data-set is transformed longitudinally and we present nine sample periods. To calculate the conditional probability of being asset poor, equation 14 is employed. The results are presented in Table 21.

In the first panel we note the probability of remaining asset poor for all individuals increases in the 2005-2007 period (preceding the financial crisis), and reaches a maximum probability of remaining poor for both NW and NW-HE households in the 2007-2009 period. In subsequent periods, there is a lower probability of remaining poor which we identify in the recovery period. Interestingly, the findings suggest that across the sample, on average approximately 62% of households stay in NW poverty for two consecutive waves. In other words, six out of ten households who are asset poor today, will remain asset poor in two years time, compared to our original estimate of NW asset poverty (see Table 15) where on average approximately 25% of all households are asset poor in any one year. From this we can deduce that 15% of the overall U.S. population have, on average, been asset poor for at least two years between 1999-2017. [43]

Table 21 also identifies some common themes found in early sections. Notably, black households are more likely to stay asset poor compared to white households. Renters are approximately 15% more likely to stay asset poor than households who own their home. Education across the years seems to have a small effect on households probability of staying asset poor. Notably, before the financial crisis, college educated households had approximately 6% less likelihood of being asset poor compared to high school educated households. However, after the financial crisis, this difference was insignificant, and both education groups followed a similar trend. Finally, we note the high probability of the 65+ age group remaining asset poor compared to other age groups. On average, across the sample, the 65+ age group had approximately 70% probability of staying poor. Intuitively, we can infer from this that elderly household who enter retirement with few assets, are unlikely to transition out of poverty.

Another interesting facet is how the poverty rates for NW-HE is occasionally

[43] Calculated by (25*0.6)

lower than the NW poverty rate in some periods. In particular, eight out of fourteen subgroups have a higher probability of being NW poor in two consecutive waves than NW-HE in the 2007-2009 wave. Notable subgroups that have higher probability of being NW poor include, "All individuals", "White households", and "35-44, 45-54, 55-64" age groups in the 2007-09 wave. A higher probability of staying NW asset poor over two waves in the 2007-09 period most likely stems from the fall in house prices that was seen during the 2008 financial crisis. For example, white households, households aged over 25, and college educated households have a higher probability to stay NW poor compared to NW-HE. This is reasonable, as previously mentioned, white households are more likely to own a home rather than rent compared to black households.[44] Households over the age of 25 are also more likely to own a home. Furthermore, as households age over the life cycle, their housing equity increases, and this is most likely why we see age groups "55-64, 65+" have higher levels of probability of being poor in future waves compared to younger households, as older households were exposed most to the largest fall in house prices. This stems from the house price collapse households experienced over the 2008 financial crisis. Falling house prices in 2008 meant households who had large LTV ratios lost the majority of their housing equity, which a large proportion (see Mian and Sufi (2015)).

Table 22 identifies the length of households stay in asset poverty across varying periods of the sample period for both NW and NW-HE. Firstly, the number of households who are asset poor more than eight years increases after the financial crisis compared to before. Approximately 10% more households are NW asset poor between 2009-2017, compared to 1999-2017. This substantial increase highlights the increased difficulty households have of building asset wealth after the financial

[44]Black households probability of remaining poor over the 2007-09 period did not increase by the same magnitude as white households

crisis compared to before. Secondly, we note that around 8% of households are asset poor across the entire sample period. Finally, on review of the crisis period (2007-11) we see that approximately 50% of households stayed poor.

5.4.8 Transition in and out of asset poverty

In this section we determine if there are certain events that can lift a household out of asset poverty, or push them into asset poverty. Some events may be planned, for example the birth of a new child can significantly raise household consumption, and therefore reduce household wealth. Other events may not be planned; for example receiving inheritance, or losing your home. In particular, identifying significant life events that can increase the likelihood transitioning out of poverty, and understanding why households transition into asset poor is important to both policy makers and academics.

We identify households who transition into and out of NW asset poverty using a probit model. We test over four sample periods, namely 1999-01, 2007-09, 2009-11, and 2015-2017. This allows us to see which events are significant in both expansionary environments (1999-01, 2015-17) and periods of economic contraction (2007-09, 2009-11). We estimate two separate probit regressions, firstly on households moving into asset poverty, defined as "In", and moving out of asset poverty "Out". We control for household characteristics, including dummies for age, race, and sex of the head. All independent variables are defined as dummies. "Inheritance" is defined as 1 if receiving inheritance across the sample period, "New child" is 1 if a child was born in the period, and "Child left" is 1 if a child left respectively. "Bought home, Lost home" dummies refer to if a household bought or lost ownership of their home. "Education" refers to if the head of the household increased their education by 1 academic year. "Married, Divorced" are dummies that reflect if a household married over the period, or they divorce or were separated due to a spouse dying. "Rent all years" is 1 if the household rented across the sample period tested. The results for NW and NW-HE are reported in Tables 23 and 24 respectively.

The results indicate that for both NW and NW-HE, households who have a new child are more likely transition into asset poverty across all waves. Similarly, having a new child reduces the probability of a household moving out of asset poverty across each wave, except for the 1999-01 wave for NW-HE.

Another strong signal highlighted is losing a home significantly increases the likelihood of a household transitioning into asset poverty, and are less likely to transition out of asset poverty. We see a mixed signal in the 2007-09 and 2009-11 wave for NW-HE, where the lost home coefficient is positive for transitioning out, indicating an increased chance of moving out of poverty, however, every other wave has expected estimated coefficient signs. This positive sign could infer that as households lost wealth through house price collapses, households who lost their homes converted their remaining household wealth (and potential savings on mortgage costs) into safer assets such as cash and bonds. Consequently this raised their chances of moving out of NW-HE poverty, compared to NW asset poverty.

We note mixed responses for both inheritance and rent all year dummies. As expected with the large sums of monies involved with inheritances, receiving inheritance is less likely to to transition into poverty for both NW and NW-HE, however for most waves we see weak or no significance for inheritance preventing households transitioning into asset poverty. We do not see expected results for inheritance of people transitioning out. Households are less likely to transition out of poverty when receiving inheritance, however, this also little significance across the sample period. Additionally, we note that renting for all years increases the likelihood of remaining in poverty, but has mixed responses for leaving poverty.

Table 25 and 26 present probit results for different type of households over the financial crisis (2007-09). Namely, we test how married households, white and black households, and male headed households transition into and out asset poverty for both NW and NW-HE. Firstly, married households are more likely to transition into asset poverty when renting across and increasing education across the period for both NW and NW-HE. Interestingly, buying a home during the financial crisis increased the chances of a married household moving out of poverty and were less likely to transition into poverty, albeit with weak significance. We can infer households could have been able to purchase properties at discounted prices over this period, and this is why significance is only found for NW and not NW-HE.

White and black households reacted similarly during the financial crisis with similar coefficients for transitions into and out of asset poverty. Notably, increasing education increased the probability of white and black households moving out of asset poverty. However, increasing education also increased the likelihood of white households moving into asset poverty, however, no significance was found for black households. This could indicate that fewer black households may not have entered into education during the crisis period and therefore they forgo the risk of moving into poverty by increasing education at the loss of current income. Secondly, inheritance decreased the likelihood of white households moving into asset poverty, however, no significance was found for black households who received inheritance. This provides support to the aforementioned literature, that black households are less likely to receive significant inheritance compared to white households. Finally, we note mixed signals for both races which differ from expected results. For example, both races who rent for all years are more likely to transition into poverty, and renters are also more likely to transition out of asset poverty. This most likely stems from endogeneity within this interaction term.

5.5 Robustness tests

In the definition of asset poverty, a household should be able to meet their basic needs for a *limited* period of time. We defined a household was asset-poor if their current assets could not support them over a minimum of three months. Caner and Wolff (2004) suggested the three month period based on the average number of weeks an individual would be unemployed for in the U.S. in the 1980s and 1990s. The average number of weeks of unemployment has risen since then. For example, the average number of weeks an individual was unemployed reached a height in July 2011 of 40.7 weeks, approximately nine months.[45] From July 2009 until March 2017 the average number of weeks an individual was unemployed for was at, or above, 25 weeks (6-months). As such, it is important to test how asset poverty rates vary when increasing the amount of time required that households need to meet for their basic needs. Consequently, we tested the asset poverty rates for a 6-month and 9-month period of time; the results are reported in Table 27 and 28 respectively.

Table 27 presents the 6-month asset poverty rates. Asset poverty rates are approximately 5 to 9% higher than the 3-month asset poverty rates. The 6-month asset poverty rates follow a similar trend to the 3-month rates, i.e. they are stable or falling during the boom period, then increase sharply during the bust, and then the poverty rates begin to reduce in the recovery period. Interestingly, the computations suggest that one in three households could not sustain their basic needs for a 6-month period. In comparison, one in four households could not

[45] Data from the U.S. Bureau of Labor Statistics. Graphical representation of this is provided by the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/UEMPMEAN).

sustain themselves under 3-month basic need requirement. Table 28 presents the results for a 9-month period of basic needs and contain the associated asset poverty rates. These rates are approximately 9 to 12% higher than the three-month time provision and follow a similar trend to the three and six month time periods.

These results indicate that asset poverty rates are significantly influenced by the number of months utilised in the definition of a 'limited time'. There have been a number of studies that support the standardised time of three months see (Azpitarte, 2011; Kim and Kim, 2013). Other countries have also seen notable increases in the length of unemployment. For example, Spain has an unemployment period of approximately eight months, and the United Kingdom has an average unemployment period of ten months (Azpitarte, 2008). Since the length of time of unemployment has not returned to pre-1999 levels (where an average of three months unemployment was the norm), we recommend revising the three month term of asset poverty to either four or six months. This increase will help better replicate asset poverty in today's economic environment.

Finally, robustness tests were conducted with population weights for the U.S. households, and clustered standard errors at the metropolitan level. No significant changes in the probit estimates were noted. Furthermore, controls for the conditional probability of being asset poor in two consecutive waves were reviewed. These included controls for employment, and a large decrease (of more than 20% variation in income where applied. We found black households had higher likelihood of being asset poor across time compared to white, indicating that black households are more significantly affected by loss of work and changes in income. This aligns with the wealth and asset poverty rates noted within the data-section.

5.6 Conclusion

In this study, we examine how asset poverty rates have evolved before and after the 2008 global financial crisis. Wealth is an important determinant of providing financial stability for households in times of uncertainty. The U.S. still officially analyses poverty rates through a households income and does not utilise data on household wealth. Wealth is a more useful proxy for financial security in comparison to household income.

When applying alternative definitions of poverty our findings suggest that asset poverty rates are approximately two to three times higher than the official measure of income poverty. Asset poverty rates have steadily risen since 1999 and reaching a height in 2011 across all three measures; net wealth, net wealth minus housing equity, and liquidity. Secondly, our results add to the catalogue of evidence that black and female households are more likely to experience asset poverty in comparison to white and married households. Thirdly, we find renters are much more exposed to experiencing asset poverty compared to homeowners. Finally, we find that the NW-HE measure of asset poverty should be utilised when analysing homeowners wealth, as a approximately 20% of homeowners do not have the assets to cover three months of their basic needs.

This study finds that U.S. asset poverty rates are higher than those suggested by U.S. government bodies, which are derived through income poverty methodologies. The main focus of U.S. poverty policies is still heavily focused on improving a household's income, not through helping households accumulate assets. Consequently, this leave a large proportion of households vulnerable to meet their basic subsistence needs in turbulent times, such as global pandemics, financial crisis, or unexpected unemployment. Policies designed to reduce poverty-persistence, for example increasing educational attainment in low-income households and providing strong youth support could help younger people avoid the likelihood of being poor across consecutive years.

5.7 Appendix

Table 13: Summary Statistics

	Observations	Percentage
Head age		
<25	6,469	4.73
25-34	25,614	18.73
35-44	32,849	24.88
45-54	32,848	24.02
55-64	20,349	14.88
64-75	11,036	8.07
75+	6,578	4.81
Head race		
White	84,600	62.62
Black	25,614	30.49
Asian	2,042	1.51
Hispanic	2,497	1.85
Head gender		
Male	105,303	76.97
Female	31,449	23.03
Head education		
High school	76,412	58.03
College	41,700	31.67
Post grad	13,568	10.70
Marital status		
Married	92,432	67.57
Not-married	44,370	35.43
Tenure		
Homeowner	87,210	63.75
Renter	43,906	32.09
Mortgage		
Yes	64,480	47.13
No	72,322	52.87
Vehicle ownership		
Yes	117,046	85.50
No	19,756	14.50

Authors calculations from the PSID data-set, waves included 1999-2017

	Observations	Percentage
Have a mortgage		
Yes	64,480	47.13
No	72,322	52.82
Behind on mortgage		
Yes	1,320	2.16
No	25,520	97.84
Restructured		
Yes	3,364	5.52
No	23,418	94.48
Foreclosure		
Yes	245	0.40
No	26,095	99.6

Table 13 (cont). Authors calculations from the PSID data-set, waves included 1999-2017

Table 14: PSID Wealth Distributions

	Mean ($)									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
NW	175.38	199.70	213.72	261.77	322.06	289.15	271.94	281.82	329.63	327.39
NW-HE	131.36	144.28	147.26	173.60	220.11	207.11	195.41	202.42	239.03	231.77
LIQ	57.23	63.53	75.62	83.44	94.93	83.29	75.43	81.76	85.55	99.12
	Percentiles									
NW										
10	0.00	-0.01	0.00	-0.06	-0.08	-7.00	-11.80	-10.80	-8.27	-4.80
25	4.50	5.00	6.00	6.80	6.90	3.00	2.26	2.50	4.00	4.20
50	37.00	45.60	51.18	65.00	76.80	57.80	48.98	51.00	60.70	59.50
75	139.00	169.00	188.00	239.90	285.00	235.00	225.00	230.00	261.75	257.00
90	365.00	439.60	486.00	610.40	724.50	630.00	695.40	693.00	773.50	786.00
NW-HE										
10	-1.80	-3.00	-3.95	-5.20	-6.50	-11.00	-12.80	-14.50	-15.50	-13.96
25	1.50	1.47	1.50	1.05	1.20	0.41	0.40	0.30	0.30	0.50
50	14.50	15.50	17.00	18.00	20.00	17.00	15.00	16.00	15.50	17.00
75	71.70	88.00	86.00	106.00	126.00	108.00	104.00	115.00	122.01	108.00
90	251.00	293.00	315.00	390.00	490.00	420.60	446.00	473.00	540.00	537.40
LIQ										
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
50	4.00	5.00	5.00	5.02	5.10	3.66	3.20	4.00	5.00	5.10
75	41.01	40.01	50.00	55.00	61.00	55.00	50.00	50.00	55.00	70.00
90	347.00	269.01	381.00	610.00	310.00	440.00	315.00	338.00	429.00	493.00

Source: Authors calculations from the PSID data-set. Values quoted in thousands of dollars. NW, NW-HE, and LIQ are calculated utilising variables from Table 13.

Table 15: U.S. asset poverty rates 1999-2017

	Asset poverty rate (%)									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
NW	23.01	22.70	21.78	21.50	22.26	26.74	28.14	27.78	25.85	26.16
NW-HE	30.89	31.29	31.45	31.60	31.80	34.15	35.14	35.01	34.44	35.47
LIQ	45.18	45.98	42.40	43.82	43.44	45.63	48.46	49.30	48.35	46.30

Source: Authors calculations from the PSID data-set. Rates are quoted in percentages and estimated using equation 13.

Table 16: U.S. asset poverty sub-samples percentage change

	Change in asset poverty rate (%)			
	1999-2007	2007-2017	2007-2011	1999-2017
NW	-3.26	17.52	26.42	13.69
NW-HE	2.95	11.61	11.20	14.83
LIQ	-3.85	6.58	11.56	2.48

Source: Authors calculations from the PSID data-set. Rates are quoted in percentages.

Table 17: Decomposed U.S. asset poverty rates 1999-2017

	U.S. asset poverty rate (%)									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
NW	23.01	22.70	21.78	21.50	22.26	26.74	28.14	27.78	25.85	26.16
NW-HE	30.89	31.29	31.45	31.60	31.80	34.15	35.14	35.01	34.44	35.47
	Household specific asset poverty rate (%)									
Age										
< 25										
NW	52.19	47.57	49.14	53.57	60.90	55.60	60.86	58.99	56.79	53.63
NW-HE	56.66	51.99	52.20	56.15	63.46	55.82	62.44	64.05	60.49	56.74
25-34										
NW	36.29	38.29	37.91	38.38	39.35	46.17	47.06	46.89	43.83	41.70
NW-HE	43.57	46.72	46.60	47.35	47.43	51.80	52.34	51.81	49.68	49.85
35-44										
NW	21.39	23.59	22.73	22.15	23.66	31.36	35.39	34.73	34.29	32.94
NW-HE	30.42	32.15	34.36	33.51	34.68	39.92	42.60	42.04	43.02	42.84
45-54										
NW	12.39	13.19	13.55	14.75	16.08	22.65	23.59	24.92	23.61	22.81
NW-HE	20.01	22.56	23.82	26.38	26.69	31.28	31.49	33.03	34.02	33.68
55-64										
NW	10.10	8.10	8.79	7.60	9.51	13.24	16.37	17.47	16.22	18.16
NW-HE	17.20	16.37	16.36	17.39	18.75	20.85	23.70	25.51	25.96	28.10
65+										
NW	11.58	11.99	11.30	12.86	11.09	11.45	10.92	10.57	11.17	10.84
NW-HE	20.75	20.57	20.52	21.16	20.22	18.62	18.42	18.73	19.18	19.49
Education										
High-school										
NW	29.40	28.31	27.18	27.34	28.92	33.27	34.47	34.07	31.59	32.50
NW-HE	39.08	38.63	39.19	39.40	33.97	42.46	43.56	44.00	41.57	43.42
College										
NW	16.61	16.49	16.82	16.69	16.68	22.41	24.57	24.60	22.98	22.53
NW-HE	23.13	23.20	24.59	24.71	24.75	29.01	30.28	30.30	30.63	30.74
Postgraduate										
NW	8.71	9.52	9.56	9.13	10.48	15.32	15.73	15.41	15.42	13.58
NW-HE	11.93	14.27	12.68	15.90	16.78	19.61	19.28	18.97	22.39	20.83
Race										
White										
NW	15.24	14.70	14.11	15.06	15.53	19.42	21.74	20.42	17.98	18.43
NW-HE	21.18	22.37	21.71	24.08	24.01	25.71	27.44	26.57	26.03	27.33
Black										
NW	37.28	36.96	37.13	35.81	37.18	41.70	41.10	42.86	41.50	39.38
NW-HE	47.46	47.56	49.18	47.69	49.10	51.64	50.34	52.57	51.24	48.54
Asian										
NW	19.28	12.56	10.10	16.40	13.37	14.29	18.42	18.57	11.03	12.06
NW-HE	22.87	19.63	22.12	29.63	19.77	17.86	27.63	23.57	18.38	23.05

Source: Authors calculations from the PSID data-set. Values quoted in thousands of dollars. NW, NW-HE, and LIQ are calculated utilising variables from Table 4.

Table 18 (cont)

	Household specific asset poverty rate (%)									
Tenure										
Homeowner										
NW	5.23	5.71	6.15	4.72	5.17	9.78	10.93	9.66	7.22	6.14
NW-HE	17.50	18.61	20.41	19.71	19.28	21.00	21.82	21.24	20.85	21.50
Renter										
NW	53.26	55.40	53.95	56.96	57.92	59.97	58.36	58.34	57.14	57.21
NW-HE	53.38	55.40	53.95	56.96	57.95	59.97	58.36	58.34	57.14	57.21
Marital status										
Married										
NW	13.99	14.67	13.70	13.44	14.06	19.33	20.11	19.65	18.17	20.92
NW-HE	21.85	23.24	22.48	23.70	23.32	26.47	26.88	26.51	26.94	30.16
Unmarried										
NW	42.26	40.76	38.61	39.07	40.03	42.64	44.45	45.21	43.55	39.76
NW-HE	50.19	49.11	50.13	48.76	50.16	50.64	51.94	53.50	51.74	49.24
Family composition										
$<$ 65years, married, male head										
NW	16.16	17.91	16.70	17.28	18.50	25.99	27.67	28.56	26.34	29.29
NW-HE	25.94	28.08	27.31	29.04	29.38	34.92	35.68	36.79	36.51	39.94
$<$ 65years, female head, children										
NW	55.71	53.98	50.88	48.67	51.03	56.71	56.89	54.54	57.45	55.46
NW-HE	62.76	63.40	63.65	58.18	64.21	66.85	65.79	68.00	64.90	63.43
$>$65years, married										
NW	4.43	5.26	4.95	5.29	5.59	5.37	6.14	5.07	5.80	5.46
NW-HE	11.87	10.66	10.89	10.98	11.68	10.30	11.98	11.32	12.77	12.43
$>$ 65years, female head										
NW	20.56	20.61	21.38	24.32	20.09	23.47	20.77	24.14	25.32	23.70
NW-HE	32.24	35.13	37.42	37.16	33.33	36.38	32.51	37.50	36.50	36.30

Source: Authors calculations from the PSID data-set. Values quotes above are percentage values.

Table 18: Asset poverty rates for households with mortgage trouble

	Asset poverty rate (%)			
	2011	2013	2015	2017
Behind on mortgage	43.11	31.73	25.33	14.71
Restructured mortgage	30.05	25.42	17.67	10.76
Foreclosure on mortgage	50.00	36.54	42.86	37.50

Source: Authors calculations from the PSID data-set. Rates are quoted in percentages.

Table 19: Official and asset poverty rates 1999-2017

	Poverty rate (%)									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
All individuals										
Official	11.90	11.70	12.50	12.60	12.50	14.30	15.00	14.50	13.50	12.30
NW	23.01	22.70	21.78	21.50	22.26	26.74	28.14	27.78	25.85	26.16
NW-HE	30.89	31.29	31.45	31.60	31.80	34.15	35.14	35.01	34.44	35.47
Gender										
Male										
Official	10.40	10.40	11.20	11.10	11.10	13.00	13.60	13.10	12.20	11.00
NW	16.88	16.76	16.15	16.24	16.60	21.40	22.75	21.98	20.51	21.96
NW-HE	24.50	25.09	25.02	26.10	25.56	28.06	29.23	28.70	28.91	31.12
Female										
Official	13.20	12.90	13.70	14.10	13.80	15.60	16.30	15.80	14.80	13.60
NW	44.07	46.95	41.01	39.99	41.60	45.04	45.63	47.64	45.04	42.55
NW-HE	52.68	53.43	53.44	50.82	53.10	55.00	54.33	57.01	56.55	52.43
Age										
Male 18-64										
Official	8.30	8.50	9.10	9.10	9.10	11.20	11.80	11.80	10.50	9.40
NW	17.45	17.75	17.08	17.13	17.67	23.24	25.03	24.94	23.48	25.34
NW-HE	25.29	26.11	26.17	27.38	26.83	30.14	31.61	31.73	32.20	34.90
Male 65+										
Official	6.80	7.00	7.30	7.30	6.60	6.60	6.20	6.80	7.00	7.50
NW	6.37	7.24	5.69	7.01	6.87	6.49	6.97	5.78	6.46	6.76
NW-HE	14.09	12.53	11.76	12.99	14.06	11.33	12.77	12.10	13.41	14.16
Female 18-64										
Official	11.80	11.60	12.40	13.00	12.60	14.60	15.50	15.30	14.20	13.00
NW	48.64	47.52	44.58	42.94	35.57	49.07	50.53	53.00	50.34	47.88
NW-HE	56.08	56.55	56.35	53.38	56.79	58.50	58.63	61.47	59.08	57.00
Female 65+										
Official	11.70	12.40	12.50	12.30	12.00	10.70	10.70	11.60	10.30	10.50
NW	20.56	20.61	21.38	24.32	20.09	23.47	20.77	24.14	25.32	23.70
NW-HE	32.24	35.13	37.42	37.16	33.33	36.38	32.51	37.50	36.50	36.30
Race										
White										
Official	9.80	9.90	10.50	10.60	10.50	12.30	12.80	12.30	11.60	10.70
NW	15.24	14.70	14.11	15.06	15.53	19.42	21.74	20.42	17.98	18.43
NW-HE	21.18	22.37	21.71	24.08	24.01	25.71	27.44	26.57	26.03	27.33
Black										
Official	23.60	22.70	24.40	24.90	24.50	25.80	27.60	27.20	24.10	21.20
NW	37.28	36.96	37.13	35.81	37.18	41.70	41.10	42.86	41.50	39.38
NW-HE	47.46	47.56	49.18	47.69	49.10	51.64	50.34	52.57	51.24	48.54
Asian										
Official	10.70	10.20	11.80	11.10	10.20	12.50	12.30	10.50	11.40	10.00
NW	19.28	12.56	10.10	16.40	13.37	14.29	18.42	18.57	11.03	12.06
NW-HE	22.87	19.63	22.12	29.63	19.77	17.86	27.63	23.57	18.38	23.05

Source: Authors calculations from the PSID data-set.

Table 20: Probit regressions on asset poor households; NW and NW-HE

	2001		2009		2017	
	NW	NW-HE	NW	NW-HE	NW	NW-HE
Age <25	2.609***	2.145***	1.788***	1.557***	1.314***	1.229***
	(0.074)	(0.065)	(0.071)	(0.068)	(0.078)	(0.074)
Age 25-34	2.682***	2.168***	1.757***	1.541***	1.204***	1.116***
	(0.060)	(0.049)	(0.049)	(0.043)	(0.049)	(0.042)
Age 35-44	2.370***	1.780***	1.494***	1.250***	1.094***	0.992***
	(0.061)	(0.049)	(0.049)	(0.041)	(0.048)	(0.042)
Age 45-54	2.156***	1.656***	1.295***	1.033***	0.901***	0.772***
	(0.065)	(0.051)	(0.048)	(0.041)	(0.052)	(0.042)
Age 65+	0.828**	0.701***	0.712***	0.533***	0.025	0.083
	(0.378)	(0.247)	(0.239)	(0.165)	(0.124)	(0.104)
High-school	0.377***	0.515***	0.576***	0.524***	0.463***	0.590
	(0.031)	(0.026)	(0.030)	(0.027)	(0.031)	(0.026)
Postgraduate	0.102	0.036	0.260***	1.204***	0.179***	0.035
	(0.069)	(0.055)	(0.053)	(0.047)	(0.053)	(0.044)
Homeowner	-1.488***	-0.601***	-1.204***	-0.532***	-1.409***	-0.440***
	(0.033)	(0.028)	(0.033)	(0.037)	(0.034)	(0.028)
White	-0.201***	-0.234***	-0.055*	-0.158***	-0.108	-0.104***
	(0.031)	(0.027)	(0.031)	(0.028)	(0.031)	(0.027)
Married male	0.415***	0.581***	1.089***	1.156***	1.505***	1.415***
	(0.048)	(0.043)	(0.046)	(0.042)	(0.048)	(0.042)
Single female	0.868***	1.137***	1.476***	1.687***	1.890***	1.892***
	(0.051)	(0.046)	(0.048)	(0.043)	(0.050)	(0.044)
Elderly female	1.800***	1.687***	1.310***	1.522***	2.147***	2.010***
	(0.381)	(0.249)	(0.239)	(0.169)	(0.130)	(0.111)
N	3,141	4,981	3,291	3,515	1,085	4,232
Log Likelihood	-5,066	-7,421	-5,759	-7,201	-5,576	-7,630

Table 20. Authors calculations from the PSID. Standard errors are in parentheses. ***, **, * is significant at the 1%, 5%, and 10% level respectively.

Table 21: Conditional probability of being asset-poor in two consecutive waves

	Probability of remaining poor (%)								
	1999-01	2001-03	2003-05	2005-07	2007-09	2009-11	2011-13	2013-15	2015-17
All individuals									
NW	58.52	57.70	58.84	62.04	69.38	67.00	65.78	61.27	61.21
NWHE	61.73	60.46	61.46	62.69	67.61	67.27	66.45	64.62	62.72
Race									
White									
NW	53.54	51.36	62.96	57.13	66.28	66.80	63.41	54.43	58.91
NWHE	59.65	55.63	67.76	57.60	63.90	64.97	64.79	60.00	59.48
Black									
NW	62.81	64.50	63.20	66.97	72.08	68.22	69.70	68.71	64.98
NWHE	63.66	65.53	64.86	69.59	75.09	69.52	70.01	70.28	66.68
Tenure									
Homeowner									
NW	44.14	46.07	31.78	47.47	56.77	55.00	48.76	45.54	51.16
NWHE	57.26	57.03	50.25	53.48	59.81	57.30	54.89	57.00	57.36
Renter									
NW	61.80	59.90	66.84	65.74	69.35	71.04	71.55	66.74	64.15
NWHE	64.54	62.40	71.61	70.01	74.24	74.06	73.48	70.40	66.99
Education									
High school									
NW	58.94	60.56	61.97	65.60	66.82	67.33	64.26	60.30	59.52
NWHE	61.87	63.47	64.28	64.75	66.86	67.66	65.29	62.83	62.11
College									
NW	52.49	54.84	54.23	57.98	75.23	66.82	66.18	60.01	61.73
NWHE	57.31	57.49	58.01	61.45	72.85	67.24	66.76	65.11	62.49
Postgraduate									
NW	58.00	61.11	56.73	55.67	68.02	66.06	74.18	64.76	61.12
NWHE	62.04	48.76	55.07	53.25	94.21	87.53	64.15	73.94	63.93
Age									
< 25									
NW	35.28	38.39	41.63	55.56	47.02	61.63	53.53	41.63	53.26
NW-HE	39.14	39.94	57.14	59.72	53.54	68.73	59.78	45.85	56.12
25-34									
NW	66.73	60.87	61.51	60.13	69.58	63.64	67.94	60.91	58.36
NW-HE	70.01	62.90	61.34	62.53	68.55	66.25	68.47	63.64	62.87
35-44									
NW	55.06	56.21	54.76	57.23	72.96	71.59	66.94	63.78	62.80
NW-HE	56.81	59.86	54.70	59.12	68.34	70.98	66.03	65.73	63.69
45-54									
NW	72.72	60.75	63.30	69.50	68.76	62.48	60.48	58.10	57.68
NW-HE	75.60	60.89	65.20	64.12	65.70	60.57	62.94	62.96	58.63
55-64									
NW	58.41	73.91	65.89	91.40	91.11	82.19	72.65	65.45	66.32
NW-HE	60.23	73.11	76.25	76.10	82.81	77.39	70.67	69.67	62.15
65+									
NW	68.89	67.36	73.24	58.00	71.71	64.67	73.37	77.65	70.28
NW-HE	64.46	68.42	73.38	61.15	63.53	62.86	70.18	73.27	72.25

Source: Authors calculations from the PSID data-set.

Table 22: Duration of asset poverty

	Duration of households in poverty (%)			
	1999-2007	2007-2011	2009-2017	1999-2017
NW	20.25	50.91	30.32	7.74
NWHE	23.01	49.61	27.18	8.28

Source: Authors calculations from the PSID data-set. Statistics shown are for all individuals. Duration is defined as the percentage of people who started as asset poor and remained asset poor throughout the whole sample period. For example, between 1999-2007 approximately 23 percent of households who were NW-HE asset poor in 1999, remained asset poor in 2007.

Table 23: Transitions into, and out of poverty, NW Probit regressions

	1999-01		2007-09		2011-13		2015-17	
	In	Out	In	Out	In	Out	In	Out
Inheritance	0.194	-0.058	0.179**	-0.294***	-0.030	-0.076*	0.281	-0.319
	(0.128)	(0.150)	(0.083)	(0.069)	(0.053)	(0.044)	(0.189)	(0.086)
New child	0.233***	-0.119***	0.068	-0.035	0.126**	-0.077	0.199***	-0.275***
	(0.057)	(0.050)	(0.049)	(0.062)	(0.053)	(0.052)	(0.053)	(0.051)
Child left	-0.294	0.117***	0.329	0.109**	0.381	0.165***	0.321	0.237***
	(0.192)	(0.044)	(0.031)	(0.046)	(0.263)	(0.028)	(0.040)	(0.042)
Bought home	0.052	1.112***	-0.218*	1.316***	-0.260**	1.326***	-0.053	1.620
	(0.081)	(0.064)	(0.115)	(0.088)	(0.128)	(0.081)	(0.122)	(0.0712)
Lost home	0.552***	-1.132***	0.758***	-1.112***	0.632***	-0.581***	0.419***	-0.758***
	(0.097)	(0.167)	(0.088)	(0.157)	(0.95)	(0.118)	(0.096)	(0.161)
Education	1.317***	-0.255***	1.754***	-0.672***	0.634***	-0.566**	1.338***	-0.523***
	(0.163)	(0.056)	(0.192)	(0.063)	(0.008)	(0.050)	(0.007)	(0.048)
Married	-0.221**	0.009	0.235***	0.092	0.109	0.114	0.210	0.238***
	(0.093)	(0.076)	(0.079)	(0.087)	(0.089)	(0.0801)	(0.193)	(0.069)
Divorced	0.219	0.211	0.201	-0.231	0.0241	0.324	0.211	0.412
	(0.182)	(0.182)	(0.192)	(0.198)	0.141	(0.241)	(0.132)	(0.298)
Rent all years	0.863***	0.956***	0.243***	1.204***	0.338***	0.910***	0.982***	0.898***
	(0.056)	(0.033)	(0.054)	(0.037)	(0.057)	(0.034)	(0.0496)	(0.035)
N	1,201	4,366	1,315	3,515	1,085	4,232	1,446	3,725
R^2	0.213	0.212	0.199	0.296	0.096	0.221	0.322	0.214

Authors calculations from the PSID. Standard errors are in parentheses "In" refers to a households transitioning into poverty. "Out" implies a household transferred out of poverty. All regressions include controls for demographics including age, race, and gender. ***, **, * is significant at the 1%, 5%, and 10% level respectively.

Table 24: Transitions into, and out of poverty, NWHE Probit regressions

	1999-01		2007-09		2011-13		2015-17	
	In	Out	In	Out	In	Out	In	Out
Inheritance	-0.189*	-0.247***	-0.220***	-0.163***	-0.025	0.050	0.081	0.104
	(0.010)	(0.063)	(0.066)	(0.049)	(0.099)	(0.038)	(0.098)	(0.091)
New child	0.186***	0.118***	0.197***	0.063	0.240***	0.119***	0.184***	-0.263***
	(0.034)	(0.035)	(0.040)	(0.043)	(0.042)	(0.043)	(0.045)	(0.044)
Child left	0.121	-0.263***	0.195	0.937***	0.091	1.145***	0.149	0.291***
	(0.090)	(0.021)	(0.132)	(0.025)	(0.103)	(0.025)	(0.121)	(0.037)
Bought home	0.164**	0.416***	0.430***	0.585***	0.615**	0.966***	-0.193**	0.631***
	(0.023)	(0.020)	(0.018)	(0.039)	(0.046)	(0.039)	(0.089)	(0.075)
Lost home	0.573***	-0.041	0.903***	0.168***	1.145***	0.274***	0.005	0.063
	(0.029)	(0.029)	(0.037)	(0.046)	(0.041)	(0.051)	(0.103)	(0.107)
Education	0.241***	-0.381***	0.328***	0.040	0.410***	0.097***	1.528***	-0.519***
	(0.031)	(0.031)	(0.034)	(0.035)	(0.037)	(0.036)	(0.010)	(0.038)
Married	0.021	0.437***	-0.036	0.126*	-0.023	-0.032	0.310	0.321***
	(0.065)	(0.063)	(0.083)	(0.076)	(0.087)	(0.081)	(0.199)	(0.064)
Divorced	0.349	0.341	0.201	(0.323)	0.131	0.410	0.292	0.192
	(0.193)	(0.242)	(0.192)	(0.200)	0.152	(0.302)	(0.194)	(0.182)
Rent all years	0.142***	0.514***	-0.037	0.796***	0.031	0.850***	0.312***	0.357***
	(0.035)	(0.025)	(0.043)	(0.030)	(0.045)	(0.029)	(0.042)	(0.031)
N	1,573	5,727	1,465	5,089	1,284	5,394	1,944	4,909
R^2	0.139	0.135	0.150	0.139	0.153	0.157	0.231	0.130

Authors calculations from the PSID. Standard errors are in parentheses "In" refers to a households transitioning into poverty. "Out" implies a household transferred out of poverty. All regressions include controls for demographics including age, race, and gender. ***, **, * is significant at the 1%, 5%, and 10% level respectively.

Table 25: Transitions into, and out of poverty, 2007 NW household characteristics

	Married household		White head		Black head		Male head	
	In	Out	In	Out	In	Out	In	Out
Inheritance	-0.179**	-0.255***	-0.216**	-0.074	0.023	-0.122	-0.174**	-0.214***
	(0.082)	(0.056)	(0.107)	(0.086)	(0.119)	(0.110)	(0.083)	(0.095)
New child	0.068	0.007	0.135**	0.364***	0.035	-0.184**	0.073	-0.531***
	(0.049)	(0.055)	(0.061)	(0.086)	(0.073)	(0.090)	(0.049)	(0.098)
Child left	0.231	0.112**	0.291	1.294***	0.294	0.845***	-0.282***	1.098***
	(0.192)	(0.045)	(0.182)	(0.047)	(0.190)	(0.057)	(0.098)	(0.039)
Bought home	-0.218*	0.696***	-0.363**	0.901***	0.182	0.582***	-0.209*	0.911***
	(0.115)	(0.079)	(0.154)	(0.075)	(0.182)	(0.115)	(0.114)	(0.105)
Lost home	0.758***	0.009	0.688***	-1.391***	0.545***	-1.059***	0.734***	-0.715***
	(0.087)	(0.081)	(0.115)	(0.216)	(0.106)	(0.255)	(0.085)	(0.083)
Education	1.754***	0.070	2.440***	0.269***	0.129	0.313***	2.695***	-0.199***
	(0.192)	(0.047)	(0.177)	(0.084)	(0.089)	(0.079)	(0.163)	(0.039)
Married	0.139*	0.431	0.143	0.249**	0.302***	0.158	0.138*	0.221***
	(0.081)	(0.070)	(0.109)	(0.112)	(0.104)	(0.124)	(0.081)	(0.078)
Divorced	0.189	0.102	0.319	0.418	0.244	0.241	0.131	0.323***
	(0.101)	(0.091)	(0.231)	(0.281)	(0.152)	(0.192)	(0.090)	(0.082)
Rent all years	0.243***	1.011***	0.239***	1.556***	0.528***	1.481***	0.263***	2.063***
	(0.054)	(0.032)	(0.071)	(0.046)	(0.078)	(0.051)	(0.054)	(0.043)
N	750	2,288	686	1,565	505	1,642	902	1,552
R^2	0.200	0.214	0.465	0.487	0.142	0.360	0.466	0.532

Authors calculations from the PSID. Standard errors are in parentheses “In” refers to a households transitioning into poverty. “Out” implies a household transferred out of poverty. All regressions include controls for demographics including age, race, and gender. ***, **, * is significant at the 1%, 5%, and 10% level respectively.

Table 26: Transitions into, and out of poverty, 2007 NWHE household characteristics

	Married household		White head		Black head		Male head	
	In	Out	In	Out	In	Out	In	Out
Inheritance	-0.068	-0.271***	-0.259**	-0.045	0.148	0.071	-0.062	-0.026
	(0.071)	(0.049)	(0.097)	(0.060)	(0.097)	(0.072)	(0.071)	(0.050)
New child	0.072	-0.078*	0.049	0.182***	0.203***	-0.059	0.079*	0.078*
	(0.045)	(0.045)	(0.056)	(0.054)	(0.067)	(0.068)	(0.045)	(0.045)
Child left	0.121	0.199**	1.576***	1.294***	0.131	1.14***	0.128	1.606***
	(0.191)	(0.037)	(0.102)	(0.035)	(0.090)	(0.043)	(0.131)	(0.028)
Bought home	0.004	0.156	0.001	0.027	-0.189	0.041	0.009	0.059
	(0.095)	(0.096)	(0.115)	(0.094)	(0.175)	(0.132)	(0.095)	(0.078)
Lost home	0.093	-0.443***	0.121	-0.664***	0.007	-0.619***	0.085	-0.697***
	(0.097)	(0.103)	(0.131)	(0.125)	(0.127)	(0.152)	(0.097)	(0.098)
Education	1.835***	-0.476***	2.733***	0.741***	0.098	0.593***	2.744***	0.761***
	(0.175)	(0.043)	(0.206)	(0.047)	(0.079)	(0.058)	(0.148)	(0.039)
Married	-0.138	0.091	-0.121	0.278**	0.018	0.031	-0.136	0.135*
	(0.086)	(0.078)	(0.112)	(0.096)	(0.119)	(0.116)	(0.086)	(0.078)
Divorced	0.109	0.210	0.192	0.178	0.244	0.129	0.289	0.103
	(0.089)	(0.131)	(0.135)	(0.151)	(0.102)	(0.092)	(0.239)	(0.097)
Rent all years	0.109**	0.541***	0.088	0.976***	0.410***	0.937***	0.123**	1.004***
	(0.052)	(0.033)	(0.070)	(0.040)	(0.073)	(0.042)	(0.053)	(0.031)
N	866	2,607	775	2,477	564	2,194	1010	3,211
R^2	0.150	0.139	0.455	0.366	0.062	0.257	0.442	0.323

Authors calculations from the PSID. Standard errors are in parentheses "In" refers to a households transitioning into poverty. "Out" implies a household transferred out of poverty. All regressions include controls for demographics including age, race, and gender. ***, **, * is significant at the 1%, 5%, and 10% level respectively.

Table 27: U.S. asset poverty rates 1999-2017, 6-month basic need threshold

	Asset poverty rate (%)									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
NW	28.83	27.77	26.53	26.18	26.06	31.02	32.37	32.33	30.18	31.15
NW-HE	38.96	39.72	38.72	39.17	38.06	41.38	42.64	42.29	41.82	43.05
LIQ	52.23	52.74	50.96	50.51	49.57	52.23	54.71	55.68	55.32	53.44

Source: Authors calculations from the PSID data-set. Rates are quoted in percentages and estimated using equation 13.

Table 28: U.S. asset poverty rates 1999-2017, 9-month basic need threshold

	Asset poverty rate (%)									
	1999	2001	2003	2005	2007	2009	2011	2013	2015	2017
NW	32.39	30.61	29.93	29.17	28.60	33.57	35.65	35.77	33.75	34.49
NW-HE	44.90	44.72	44.04	44.19	43.12	45.86	48.06	47.62	47.53	48.31
LIQ	56.11	56.74	55.70	54.42	53.44	56.20	58.50	59.29	58.81	56.86

Source: Authors calculations from the PSID data-set. Rates are quoted in percentages and estimated using equation 13.

6 House Prices and Household Consumption: A Micro Panel Study

Housing is typically the single largest asset held in a household's wealth portfolio. Increasing house prices have historically led to higher household borrowing and consumption, a phenomenon attributed to the 'wealth effect'. Negative changes in house prices have caused higher delinquency rates, reduced household consumption, and was an underpinning factor of the global financial crisis. There is empirical evidence documenting the relationship between house price changes and household consumption. The various explanations for the relationship, and magnitude, is not well understood. This paper investigates whether unexpected house prices innovations significantly affect U.S. household consumption through the 'wealth effect' channel. In this chapter we study the relationship between unexpected changes in house prices and household expenditure. We link detailed information on household consumption and financial decisions available in the Panel Study of Income Dynamics, to house price appreciation rates in neighbourhoods where these households reside. To compare house price appreciation, we use local house price data from the online real estate database company, Zillow. By combining the datasets in a novel approach, local house price appreciation can be linked to the household survey at a finer geographical precision than previous studies. This allows us to directly test the wealth effect and its magnitude for U.S. households. We find little significance of the wealth effect, except for young and old households who have low liquidity. They experienced negative wealth effects after the global financial crisis in 2008, most likely due to losses in wealth during the crisis. We believe this is due to a combination of the collateral effect channel and the wealth effect channel. We find the average MPC in young and old, illiquid households to reduce consumption by 0.65 and 0.63 percentage points out of housing wealth after the crisis. This is relatively small compared to the prior literature's findings.

6.1 Introduction

Housing is typically the single most significant asset a household holds in their wealth portfolio (Knoll et al., 2017). Piketty and Zucman (2014), suggest that the late twentieth century's surge in wealth-to-income ratios in Western economies is primarily due to increasing housing wealth. The importance of housing is more evident for poor U.S. homeowners, which according to Mian and Sufi (2015), hold \$4 of housing equity for every \$1 of other assets.[46] Consequently, homeowners who are highly leveraged, or are credit constrained, are more vulnerable to house price changes.

The collective agreement in the literature is that there is a positive relationship between household wealth, house price growth, and household consumption (Campbell and Cocco, 2007; Cooper, 2013). However, there are multiple proposed channels that drive both the magnitude and reasoning as to why these relationships exists. The most common channels used to describe this relationship include the wealth effect (Browning et al., 2013), and the collateral borrowing (Cooper, 2013) channels. Understanding how household wealth and household consumption are intrinsically linked has become an important question to understand for both academics and policymakers, especially since the great financial crisis.

From 1996 to 2006, U.S. house prices increased cumulatively by 92%, as documented by Reinhart and Rogoff (2009). Housing differs from other financial assets in that housing serves as a dual purpose: it is both a consumption and investment vehicle. The former derives utility for the homeowner, and the latter is an investment that allows the investor to hold, and generate, home equity (Yao and Zhang, 2005).

[46] The median U.S. household held 37.4% of their total wealth in housing wealth between 2001 and 2010 (Cooper and Dynan, 2016; Wolff, 2016)

It is widely accepted that housing is a risky asset (Cardak and Wilkins, 2009; Case and Shiller, 2003; Sinai and Souleles, 2005). Home-ownership exposes households to both financial risk, through unpredictable movements in housing markets, and liquidity risk, as housing is an illiquid investment compared to stocks and other financial instruments. A certain proportion of the volatility within house prices can be attributed to the locality of the home (Lee, 2009; Miller and Peng, 2006). However, national volatility also significantly affects the price fluctuations of housing prices for the U.S. and the United Kingdom (Campbell and Cocco, 2007). Hence, with the value of a home being the dominant asset in the wealth portfolio of a household, identifying whether innovations in house prices affect household consumption has become an essential area of research.

This study aims to analyse the effects of expected and unexpected changes in housing wealth on U.S. household consumption, commonly known as the wealth effect. Furthermore, we aim to study how different compositions of households and different ownership options react to expected and unexpected changes in housing wealth.

There are alternative theories within the literature as to why there is a correlation between house price changes and aggregate consumption. Firstly, some authors suggest that, through the life-cycle model, when there is an unexpected increase (decrease) in house prices, this can permanently increase (decrease) a household's consumption in subsequent years by allowing them to utilise the increase in wealth. This is known as the wealth effect (Campbell and Cocco, 2007; Case and Shiller, 2003; Gröbel and Ihle, 2018).

The second channel is known as the 'collateral effects channel'. This channel postulates that increases in house prices relax borrowing constraints on households. This in turn, can increase their consumption as a household can utilise their new-found equity in their property through the use of mortgage contracts and loans (Aoki et al., 2004; Cooper, 2013; Iacoviello, 2004). This channel directly affects credit-constrained[47] homeowners, who borrow money today so they can perform consumption smoothing over future periods.

Finally, a few authors suggest that there is no reason to believe that house prices and consumption are intrinsically linked. Instead, the correlation between unobserved macroeconomic co-factors explain the relationship between house prices and consumption (Attanasio et al., 2009). Furthermore, financial liberalisations of national and local banks within individual countries can ease credit constrains on households (Muellbauer, 2007). According to Buiter (2008), housing is both a consumption good and investment vehicle, and house price changes are purely re-distributive and have no impact on the aggregate consumption of households. The literature highlights several possible channels and theories as to why there is a relationship between house price changes and household consumption. This study will explore if the wealth effect channel drives the correlation between house price changes and household consumption.

This study is most closely related to Browning et al. (2013) and Cooper (2013). Browning et al. (2013) uses Danish data between 1987 and 1996 and found that young households are likely to be affected by credit constraints compared to older households, who do not react to house price changes. Furthermore, households were found to use housing equity as collateral for consumption loans, providing further evidence for the collateral channel. The methodology employed in this paper builds upon the framework outlined by Browning et al. (2013). This allows this study to analyse expected and unexpected house price and income level changes for different household types (renters; homeowners with a mortgage; homeowners

[47] We define a 'credit-constrained' household who would consume more today if it were possible, but cannot due to borrowing constraints.

without a mortgage), different ages (young and old) and different liquidity levels (liquid and illiquid households).[48] Cooper (2013) investigates the Panel Study of Income Dynamics (PSID) data-set in respect to the collateral borrowing channel. The author findings suggest that borrowing constrained households increase their consumption between $0.06 and $0.10 per dollar increase in housing equity, with unconstrained households not changing their consumption in response to changes in house prices.

Previous literature omits household debt and leverage when investigating the wealth effect or collateral channel. Traditional models indicate that debt does not independently influence consumption (Cooper and Dynan, 2016).[49] However, there is a growing literature that suggests household debt and leverage levels can cause a household to reduce their consumption. Firstly, households may target a specific level of debt relative to their income or assets. Subsequent changes in wealth could affect their predefined ratios, and households react by changing their current consumption levels. Secondly, households who are concerned about credit constraints may restrict their consumption in order to increase savings. Thirdly, high debt-to-income levels will require substantial service payments. This can affect consumption when there are changes in interest rates (especially in countries with high proportions of variable rate mortgages such as the UK). These ideas highlight how household debt and leverage can affect consumption in future periods (Dynan and Edelberg, 2013). As such, this study will investigate how highly-indebted households consumption changes to innovations in house prices.

This study contributes to the existing literature in a number of ways. Firstly, we use a novel approach by combining the PSID data-set with data from the

[48]We define a liquid household as having cash savings equal or more than two months of their disposable income, and illiquid households as having cash savings less than two months of their disposable income. More information is provided in the results section

[49]It is known that there is an endogenous relationship between debt and consumption as debt can finance consumption habits

online real estate database, Zillow. The combination of both data-sets allows us to geographically locate house price movements to a higher accuracy than the previous literature (Browning et al., 2013). Secondly, we study the wealth effect between 1999 and 2015. This period encompasses the global financial crisis of 2008. By analysing this period, we can separate our study into three periods: the 'pre-financial crisis' (1999-2007), 'post financial crisis' (2009-2015) and the whole sample period (1999-2015). By using three sub-periods it allows us to study how financial regulation impacted households as borrowing constraints increased dramatically after the crisis.

6.2 Literature review

This study follows a substantial amount of literature reviewing the wealth effect, which have used different time periods, data-sets, and methodology employed. However, one area that is agreed upon is the general principles underlying the life-cycle model (LCM), and the permanent income hypothesis (PIH). Under the LCM, households update their lifetime consumption plan when they receive new information about their future expected wealth. Households update their plan since they can anticipate this change in wealth, for example, through a change in labour supply etc (Browning et al., 2013). Therefore, households can attempt to maintain their marginal utility of consumption constant over time, referred to as consumption smoothing.

Generally, households aim to smooth income fluctuations by borrowing against future earnings early in life and accumulate wealth through saving when income levels are substantially high. This is usually the case when households are middle-aged (Atalay et al., 2016).[50] As the household ages, they begin dis-saving when their income drops below their current consumption, and households then begin to utilise the accumulated wealth they have gained over their lifetime. This follows the assumptions determined by Ando and Modigliani (1963) regarding the shape of a households utility function, where "*The consumer at any age plans to consume his total resources evenly over the remainder of his life-span*", and "*The individual neither expects to receive nor desires to leave any inheritance*".

According to Browning et al. (2013), if an individual expects a change in household wealth at the beginning of the planning period, then they would incorporate this information into their consumption plan, and would perform consumption smoothing (by deciding whether to borrow or save today dependant on the

[50] We define middle aged as the head of the household being between the age of 40 and 55.

change in their future wealth) to incorporate the expected change in house prices. Furthermore, if consumption changes are linked to expected house price innovations, then this indicates that a person/household is potentially credit constrained due to in-perfect credit market conditions. Hence, the notion of anticipated and unanticipated changes in household wealth is at the heart of this study.

In principle, Ando and Modigliani (1963) statements are not truly reflective of the decisions households make day-to-day, as these definitions require the assumption that households are forward-looking and that there are perfect credit markets. Households often have bequest motives and income uncertainty, and employ consumption smoothing so that they can plan for expected changes in wealth, due to changes in financial assets or housing capital. Consequently, expected changes in financial wealth are incorporated into their consumption plan at the start of the planning horizon and are updated when an expected change occurs (Browning and Lusardi, 1996). New information, such as a change in a households income level or in housing wealth, can alter a households' lifetime consumption plan significantly. This is often termed as an unanticipated change. Unanticipated changes in income, for example, will lead to changes in a household's permanent income level. Households will then update their consumption plan since they will acquire a different amount of resources over their lifetime than previously expected. Applying this logic to house price innovations, if there is a unanticipated increase in wealth due to house price increases, then households may increase their current and future consumption levels because they now have more resources at their disposal. This is known as the wealth effect.

Another channel through which household wealth can affect consumption is known as collateral borrowing. This is where households utilise the increases in house prices (as the homeowner's equity in the property increases), allowing them to secure increased borrowing capabilities. In turn, this may allow households to use their new-found equity to facilitate increase in consumption levels. Campbell and Cocco (2007), and Leth-Petersen (2010), added to this theory by studying how collateral constrains affect the UK and Danish households, respectively. Both studies found that non-housing expenditure increased when homeowners were allowed to access their housing equity.

There are a number of alternative channels that have been suggested within the literature which attempt to explain the link between house price changes and household consumption, with two notable channels to mention. Firstly, house price increases and consumption are attributed to the effects of financial liberalisations (FL). Financial liberalisations can increase both house prices and consumption levels by relaxing credit constraints. A household is credit-constrained when they would like to have a higher consumption today but can not do so. Aron et al. (2000) suggest that financial liberalisations have three broad effects on consumption. Firstly, FL alleviates credit constraints that households face when expecting income growth and increasing house prices. Secondly, FL reduces the size of the deposit needed for a first-time buyer. This occurs since mortgage providers set the limits on the minimum deposit required by the lender, based on their current income level or fraction of the value of the home that they wish to purchase. When credit constraints are reduced, and credit becomes more readily available, minimum deposit requirements for first-time buyers is reduced. This allows households to raise their current consumption levels by running down their deposit to the minimum amount required by the lender. Finally, FL can increase the availability of collateral-backed loans for households who own their own home. This emerges due to rises in housing prices, allowing a homeowner to raise debt or refinance current debt through lower interest rates using their home as collateral.

Financial liberalisations significantly change for each country and are dependant on the strength of the financial sector of each nation. For example, liberal countries, such as the U.S., where consumer credit information is freely available to lending institutions (and the U.S. has a robust legal system), lenders have significantly more confidence in providing loans and mortgages to consumers. This confidence is derived from lower asymmetric information (Muellbauer, 2007). However, due to the rigidity of laws in countries like Italy, banks are wary of lending to consumers who wish to use their properties as collateral because the legal system impedes banks taking over properties in the event of a default. This dampens the collateral channel. A common issue surrounding the literature on FL has been to find a sufficient benchmark to identify when there has been a credit market deregulation, and how to determine what role and size FL had on house prices and household consumption.

Finally, the least commonly addressed channel is referred to as the common economic channel. The common economic channel suggests that house prices alone do not affect household consumption. Instead, multiple common factors cause the relationship between both variables. For example, other factors include expected productivity growth, which can alter expected income over a household's life-cycle (Browning et al., 2013; King, 1990; Pagano, 1990). These common factors simultaneously drive both house price and household consumption growth (conversely, co-factors can reduce consumption growth), and therefore provide evidence against the existence of the wealth effect. Attanasio et al. (2009) conclude that common factors could be the driving factor between household wealth and consumption.

6.2.1 Data sources and limitations

Two main types of household level data are used across the literature: pseudo-panel data (synthetic cohorts created form repeated cross-sectional surveys); or true micro-panel data (the same set of households analysed over a sample period). Notable pseudo-panel studies include Atalay et al. (2016); Attanasio et al. (2009); Attanasio and Weber (1994); Campbell and Cocco (2007) where they rely on pseudo-panel approaches when studying the link between housing wealth and household consumption. There are a few critical limitations to using pseudo-panel data. Specifically, their cohort dependence requires the use of time-invariant variables (Browning et al., 2014). Consequently, this prohibits the use of time-dependant variables such as the number of homeowners, which vary from one period to the next. Furthermore, sample bias is a standard issue founding within synthetic cohort, even when sampling a large number of households. Devereux (2007) studies labour supply and finds that there are biases of approximately ten percent in income elasticity with sample sizes of up to 10,000.[51] This result demonstrates that sampling error can potentially drive the results of pseudo-panel methodologies. Finally, measuring household consumption using pseudo-panels was historically completed using the Family Expenditure Survey and the Consumer Expenditure Survey, found in the U.K. and U.S. respectively. These datasets fail to detail the longitudinal variables such as wealth and income variables that are needed to analyse the wealth effect channel.

The second type of empirical data used is true micro panel studies (such as the PSID and the British Household Panel Survey) which has collected data over numerous years of the same households. [52] Authors who have used micro panel data

[51] Most pseudo-panel studies have less than 10,000 observations.

[52] Commonly referred to as waves of data.

include Disney et al. (2010), Browning et al. (2013), Cooper (2013), and Gröbel and Ihle (2018). Micro panel studies have several advantages over pseudo-panel studies since they allow for the control of unobserved factors, such as changes in demographic information. Furthermore, they allow for the comparison of different theories such as the wealth effect, collateral borrowing, or FL, which could drive the relationship of wealth effects on consumption by allowing one to test reactions of heterogeneous household types Cooper (2013). The longitudinal dimension of panel data-sets often limit the number of household participants due to attrition, however, they are becoming the more favoured approach due to the expansion of collected variables amongst the data-sets.

6.2.2 Life cycle expectations

Although this paper is primarily focused upon detecting the presence of the wealth effect in U.S. households, due to the detailed nature of the PSID data-set, we can decompose the U.S. population by household characteristics to identify if different households consumption pattern react more (or less) strongly to innovations in house prices. Firstly, we analyse how renters, homeowners with a mortgage, and homeowners without a mortgage (outright homeowners), change their consumption over the life cycle. If the wealth effect is present, an unexpected increase in house price would cause renters to either reduce or maintain their total consumption. If a renter wishes to acquire a property in the future, unexpected increases in house prices would require a higher down-payment, as they do not benefit from the increase in housing wealth. A renter then faces two choices: a) increase their current saving rate in order to accumulate enough money for the new, increased down-payment, or b) maintain their current savings rate, but increase the time-span in which they accumulate the down-payment (Browning and Lusardi, 1996;

Gröbel and Ihle, 2018).

The wealth effect affects homeowners differently than renters. Assuming an unexpected increase in house prices, a young homeowners non-durable consumption is expected to react less strongly to house price increases compared to an older homeowner. This is due to younger households having considerable future costs as they advance through the life cycle and will have higher future housing costs. Future costs include, child care, saving to move up the property ladder, education fees, mortgage repayments, and precautionary savings.[53] Older households, who have fewer years to utilise their new-found wealth, are expected to react more strongly to unexpected changes in house prices. In the event of an unexpected house price increase, older homeowners will have more wealth to consume over their life time, consequently, with fewer periods to consume this new wealth increase, their consumption will increase more strongly compared to younger households, as older homeowners perform consumption smoothing over fewer periods.[54] Browning et al. (2013) notes that if the productivity hypothesis is the common driver between house prices and consumption, younger households will react more strongly to unexpected house price innovations as they expect wages and income to rise in future periods and they have more periods left to maximise their use of this wealth. (King, 1990; Pagano, 1990)

An interesting facet is how homeowners with a mortgage respond to changes in housing wealth. Firstly, homeowners with a mortgage could use an increase in housing wealth to facilitate a property purchase in another location where house prices appreciated more slowly, e.g., moving from New York City to Kansas. Secondly, highly indebted households could use their increase in housing equity

[53]Precautionary saving would include saving for income losses due to unemployment, or beliefs that there will be an economic downturn in the near future.

[54]This statement assumes Ando and Modigliani (1963) no bequest motives.

to renegotiate their mortgage for more favourable interest rates as they will have reduced credit risk due to a higher collateral amount. Conversely, they could exhibit 'renter like' properties where they reduce consumption to fund future house purchases as the cost of moving up the property ladder has risen.[55] It is unknown how homeowners with a mortgage will react to the wealth effect as no previous study has included them as a sample group, rather, they have been grouped within the homeowner category.

6.2.3 Current literature

There have been a few recent studies that use the same PSID data-set as this paper where they review U.S. house prices and household consumption. For comparison purposes we review their findings. Cooper (2013) uses the PSID data-set to deconstruct which channel, wealth effect, or collateral borrowing affects U.S. households. The authors find that unconstrained households exhibit little to no response to innovations in housing wealth. Furthermore, the author suggests that constrained households' consumption levels are significantly affected by housing wealth changes. Cooper finds evidence for the collateral borrowing channel through which credit constrained households increase consumption due to new-found housing equity when house prices unexpectedly increase. Finally, the author estimates that for an increase of $1 in household wealth leads non-housing expenditure to increase by $0.02 to $0.06 for all households. This value is in line with other previous estimates such as Juster et al. (2006), and Bostic et al. (2009). There are a few fundamental differences between this paper and Cooper (2013). Firstly, Cooper (2013) used a sample period between 1984 and 2007, which meant they did not consider the effects of the 2008 global financial crisis.

[55] It can be suggested that all house prices will appreciate so the increase in housing wealth will translate to no real increase in wealth. However, house price appreciation is not uniform across the country so wealth changes will be larger in some locations compared to others.

This is an important period to study as there were significant changes in house prices and household wealth during this time period. Moreover, the methodology employed in this paper differs from Cooper's (2013) paper. Namely, we explore how renters, homeowners with, and without, a mortgage, react to house price changes. Cooper investigated homeowners only. This is a notable difference as approximately one-third of U.S. households rent their home. Secondly, this study investigates the role of local house price changes by utilising the Zillow data-set. Consequently, a finer geographic measure is used to locate households, thereby determining whether local market conditions are significant in predicting house price changes. Conversely, Cooper uses the Federal Home and Finance Administration as the house price index, which is less geographically sensitive relative to the data found in Zillow.

Another study which is closely related with this paper is by Loewenstein (2018). The author uses the PSID data-set between 1998 and 2007. Lowenstein finds that as existing homeowners progress over the life cycle, homeowners purchase larger dwellings and only marginally increase non-housing related expenditures. Additionally, the author identifies that high house price growth areas have significantly fewer renters transitioning toward home ownership and, if they did, they bought smaller dwellings. In contrast, we consider how different households, at varying stages in the LCM change their spending as a result of changes to the value of their homes.

Two influential studies conducted by Campbell and Cocco (2007) and Attanasio et al. (2009) utilise the Family Expenditure Survey (FES).[56] Both studies use the FES data-set by creating pseudo-panel cohorts that share the same characteristics. However, the composition of both pseudo-panels was different, which

[56] A UK based survey.

resulted in two diverging results on whether the wealth effect causes consumption changes or not. Campbell and Cocco (2007), find evidence of heterogeneity in the wealth effect across different age groups, and provide support that older homeowners react most significantly to the wealth effect channel while young renters exhibit no reaction. Additionally, they theorise that either borrowing constraints or financial liberalisation could be the reason behind the intrinsic link between house prices and household consumption. Alternatively, Attanasio et al. (2009), find the opposite. The authors suggest that younger households, who are less likely to own their property, experience innovations in future income most acutely, which can significantly change their current consumption level. Moreover, the authors comment that common economic causality is the most reasonable explanation for the co-movements of house prices and consumption growth. Finally, they conclude that, although the wealth and collateral channels are not as significantly important as the common economic causality channel, they still may be important for certain households at different stages in the life cycle. Cristini and Sevilla (2007) review the methodology of both Campbell and Cocco (2007), and Attanasio et al. (2009) and find that pseudo-panel defined by both Campbell and Cocco (2007) are based on age-homeownership status, while Attanasio et al. (2009) base their cohorts on age. They conclude that both papers outcomes are dependent on the specification of the methodology used. The PSID does not require these pseudo-panel assumptions as they are captured within the dataset.

6.3 Empirical model

To model the consumption habits of individuals across time, the life cycle model is exercised following a similar approach used by Browning et al. (2013). We assume individuals are forward-looking and have rational expectations, meaning households attempt to smooth their consumption levels over their lifetime (Ortalo-Magne and Rady, 2006). In other words, individuals attempt to maintain their marginal utility of consumption constant using all available information to plan their future wealth expectations (Attanasio et al., 2009). Households diverge from their consumption plan for two reasons: 1) the arrival of *new* information that informs households that their current consumption level can change due to a new event; or 2) due to *unexpected* changes in wealth.

Expected changes in house prices will not affect the overall consumption of the household. If households are observed to react to *expected* house price changes, then we assume that households are either myopic or credit constrained.[57] A household which expects a change in their wealth will perform consumption smoothing (either by borrowing or saving today) to maintain their consumption level.[58] Hence, it is unexpected changes in housing wealth that lead to changes in total household expenditure. Households who do not anticipate a change in housing prices cannot perform consumption smoothing before the event has occurred. Significant unexpected house price changes may cause households to perform unexpected consumption smoothing. The shift in household consumption is dependant on the change (either positive or negative) in the house price.

This section will test an empirical model in which changes in log consumption are regression on expected and unexpected changes in house price, disposal income, and real after-tax interest rate. This can be defined as:

$$\Delta c_{it} = \beta_0 + \beta_1 r_{it} + \beta_2 E(\Delta I_{it}) + \beta_3 \theta_{it}^{I} + \beta_4 E(\Delta P_{it}) + \beta_5 \theta_{it}^{P} + \beta_6 Z_{it} + \lambda_t + u_{it}, \quad (17)$$

[57] This paper is not focused on credit constraints or myopic households, rather, we emphasise that household consumption is dependant on *unexpected* changes in wealth rather than expected changes.

[58] Under the assumption of perfect capital markets and no credit market constraints.

where c_{it} is the log total household consumption expenditure (excluding housing expenditure) for household i at time t. Real after-tax interest rate is denoted as r_{it}. The variable $E[\Delta I_{it}]$ signifies the households expected change in disposable income between t - 1 and t. θ_{it}^{I} is the unexpected income changes in period t.[59] $E(\Delta P_{it})$ is the expected house price change. θ_{it}^{P} is the difference between expected house price changes at t-1 and real house price change at period t. β_5 is the central coefficient of study of this chapter. Controls for both state and census tract-specific effects are found within the λ_t term.[60] u_{it} is the independent error term. To estimate equation (17), the house price process and income process must be calculated first.

6.3.1 Income process

Households generally form expectations about their disposable income based on past earnings. We assume income earned in time "t" is associated with lagged income. This assumption is self explanatory considering households are normally paid a base salary from month to month. Fluctuations often stem from changing productivity (i.e. working more hours) or receiving bonuses. These are normally expected income changes. Unexpected income changes may occur due to an event such as unemployment or an inheritance windfall. We model the income process using an auto-regressive model,[61] where the log disposable income in period t is related to the historical household disposable income. The model is described and adapted from Browning et al. (2013);

[59] Alternatively, defined as the difference between expected income at t-1 and the real income at period t.

[60] Shocks common to both households at state and census track level are captured within this term.

[61] There are various dynamic income models such as Deaton and Paxson (2000). However, the income process plays a small role in the consumption model and as such, a more complex income model is believe to have little impact on the estimations.

$$I_{it} = \gamma_{it-1} + (1-\gamma)\mu_i + \Theta Z_{it} + k_t + u_{it}; i = 1, ..., N; t = 2, ..., T \tag{18}$$

where μ_i is the individual fixed effect and Z_{it} is a vector of the household characteristics (number of adults, children, and age of the head). k_t captures the fixed year dummies. u_{it} is the independent error term.

The model prescribed above allows us to identify the expected and unexpected changes in disposable income. Hence expected income growth can be described as:

$$E(\Delta I_{it}) = \hat{I}_{it} - I_{it-1}, \tag{19}$$

and unexpected income growth can be shown to be;

$$\hat{\theta}^I_{it} = \delta I_{it} - E(\Delta I_{it}) = I_{it} - E(I_{it}) = I_{it} - \hat{I}_{it}. \tag{20}$$

6.3.2 House price process

Similar to the income process, households value their property based on historical local house price data. Households base their future expectations on their house price on currently traded local properties which have similar characteristics to their property (i.e. property type, age, condition). Consequently, we can assume house prices follow a first-order auto-regressive (AR1) model, with unobserved individual effects and serially uncorrelated disturbances:

$$p_{it} = \alpha p_{it-1} + (1-\alpha)\eta_i + \beta x_{it} + v_{it}; i = 1, ..., N; t = 2, ..., T \tag{21}$$

where p_{it} is the log average house price of a similar property in a similar property type (i.e. detached, townhouse, etc) in the census tract area. η_i measures the unobserved heterogeneity in house prices. The variable x_{it} captures the characteristics of similar house properties in the sample census tract area (number of rooms, square footage). v_{it}, is the independent error term.

Persistence stems from two sources, the auto-regressive mechanism described by the AR parameter (α).[62] The second source of persistence comes from unobserved heterogeneity, η_i. A higher AR parameter implies that the majority of the persistence is due to the common auto-regressive mechanism and less to unobserved municipality-specific effects (Browning et al. (2013)).

Households expect local house price dynamics to change by the difference between the current estimated house price and the historical house price:

$$E(\Delta p_{it}) = E(p_{it}) - p_{i,t-1} \tag{22}$$

alternatively, unexpected changes in house prices can be described as:

$$\hat{\theta}^p_{it} = \Delta p_{it} - E(\Delta p_{it}) = p_{it} - p_{i,t-1} - (E(p_{it} - p_{i,t-1}) = p_{it} - E(p_{it}). \tag{23}$$

Unexpected change in house prices, is the difference between current local house price (estimated with Zillow), and expected local house price (estimated by the PSID respondent).

[62] Which is constant across individuals

6.4 Data and summary statistics

In this chapter we will utilise the data-sets from the PSID and Zillow, previously described in Chapter 3. Variables unique to this Chapter are detailed below.

6.4.1 Expenditure data and imputation

Initially, the only consumption data taken by the PSID survey was households' food consumption. In 1999, and in subsequent waves, further consumption variables were added to the survey, and it now contains over thirty-five[63] measures of household consumption. For this reason, we start our analysis from 1999. In total, the PSID survey covers around 70 percent of all consumption measures available in the Consumer Expenditure Survey. From Appendix 1, Table 35, housing is the single largest expenditure a household consumes, with a median value of $14,517 p/a, followed by vehicle costs at $7,233 p/a.

Since there are several ways of deriving total household expenditure, we assume the aggregation of the PSID consumption variables is a comprehensive measure of household consumption. This will be the primary measure of household consumption used in this paper. However, for comparison purposes, we will also compute the total expenditure similar to Browning et al. (2013) paper, where total expenditure can be defined as:

$$c_{it} = y_{it} - \Delta W_{it}, \tag{24}$$

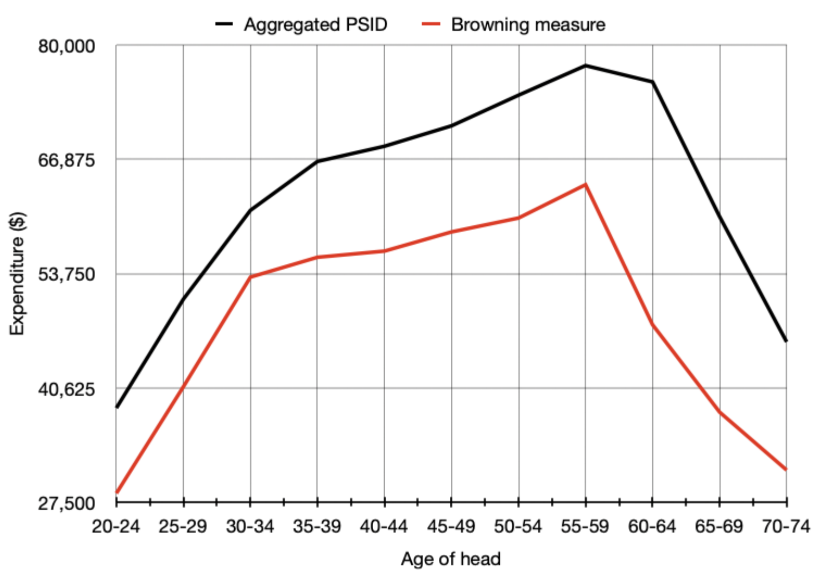
where c_{it} is the total expenditure of a household, y_{it} is the disposable income for household i at time t, and ΔW_{it} is the change in total household financial wealth from period t-1 to t. Both total aggregated household expenditure and

[63]This included child care, school fees, vehicle cost, housing and transportation expenditure. This was further increased to over 40 variables in 2005.

total consumption are deflated with the relevant price indices which are based on 1999 dollar values.

Figure 38 illustrates the median non-durable household expenditure against the age of the head of household for the both the aggregated PSID measure, and using the Browning measure of household consumption, described in Equation 24. Similar to previous studies, a clear hump back curve can be seen with a peak at the age of 55 years. The peak coincides with the children leaving the home, and consumption thereby reduces. A linear reduction in consumption can be seen from sixty years and over. Household consumption is approximately twenty percent less using the Browning measure compared to the aggregated PSID. However, both measures follow the same humped back curve pattern.[64]

Figure 37: Median household expenditure as a function of head age



[64]This will be discussed in the robustness section in more detail.

6.4.2 House price data and imputation

To be able to determine the house price process, we use home valuations provided by the PSID participants who value, to the best of their ability, the market value of their own home (at the time of interview). Since interviews of PSID participants are taken across several months, homeowners interviewed near the end of the interview process could cause downward or upward bias in their estimates due to the time lag in the interview process. Since the PSID households are not interviewed in any known methodical order, and there are no time stamps given on the order of interview, we assume this effect will be negligible.

The second novel dataset used in this paper is data from the online real estate database company Zillow. Zillow has estimated over 100 million house values in the US since its inception in 2006. Households enter household characteristics such as the number of bedrooms, last renovation date, and square footage. Zillow utilises this data and calculates the value of the home based on this information and local house price information (detailed more in Appendix 2). Figure 39 presents the median home valuations from both the restricted PSID and Zillow data-sets.

From Figure 39 we can see the median house price value from Zillow is approximately 25% higher than the valuations given by the PSID participants. This is most likely due to the oversampling of low income households. This difference remains constant over the period up until the 2007 financial crisis. Consequently, the house price reduction between 2007 and 2011 for the Zillow index is higher than PSID data-set. This house price reduction also seen in the PSID data-set could be an example of overconfidence in the value of their homes by U.S homeowners. Overconfidence in their home valuation leads to a lower overall price decline after the crisis, whereas Zillow represents actual house price declines. After the financial crisis the two data-sets follow the same trend.

To look at the differences between expected and unexpected house price changes, we use restricted data from Zillow and we create three house price indices. Namely, bottom, middle, and top tier house price valuations aggregated at the zip code level and state level. These tiers are used to calculate the unexpected house price valuations used in both the house price process and the consumption regression. Households' houses are assigned to a tier which is closest to their value. More information about the construction of the tiers can be found in the Appendix. The tiers are illustrated below in Figure 40.

Figure 38: Present median house price values for the restricted Zillow and PSID data-sets.

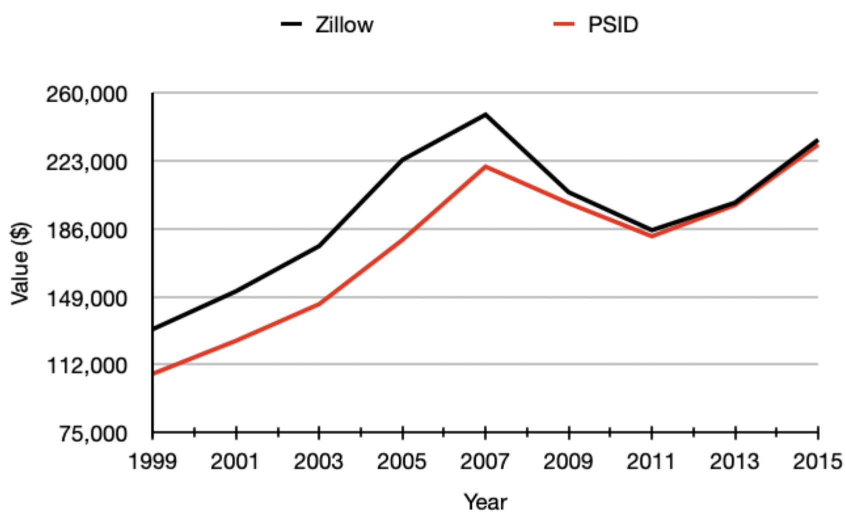
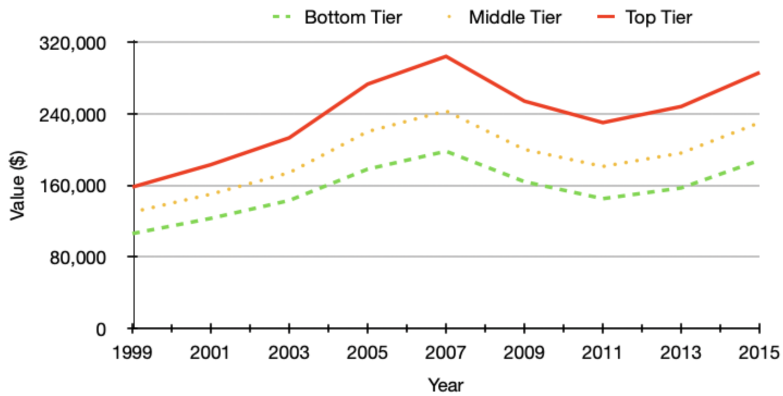


Table 36 (see Appendix) details the distribution of homeownership rates and dwelling type. Notably, as households age over the life cycle, they trade-up their property and move into single-family detached homes, with a 5% increase in homeowners moving to detached properties over the period of study. Over time, house-

Figure 39: The average Zillow valuation for bottom, middle and top tier homes.



holds move from renting properties to purchasing properties with a mortgage; this is consistent with the literature (Campbell and Cocco, (2007). It is clear that the financial crisis caused some homeowners to either default or sell their property as rental rates increased 2.5% after the financial crisis.

Table 37 summarises the housing values with the mean estimated house value being $161,173, and the average number of rooms in each property being five. One concern with self-assessed house values is that households do not rationally predict their house value. Previous literature, such as Skinner (1994) and Cooper (2013), have found the PSID home values to be a close estimate of other data-sets such as the Commerce Department and the Federal Housing Finance Agency (FHFA).

6.4.3 Income, wealth, and debt measurements

The PSID dataset provides a broad range measure of income variables except for disposable income. To calculate disposable income, we follow the TAXSIM model first described by Butrica and Burkhauser (1997). In addition, using the updated TAXSIM files provided by Kimberlin et al. (2014) we apply this model over the period of this study, from 1999-2015. Disposable income for each household is calculated by aggregating accounts for state credits and taxes, and mortgage interest for itemised deductions. Consequently, this yields accurate disposable income values for each household.

Household wealth is detailed in Table 38. Households generally hold more cash savings than stocks. Only the top twenty-five percent of wealthiest households hold stocks. Comparatively, ten percent of the poorest households have no liquid savings, and are in debt.

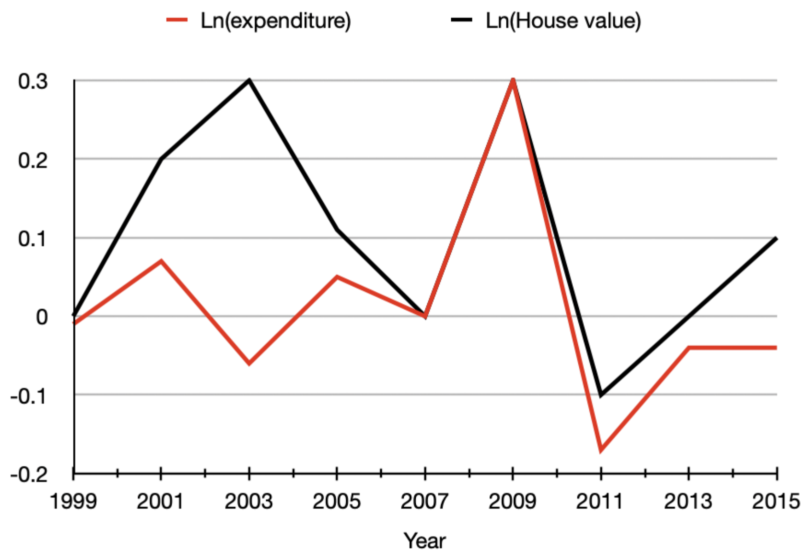
6.4.4 House price and expenditure

The main focus of this paper is to analyse the correlation between house price changes and total non-durable household expenditure. Hence, we illustrate from the PSID data set the relationship between average biannual log house price changes, and log expenditure (Figure 41). Similar to Browning et al. (2013), we regress the first difference of log total non-durable expenditure on a constant, and the first difference log house prices. We find a significant parameter estimate of 0.10. Comparatively, Browning found a parameter of 0.08 and this was also significant.

6.4.5 Sample selection

To avoid the results being skewed by outliers, and other idiosyncrasies in the datasets, a number of sample selections have been made. Firstly, we omit households who separated from their spouse over the sample period. These are known as stable couples. Divorce is the single, largest, and (generally) most unexpected event a household can experience. Divorce proceedings and unemployed households can have a significant impact on total expenditure, income, and wealth of the house-

Figure 40: Average change in ln(house value) and ln(expenditure)



Source: Data used from the PSID

hold, hence, we believe it is important to omit such households. Secondly, we omit households over the age of seventy-five. Households over the age of seventy-five are generally making retirement decisions and smoothing their consumption considerably. Furthermore, households over this age have a higher probability of death, increasing attrition rates, and a higher likelihood of top or bottom coding PSID values. For these reasons, households whose head age is over 75 at the start of the sample period are omitted. Therefore, our sample is limited to households between the ages of 18 and 74. Finally, we clean the data at the 1 and 99% level to remove outliers.

6.5 Results

Firstly, the results are presented with estimations of the income and house price processes. Following this, the total expenditure regression can be estimated using the results from these two processes. This allows us to predict the effects of expected and unexpected house price changes on non-durable household consumption.

6.5.1 Income process

To estimate the income process, we make use of the total family disposable income.[65] The household disposable income is defined as the total household income of the head and spouse, net of federal and state income taxes, which were estimated using the National Bureau of Economic Research (NBER) TAXSIM model, outlined in the Appendix.

Four educations cohorts were created, and households were assigned to a group which met their education level. Households were separated by the highest academic achievement obtained by either the head and/or spouse at the commencement of the study period. The groups are; primary school education, secondary school education or short term higher education,[66] university education, and postgraduate education.[67]

Firstly, we perform stationarity testing on the income process in levels OLS. The natural log disposable income is our dependent variable. Explanatory variables are the lagged disposable income, log age of the head, log age squared, and the number of children. Year-specific shocks are also controlled for as different education groups are assumed to react differently to national shocks, an interaction variable for time dummies and log age is also included.

We find the OLS estimates of gamma vary around 0.7-0.75 for each educational

[65]Total family income is calculated from a summation of all income sources asked by the PSID interviewers, variables include rental income, social security income, labour earnings etc.

[66]These include certificates from universities but no degree was awarded.

[67]We determine education level attainment by the number of years of study. Therefore, we assume households pass each year of study. We are unable to tell what postgraduate qualification they receive as this figure is top coded in the data-set.

group. Using t-tests on the OLS estimates of the AR(1) model, we reject the hypothesis of a unit root in the income process. Hence, to estimate the parameters, Arellano and Bover (1995) estimator are used. The auto-regressive parameter estimates presented in Table 29 varies between 0.69 and 0.8 across education groups. Expected and unexpected changes in disposable income are thereby calculated (as previously mentioned).

Table 29: Estimation process for disposable income.

	Education status			
	Primary school	Secondary school	University	Postgraduate
I_{it-1}	0.779***	0.800***	0.749***	0.681***
	(0.065)	(0.026)	(0.025)	(0.051)
No. children	0.140**	0.190***	0.130***	0.090***
	(0.020)	(0.030)	(0.030)	(0.020)
ln(age)	1.58	1.633***	2.070***	2.72***
	(0.970)	(0.140)	(0.140)	(0.260)
$Age^2/100$	0.070***	0.100***	0.130***	0.190***
	(0.020)	(0.030)	(0.030)	(0.020)
N	2,156	35,068	31,175	8,615
R^2	0.29	0.37	0.39	0.40
Sargan test	p=0.00	p=0.00	p=0.00	p=0.00
Arellano-Bond test	p=0.12	p=0.59	p=0.51	p=0.05

Where ***,**,* indicates significance at the 1, 5 and 10% levels. Year dummies and interactions between year dummies and age are included in the regressions, but results are not reported. Arellano-bond test for 3rd auto-correlation in residuals. Sargan test of over identifying restrictions are also used.

6.5.2 House price process

Unanticipated housing effects could have long-run impacts; this means stationary testing is required on the AR1 process. If the house price process is non-stationary and carries a unit root, the model reaches a random walk ($\alpha = 1$). Shocks to a non-stationary house price process will permanently affect house prices. Therefore, we are interested in a one-sided hypothesis that the null hypothesis that $\alpha = 1$ against the alternative that $\alpha < 1$. Three different test statistics are employed to test for a unit root. Namely, Levin-Lin-Chu (LLC), Breitung and Meyer (1994) (BM), and Arellano-Hansen-Sentana (1999) tests (AHS). These three tests are chosen based on the recommendations from Bond, Gauges, and Windmeijer (2005) study. They verify the efficiency of varying unit root tests on micro panel data with large cross-sectional dimensions that have a small number of time periods (similar to this study). All three stationarity tests reject the hypothesis of a unit root; the results can be found below in Table 30.

Table 30: Unit root test of the house price process

	OLS	Breitung-Meyer	AHS
P_{it-1}	0.803***	0.612***	0.715***
	(0.007)	(0.016)	(0.008)
$ln(FloorArea^2)$	0.366***	0.203***	0.121
	(0.004)	(0.007)	(0.740)
ln(No. rooms)	0.335***	1.221***	-0.101
	(0.012)	(0.016)	(0.083)
Constant	1.540***	4.110***	2.120***
	(0.071)	(0.063)	(0.145)
N	50,312	50,369	32,632
R^2	0.75	0.25	
Test $H_o \alpha = 1$	0.00	0.00	0.00

Where ***,**,* indicates significance at the 1, 5 and 10% levels. Regressions include county dummies, standard errors are in parentheses.

Since we reject stationarity being in the house price process, generalised linear method of moment (GMM) estimators are used to predict the stationary house price process. Developed by Arellano and Bover (1995), fixed effects are eliminated by taking the first difference of the house price regression (removes orthogonality conditions between regressors and the measurement error). Then the (endogenous) dependent variables can be used to analyse the regression by taking the lags. However, the Arellano and Bover (1995) estimator fails for finite samples and, by taking higher lags, you reduce the degrees of freedom in your regression. To fix this, Blundell and Bond (1998) furthered the Arellano and Bover (1995) study by imposing an additional restriction, known as the moment condition. A linear GMM estimator can be made significantly more efficient when using this restriction on moderately-sized panel observations and have a reasonably high autoregressive coefficient. These results are described below:

Table 31: Estimation result of the house price process.

	Coefficient
P_{it-1}	0.762***
	(0.031)
$ln(FloorArea^2)$	2.430***
	(0.832)
ln(No. rooms)	0.129
	(0.091)
N	50,369
Sargan test	p = 0.00
Arellano-Bond test	p = 0.00
Test $H_o \alpha = 1$	0.00
0.00	0.00

where ***,**,* indicates significance at the 1, 5 and 10% levels. Regressions include county dummies and a constant. Standard errors are in parentheses. The Arellano-Bond test is quoted for the 3rd order auto-correlation.

We find our parameter estimates are similar to results found within the (Browning et al., 2013) paper. We calculate expected and unexpected house prices within the methodology section.

6.5.3 Consumption regression

After identifying that we do not have a unit root in the income process and house price process, we are now able to estimate the consumption regression to identify if expected and unexpected house price innovations significantly affect total household non-durable consumption. Hence, Table 31 presents our baseline regressions;

Table 32: Baseline regressions

	(1)	(2)	(3)	(4)	(5)
ΔP_{it}	-0.064***	0.015**			
	(0.007)	(0.006)			
$E(\Delta \hat{P}_{it})$			0.019		
			(0.014)		
$\hat{\theta}^p_{it}$			0.010		
			(0.020)		
ΔP_{it} (young)				-0.132***	
				(0.009)	
ΔP_{it} (old)				-0.043***	
				(0.012)	
ΔP_{it} (young, <2007)					0.009
					(0.011)
ΔP_{it} (old, <2007)					0.148***
					(0.024)
ΔP_{it} (young, >2007)					-0.045**
					(0.018)
ΔP_{it} (old, >2007)					-0.095***
					(0.014)

Where ***,**,* indicates significance at the 1, 5, and 10% levels. Regressions include county dummies and a constant. Standard errors are reported in parentheses.

Five baseline parameters are estimated. Column one presents the regression result of the first-differenced log total non-durable expenditure on the first difference of log house price. Interestingly, we find a significant negative coefficient indicating as house prices increase by one percent, total non-durable consumption decreases by 0.064%. In other words, this implies the marginal propensity to consume based on the mean US home value of $164,000, which experiences a one percent increase in value (+$1,640) would impact the mean total household consumption ($45,000), would lead to a reduction in consumption of (-$28.8) per household. This implies that the wealth effect does not drive the positive correlation between house price changes and consumption. However, this simple regression does not necessarily indicate that there is not a wealth effect, as expenditure also varies with income.

Column two includes the first-difference of log-income as a regressor and includes controls for changes in income. As previously noted, the productivity hypothesis suggests that house prices are correlated with income as well as household consumption, and this can now be seen to impact consumption changes positively and significantly. Column three separates house price changes into expected and unexpected movements and is estimated by the income and house price models described in the previous section. We see no evidence of unexpected house price movements which would give an indication that a wealth effect channel is present. However, this does not mean there is no wealth effect, with stationarity in the house price process we know the wealth effect is not long lasting, so it may become evident in sub-samples of the data.

Column four separates age into young and old households. As previously defined, young households are aged between eighteen and fifty, and older households are between fifty-one and seventy-four. Households are separated into different ages as previous studies indicate that household budgeting and time horizons vary over the life cycle, therefore affecting consumption. We include controls for the real interest rate and level of educational attainment. It can be seen that both coefficients for young and old households are highly significant and negative. Young households react more than twice the amount compared to older households; this indicates that they react to house price changes more severely than older households. Since this encompasses the entire time period, which includes the financial crisis, column five is a better indicator of how households are reacting to house price changes.

Finally, column five reviews how different age groups react to house price changes before and after the financial crisis. Interestingly, elderly homeowners react strongly to house price increase prior to the financial crisis. As older households generally have more of their wealth in housing compared to younger households, they can be seen to benefit the most from house price rises. Since they have fewer periods left to utilise unexpected gains this supports the wealth effect hypothesis previously outlined in the literature review. Conversely, after the financial crisis, we can see that both young and old households significantly reduce consumption. However, the older households react around twice as much as younger households. Similar to before the financial crisis, older households have fewer periods to adjust their consumption to a reduced total wealth. Hence, when performing consumption smoothing they must cut consumption more to maintain the same life-time consumption plan. Alternatively, the large and potential overreaction from older households could indicate reinforcement learning elderly generations experienced from prior crises pre-2008.

We now estimate equation 17 while utilising variation in age, income, and house price changes by their estimated values. Consequently, expected and unexpected changes in income become $\Delta\hat{y_{it}}$ and $\hat{\theta}_{it}^{y}$ and expected and unexpected innovations in house prices are denoted as $\Delta\hat{p_{it}}$ and $\hat{\theta}_{it}^{p}$ respectively. The error associated with the income computation may add upward bias, however, we assume this affect to be negligible. Table 33 presents our results.

The pooled regression in Table 33 shows all anticipated and unanticipated parameter estimates to be insignificant for owners which aligns with Campbell and Cocco (2007) and Browning et al. (2013). These results notably align with Campbell and Cocco (2007) and Browning et al. (2013). Campbell and Cocco find an MPC of approximately ten percent, whereas Browning et al., and this study, find no significance in expected and unexpected house price changes for both young and old households. There is no change in significance for the two sample periods (pre and post 2007) financial crisis, which indicates there was no wealth effect present for homeowners.

With no significance found in expected and unexpected changes, we now test expected and unexpected house price changes in renters. The results can be seen in the second column in Table 33. Similar to owners, no significance can be seen for young, old, before, and after the financial crisis. This is to be expected as renters should not react to house price changes in the long term, as they have no housing wealth. Only renters who are looking to join the market in the next few periods may react strongly. This provides validity to the instruments utilised within this study and follow our hypothesis outlined in the methodology.

In the third and fourth column in Table 33, we present the results for household with high and low liquidity. We define low liquidity as households who have liquid assets of less than two months of disposable income in year t-1, and high liquidity households those who have liquid assets of more than, or equal to, two months disposable income in year t-1.

Table 33: Expected and unanticipated house price innovations

	Owners	Renters	Low liquidity	High liquidity
$E(\Delta\hat{P}_{it})young, < 2007$	0.065	-0.022	-0.044	0.022
	(0.050)	(0.039)	(0.087)	(0.065)
$E(\Delta\hat{P}_{it})old, < 2007$	-0.012	-0.012	-0.022	0.011
	(0.010)	(0.009)	(0.019)	(0.019)
$E(\Delta\hat{P}_{it})young, = 2007$	0.031	0.041	0.054	0.032
	(0.027)	(0.056)	(0.087)	(0.030)
$E(\Delta\hat{P}_{it})old, = 2007$	0.054	0.014	0.043	0.058
	(0.043)	(0.010)	(0.050)	(0.076)
$E(\Delta\hat{P}_{it})young, > 2007$	0.081	-0.010	0.013	0.009
	(0.089)	(0.010)	(0.020)	(0.020)
$E(\Delta\hat{P}_{it})old, > 2007$	0.079	0.059	0.042	-0.023
	(0.600)	(0.480)	(0.053)	(0.058)
$\hat{\theta}^P_{it}$ young, <2007	-0.071	-0.027	0.087**	0.022
	(0.060)	(0.053)	(0.042)	(0.037)
$\hat{\theta}^P_{it}$ old, <2007	0.012	-0.010	0.093	-0.009
	(0.090)	(0.070)	(0.079)	(0.020)
$\hat{\theta}^P_{it}$ young, <2007	0.043	0.042	0.023	0.087
	(0.038)	(0.059)	(0.054)	(0.068)
$\hat{\theta}^P_{it}$ old, <2007	-0.032	0.012	-0.043	-0.012
	(0.023)	(0.010)	(0.074)	(0.021)
$\hat{\theta}^P_{it}$ young, <2007	0.047	-0.083	-0.024**	0.017
	(0.059)	(0.062)	(0.011)	(0.028)
$\hat{\theta}^P_{it}$ old, <2007	0.002	0.045	-0.031*	0.042
	(0.052)	(0.051)	(0.018)	(0.029)

where ***,**,* indicates significance at the 1, 5, and 10% levels. Regressions include county dummies and a constant. Standard errors are reported in parentheses.

We test for liquidity as this is a basic test for the collateral channel. Homeowners after the crisis can be viewed as credit-constrained households. This is due to new regulations imposed by the US government. This led to an increased lending criteria for households, and this subsequently reduced borrowing after the financial crisis. Although this is an imperfect measure of collateral borrowing, it does give insights into the financial health of homeowners and is a test for collateral borrowing. We find no significance in results in homeowners with high levels of liquidity before, or after, the crisis.

Interestingly, we note, young households who have low liquidity, reacted positively to unexpected house price changes before the financial crisis, and negatively afterwards. Significant, positive unexpected house price changes for young, illiquid, households, infers that the productivity hypothesis and collateral channels are exhibited. This infers young households expect wages and total income to rise in future periods, consequently, they have higher consumption today. With this in mind, combined with easing credit constraints, young households increased consumption through unexpected housing wealth increases. We would expect to see a larger, positive reaction in older households if the wealth effect was present before the financial crisis.

On the other hand, we find both older and young household react negatively and significantly to unexpected house price changes after the financial crisis. Older households reduce consumption slightly more than younger households after the financial crisis. However, this is less significant than younger households. This would be due to losses in wealth due to the financial crisis. This finding supports the wealth effect hypothesis that older households react more strongly to the wealth effect as they have a shorter time horizon and more of their wealth is in housing. From this estimated house price elasticity for young and old was -0.024 and -0.031, house values for each group was \$145,000 and \$230,000 and consumption was \$39,000 and \$47,000. The average marginal propensity to consume out of housing wealth increase was -0.63% and -0.65% respectively.

6.5.4 Robustness tests

To ensure the results are not driven by issues within the specifications utilised, several robustness tests have been implemented. Firstly, house price data is averaged across the year for the Zillow data-set. However, PSID households are interviewed at random across the year, so house price valuations may have changed substantially by the time the last household is interviewed. Hence, seasonal house price effects may affect our estimates. Consequently, we test house price valuations from Zillow taken in December of each year of data. We find no significant changes in results.

Browning and Leth-Petersen (2003) note that total expenditure can be affected by large unobserved capital gains, which affects households with large stock portfolios or multiple investment properties. Since the PSID over-sampled low-income households, the majority of households in our study do not own significant stock or housing portfolios. We estimated the model without households with such portfolios; the results were also unaffected.

Although our data spans a large sample period, our analysis is based on an economic environment that experienced significant house price, income, and consumption level changes. Unfortunately, due to limitations in the data, we are unable to provide an analysis in stable market periods, as detailed consumption statistics are not taken prior to 1999, and the sample population also changes due to balancing corrections made by the PSID. However, Browning et al. (2013), using a similar methodology found only young, illiquid households reacted positively to the wealth effect.

A third issue is the fact we assume Zillow house price estimates to be correct for each geographical area. As explained in Appendix 2, Zillow house price valuations are comparable to other notable data-sets; however, there are errors in their estimation techniques which are not accounted for in our analysis. Error in Zillow estimates comes from both errors in their estimation techniques, and false or misguided information entered by households on their website. This ultimately affects the predictive power of the Zillow's "Zestimates", and this will add error into our analysis. However, we believe this error will have a small effect on the results as Zillow update their local historical house appreciation indices to reflect improved estimation techniques. Finally, robustness checks on household weights and clustered standard errors at the municipal level were conducted and no significant changes to the results were identified.

6.6 Conclusion

This paper investigates the relationship between household consumption and house prices. The literature has suggested two main channels to explain this effect and a multitude of alternative theories. To test the relationship we regress total non-durable household consumption on expected and unexpected house price changes and disposable income. Households are expected to react solely to unexpected house price changes due to assumptions made in the life-cycle model. Collateral constraints on households who want to consume more today, but are financially limited, could also drive the correlation between house prices and consumption.

We combine two restrictive data-sets: the Panel Study of Income Dynamics, and data from the online real estate agency, Zillow. The novel combination of these two data-sets allows one to analyse a sample of 6,000 households between 1999-2015.

The findings presented in this study provide little support for the wealth effect. The wealth effect channel was seen in illiquid, young and old households after the financial crisis. Firstly, the house price process was found to be stationary and persistent, thereby indicating the house price shocks do not have a permanent change on household consumption. Consequently, we can imply that the wealth effect would be short-lived and small, if present. Secondly, the expenditure regressions find no statistically significant relationship between house prices before and after the crisis for most households, except for the aforementioned groups. We do find evidence that young households react positively to unanticipated house price increases before the financial crisis. This is due to the collateral borrowing channel and the productivity hypothesis. Our results indicate that households experience both collateral borrowing and the wealth effect. Therefore, both channels may work in unison to produce the correlation seen between house prices and household consumption.

Finally, the findings suggest house prices and household consumption are not correlated due to the wealth effect. Therefore, government policies that affect U.S. house prices, such as mortgage support measures introduced during the pandemic, or decreasing loan to value ratios are likely to impact on household consumption. However, reducing credit constraints on households will likely positively increase household consumption for younger households. Furthermore, financial advisors should review younger households consumption patterns and recommend adjustments to consumption if credit constraints are reduced by governments.

6.7 Appendix

Table 34: Income summary statistics

	Mean ($)	Median ($)	SD	Minimum ($)	Maximum ($)
Labour income head	34,016	43,763	43,415	0	194,892
Labour income spouse	17,955	1,619	25,274	0	113,805
Rental income	809	820	478	0	1,678
Taxable income	3,123	1,024	7,264	0	35,564
Total income	85,176	67,991	65,142	7,350	319,213
Disposable income	79,423	64,549	57,829	5,035	264,144

Source: Author's calculations from the Panel Study of Income Dynamics. All income is yearly except rental income, which is monthly. Number of observations is 93,143. Total income is the sum of all income measures for both the head and spouse (if applicable). Disposable income is calculated using the TAXSIM model. Values are adjusted for CPI and are quoted in 1999 dollars.

Table 35: Household expenditure summary statistics

	Mean ($)	Median ($)	SD	Minimum ($)	Maximum ($)
Utilities	3,163	2,892	1,917	0	9,559
Vehicle	7,233	4,543	4,567	0	28,596
Child care	481	0	1,994	0	19,362
Health	3,401	2,050	3,896	0	20,627
Food	10,043	7,877	8,737	1,380	67,003
House	18,417	14,517	13,840	1,977	62,214
Other	5,325	2,094	6,677	0	25,166

Source: Authors calculations from the Panel Study of Income Dynamics. All expenditure variables are expressed as yearly except for child care which is monthly. Number of observations is 91,243. Expenditures variables were expanded in 2005 but these are not included in our sample. Values are adjusted for CPI and are quoted in 1999 dollars.

Table 36: Distribution of homeownership types

	1-Family house (%)	Apartment (%)	Mobile home	Terrace (%)	2-Family house (%)	Rent (%)	Own (Mort) (%)	Own outright (%)
1999	70.5	15.5	6.1	2.0	3.9	35.6	48.9	15.4
2001	71.2	14.5	6.7	2.2	3.8	32.8	51.4	15.6
2003	73.1	13.5	6.5	2.1	4.1	30.6	53.1	16.1
2005	74.2	13.4	5.7	2.4	3.5	30.4	53.3	15.9
2007	75.1	12.7	5.7	2.4	3.5	29.7	52.8	14.7
2009	76.0	12.5	5.1	2.6	2.9	30.4	52.3	16.7
2011	75.2	12.9	5.4	2.2	3.5	31.5	49.2	18.7
2013	75.6	12.9	5.5	1.8	3.5	32.1	47.1	20.6
2015	75.8	13.4	5.2	2.0	1.8	31.8	47.2	21.0

Source: Authors calculations from the Panel Study of Income Dynamics. Number of observations is 92,109. Households who did not know what type of property they lived in, and how they owned property were dropped from the sample. Source: PSID.

Table 37: Housing summary statistics

	Observations	Mean ($)	Median ($)	SD	Minimum ($)	Maximum ($)
Home value	91,501	161,773	105,504	189,397	0	825,090
Rent	33,158	649	550	589	0	31,956
Mortgage	45,546	6,528	2,319	8,418	0	32,109
No. Rooms	91,582	5	5	2	2	10

Source: Authors calculations from the Panel Study of Income Dynamics. Rental and mortgage values are quoted as monthly. Values are adjusted for CPI and are quoted in 1999 dollars.

Table 38: Household wealth

	Mean ($)	Median ($)	SD	Minimum ($)	Maximum ($)
Saving value	16,310	3,000	31,331	0	170,708
Stock value	15,574	0	47,691	0	284,513
Value of other assets	4,006	0	11,871	0	64,257
Home equity	86,357	34,016	122,331	-6,749	540,576
Total wealth w/o equity	151,734	23,472	300,237	-53,346	1,678,632
Total wealth w equity	244,542	75,687	401,007	-49,272	2,190,756

Source: Authors calculations from the Panel Study of Income Dynamics. In the top panel are selected categories of household wealth and the bottom panel contains the total wealth with and without home equity. Values are adjusted for CPI and are quoted in 1999 dollars.

6.7.1 Zillow Home Value Index

Zillow's Home Value Indices (ZHVI) are used to capture the changes in the value of residential real estate over time.[68] The indices are available for more than 350 metropolitan statistical areas, capturing more than 95% of the total housing stock by value. The ZHVI also capture individual housing features such as the number of bedroom, bathrooms, and home value. Furthermore, Zillow has various geographical levels (finer geographical units are restricted for research purposes and are available through a contract with Zillow), which will allow us to link geographical locations between the PSID data-set and Zillow.

Zillow creates an index through estimating the sale price of every residential home. This includes homes that were not sold in any single time period. Zillow's ZHVI uses hedonic regressions to update the value of all homes in a region in response to each transaction in the near geographical region. The estimation method can lead to minimal systematic error in their house price predictions. Zillow has a median error rate of 4.6% across the U.S.[69]

There have been several studies that have investigated the accuracy of the Zillow data-set. Robustness test by Mian and Sufi (2009) used the Zillow data aggregated at the zip code level. They find from 2,248 zip codes that house price changes from the Zillow index and the Fisery's Case Shiller Weiss index have a correlation of 0.91. Other studies, such as Huang and Tang (2012), find the Zillow and FHFA index are also highly correlated. Hartman-Glaser and Mann (2017), find that the ZHVI is similar to the CoreLogic's single-family combined home price index. The authors detail that at the zip-code level, housing return volatility

[68]Non-residential properties, such as office buildings, shopping centres, and farms are not included.

[69]More information can be found on the Zillow Zestimate website (https://www.zillow.com/zestimate/acc)

was lower and slightly skewed for Zillow compared to CoreLogic. Furthermore, a negative cross-sectional relationship between income and return volatility was present, highly stable, and was statistically different from zero for the Zillow dataset.

Table 39: Zillow summary statistics

	Bottom Tier Avg ($)	Middle Tier Avg ($)	Top Tier Avg ($)	Bottom Tier Dec ($)	Middle Tier Dec ($)	Top Tier Dec ($)
1999	106	130	158	110	134	164
2001	123	150	183	128	154	188
2003	143	174	213	149	182	223
2005	178	220	273	189	233	291
2007	198	243	304	194	236	296
2009	164	200	254	160	195	248
2011	145	181	230	141	178	227
2013	157	196	248	166	205	258
2015	188	230	286	195	239	297
Min	100	121	146	101	125	156
Max	205	252	299	210	258	301
St.Dev	30	37	47	30	38	47

Source: All values quoted are in thousands. The number of observations for bottom, medium, and top tier homes is 29,403, 34,416, and 36,747 respectively. Avg is the average home value of that respective tier, calculated across one year. “Dec” stands for the valuation of the home in December of said year.

We allocate households to a tier at the start of the sample period, 1999. Households are allocated a tier based on their predicted home value of their property to the closest tier found in Zillow. Households who fall directly in the middle of two tiers are allocated to the highest applicable tier.

6.7.2 TAXSIM model

7 Limitations and further research

The main limitation for Chapter four is the relatively small number of current machine learning studies applied to household finance questions. The most applicable machine learning literature that focuses on a similar style of research question are based on predicting residential house prices. This prevents us from comparing our results to other notable studies. With a larger volume of comparable papers, this would allow us to identify if the architectural structure of our decision tree, decision forest, and artificial neural network models perform well and work as expected. In order to compensate for this, we employed a wide variety of robustness tests and varied the hyper-parameter setups to ensure the results were both robust and consistent. However, alternative supervised machine learning techniques such as support vector machine models could also be beneficial in understanding the underlying relationships asked within Chapter Four. For further research, Chapter Four has laid the groundwork for a number of potential machine learning studies. In particular, identifying when a household is most likely to default, either strategically or due to other circumstances is an exciting avenue, which could also build on the novel work of Gerardi et al. (2018). Moreover, this topic could be applied to Chapter Three where one could identify which household characteristics are likely to move a household into, or out of poverty.

In Chapter five we model transitions in and out of asset poverty thresholds using probit models. One limitation is found within the PSID data-set is due to the lack of indicators that are found across the whole sample period, which could in turn, potentially explain the transitions into and out of asset poverty. Indicators such as mortgage distress, severe changes in health etc, are only available for a small subsection of the sample period. Future research in this area could be to widen the number of countries sampled in our study. This would allow one to identify how asset poverty rates vary across countries, and determine if certain asset-based poverty policies are better at reducing poverty rates, that could be then implemented in other regions of the world through policy makers.

Chapter six has a few notable limitations. Firstly, since the PSID data-set doesn't report disposable income,[70] we employ the TAXSIM model to calculate household disposable income. This will add potential bias as the tax codes aren't updated within the TAXSIM model as frequently as local and state income taxes, which could distort our disposable income values. The varying channels[71] that potentially explain the relationship between house price innovations and household consumption are still contested. During the COVID-19 pandemic we have seen, (especially within the United Kingdom) house price increases and reduced household consumption due to government lockdown regulations. It will be interesting to see, once the PSID data is released, if the wealth effect, or other channels, were present during this period, as the pandemic is a unique example of an exogenous shock that could be utilised to great effect within the estimations.

[70] I.e. after tax income

[71] Such as collateral borrowing, wealth effect, macro-economic conditions etc

8 Conclusion

This thesis aims to contribute and further the existing literature relating to the areas of household finance and household poverty. Household wealth has become an important focal point for both policy makers and academics since the 2008 global financial crisis, and more recently due to the 2020 Covid-19 pandemic. Through utilising the Panel Study of Income Dynamics throughout these studies, the thesis has specifically reviewed the role the wealth effect channel; where house prices can affect household consumption. Secondly, this study explored how income poverty may underestimate household poverty by comparing income poverty and asset poverty rates, and identified potential reasons as to why households transition into, and out of asset poverty thresholds. Finally, we employ novel machine learning techniques to understand the determinants of household net wealth, and net wealth minus housing equity which were compared to classical weighted least square regressions, and provided new insights into the differences in wealth prediction for different types of households.

Overall the thesis findings suggest there is a weak statistical evidence supporting the wealth effect channel. Unexpected and expected house price innovations did not significantly influence non-durable household consumption. Interestingly, the findings highlight that only illiquid, young and old households react to unanticipated innovations in U.S. house prices, which was determined to most likely stem for the borrowing collateral hypothesis. If the wealth effect channel is present, shocks are unlikely to be persistent in nature, therefore indicating potential wealth effects in U.S. households would most likely be short lived. These results align with Campbell and Cocco (2007) and Browning et al. (2013) who also did not find evidence of housing wealth effects in U.K. and Danish data. This study contributed to the literature for several reasons. Firstly, it developed the existing literature by combining data from the restricted data-set from the PSID and restricted data from the online real estate agent Zillow, which has yet to be done within the literature. These data-sets were applied to test for the presence of "The Wealth effect". Secondly, we add to the growing literature of micro-panel studies, compared to historically favoured pseudo-panel studies. Pseudo-panel studies observe similar groups of households over time, compared to the same households. This approach demands a number of requirements, such as the characteristics of the pseudo-panels participants remain the same over time, for example, their age and gender. Often they suffer from a small number of observations or high variance within their measurement error. Therefore, by using panel data this allows us to control for time-variant variables and allows a much richer list of variables to use within the study and reduces potential sampling bias issues.

In the fifth Chapter income and asset poverty rates were calculated for the PSID data-set. The findings suggest that asset poverty rates are approximately two to three times higher than the official measure of income poverty. Asset poverty rates have steadily risen since 1999 and reaching a height in 2011 across all three measures; net wealth, net wealth minus housing equity, and liquidity. Secondly, our results add to the catalogue of evidence that black and female households are more likely to experience asset poverty in comparison to white and married households. Thirdly, we find renters are more exposed to experiencing asset poverty compared to homeowners. Finally, we find that the NW-HE measure of asset poverty is a preferred measure to test asset poverty compared to net wealth, as approximately 20% of homeowners do not have the assets to cover three months of their basic needs.

Chapter Four employed decision tree, decision forest, and artificial neural networks (three common statistical recognition tools) to identify which household characteristics best explain household net wealth and net wealth minus housing equity. This novel study is the first application[72] of machine learning models to the PSID data-set. We show that decision trees found significant determinants of household net wealth and net wealth minus housing equity. Namely, profit on stock, IRA value, profit on business, house value, and other real estate were found to be significant determinants for NW. Similarly, profit on stock, IRA value, profit on business, and other real estate were found to be significant for NW-HE. Interestingly, we find variables such as the number of years left on a mortgage, dividend income, and interest income are consistently found to be useful splitters for predicted NW and NW-HE.

Our results indicate that decision forests provide more consistent and significant estimates for household wealth, and have approximately 24% higher predictive power compared to decision trees. In particular, our decision forest model had a MdAPE of 15.74%, and the best decision tree model had a MdAPE of 24.07%. ANN models had the best model performance for wealth predictions with a MdAPE of 15.55%. However, since ANN models do not allow for feature rankings to be calculated and with only low marginal decreases in the MdAPE, decision forest models have increased functionality for household finance researchers. These novel results highlight the applicability of machine learning models to household level data.

[72]We believe to be the first, especially in terms of applying ML models for financial analysis on the PSID

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