

Are Millennials Spoiled Kids?

Age and Generation Effects on Luxury Expenditure

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Job Market Paper
(preliminary draft)

September 12, 2021

Abstract

Considered as a protected and indulged generation, Millennials attract attentions in luxury market for their seemingly extraordinary spending power. But since they are also biologically younger, it remains unclear whether they would still behave differently conditional on age. Using data from the Consumer Expenditure survey (CE) of the U.S., I firstly classify individual expenditure categories into luxury and necessity based on estimated total expenditure elasticity. After descriptively presenting overall luxury expenditure patterns over life cycle and across time, I decompose age and generation effects on luxury expenditure according to a textbook regression identification. I find all generations follow a trend of decreasing luxury expenditure over life cycle, while earlier born generations tend to buy more at any given age. The results are consistent even in a flexibly nonlinear and interactive machine learning setting, i.e., neural network. The findings in this paper attribute the stereotype of Millennials to the effect of their young age which counteracts the opposite generation effect, and challenges the conventional image of Millennials by relabeling them as actually abstinent from luxury.

JEL classification: J11, D12, M31

Keywords: Luxury expenditure, Millennials, Generation effect, Age effect

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1 Introduction

Since the recession, American luxury market has grown dramatically (Panteva, 2011; Rubin, 2011). The emergence of new consumers, Millennials, was fueling this resurgence with unprecedented spending power (Lafayette, 2011; Rubin, 2011; Jay, 2012; Giovannini et al., 2015).

Based on the U.S. population structure, luxury market has been experiencing a transition from targeting Baby Boomers and Generation X to focusing on Millennials until the end of 2030s (Danziger, 2015). As for market size, Millennials have overtaken their boomer parents and become America's largest generation (Fry, 2020). Fromm and Garton (2013) show a direct annual purchasing power of Millennials estimated to \$200 billion, and indirect annual value of \$500 billion keeping in mind their impacts on their parents. Besides, income potential of Millennials would further accelerate this trend. While Baby Boomers are retiring to a large extent, Millennials have been becoming the leading force in the labor market. As the improved education background promotes career prospects and thereby future income, they might be gradually dominating the luxury market as well (Danziger, 2015). Moreover, Millennials express unparalleled preference for shopping. Not only did they have total spending on luxury not retarded by the recession, Millennials also surpassed older generations subject to even lower income growth (Panteva, 2011). Continuously exposed to the state of the art, Millennials view luxury as must-haves instead of privilege (Halpert, 2012; Giovannini et al., 2015), so they tend to shop discretionarily without considering the long-term consequences (Halpert, 2012).

But this consumption phenomenon of Millennials could just be the result of their young age. Unity Marketing reveals that among all affluents, people from younger age groups consistently buy more luxury goods (Danziger, 2015). While mature consumers have already experienced enough during lifetime, the young are still at a preliminary stage of curiosity and excitement (Danziger, 2015), possibly giving rise to a faster growth of luxury expenditure of Millennials. Additionally, Nye (2011) argues new generations always have the most substantial influences on all markets. What's more, Millennials prove to transmit attitudes towards luxury from their parents (Kapferer and Michaut, 2019), so it is unclear whether generation differences really exist here. Accordingly, as a predictor of consumer behaviors, age might be the intrinsic factor causing Millennials' distinguishable characteristics in comparison to other generations, so we don't know the true reason is because they are Millennials or just because they are young (Howe and Strauss, 2000).

The segmentation of market by both age and generation has been substantially pointed out,¹ but it is not addressed very well by most of the empirical research, especially in the field of luxury. Using data from the Consumer Expenditure Survey (CE) conducted by the U.S. Bureau of Labor Statistics (BLS) from 2000 to 2018, I study age and generation effects on luxury expenditure, and explore how Millennials behave differently from predecessors. I combine generational segments defined by both the Pew Research Center and McCrindle (2007), and divide households in the refined sample into four generations based on the birth year of household heads: Builders (1906–1945), Baby Boomers (1946–1964), Generation X (1965–1980),

¹For example, McCrindle (2007) thinks age alone is inadequate to segment the market because today's teenagers are not comparable to Generation X in 1980s or Baby Boomers in 1960s; Danziger (2015) already realizes that when possessed of wealth, Millennials are not following generations that went affluence before, as they are actually reforming luxury system.

and Generation Y, or Millennials (1981–1996). I follow the microeconomic definition of luxury as having total expenditure elasticity larger than one to classify expenditure categories into luxury and necessity. Specifically, I use the approach of nonparametric estimation developed by Fan (1992) and applied by Heffetz (2004, 2011, 2018) to estimate elasticity of each individual category, and define luxury expenditure as the sum of expenditure on all categories with elasticities larger than one.

I start with descriptive analysis which presents age profiles and time trends of luxury expenditure. Overall, the level of luxury expenditure is “hump” shaped over life cycle, peaking at middle adulthood, while the share of luxury expenditure is monotonically declining, more drastically at young age. Across time, both level and share of luxury expenditure had been declining from the first few years of the sample period until 2014, and then started recovering a bit, which could be explained as the persistent influences of the recession. As for each generation, the same time trend remains.

Despite the fact that on average younger generations have lower luxury expenditure conditional on age, the descriptive results evolve from entangled effects of all characteristics. Therefore, I conduct regression analysis to detect the part of variations resulting from age and generation effects, with proxy variables approach being used to solve the collinearity problem. I find that age and generation effects work oppositely: luxury expenditure decreases over a lifetime, yet older generations tend to consume more of it at the same age, in terms of both expenditure level and share. Millennials actually spend about 8 percent less on luxury than do Generations X conditional on age and other controls, while the share of them is around 1.5 percent less than the share of Generation X, let alone the differences from those of Baby Boomers and Builders. Based on the regression results, I build counterfactual luxury expenditure over life cycle for all generations as a visual representation of pure age and generation effects, which deviates from the descriptive “hump” shaped age profiles that show the aggregate effects and graphically explains the intuition of Millennials’ stereotype as the cross-generational comparison at different life stages. Next, I consider heterogeneous effects by interacting age and generation effects, and the estimated coefficients show that main findings still remain.

Afterwards, I show that the results are robust to alternative model specifications. Similar generation effect can be found when using generation specific ways to define luxury items or restricting the regression to common age range of any two neighboring generations. Besides, the way of modeling age and generation effects also doesn’t matter: the same luxury expenditure patterns prevail when I use cohort dummies as proxies for generation effects, or bunch individual age dummies into groups. Furthermore, adjustment of controls doesn’t lead to different results as well: firstly, for the low quality of CE income data, I refer to Charles et al. (2009) who control for total expenditure instead, and instrument for it using income; secondly, I apply different choices of household scales in the literature to adjust household size to address the concern about economies of scale in consumption; thirdly, I try a more disaggregated generational segments; fourthly, I implement the method developed by Deaton (1997) as an alternative solution for the collinearity problem.

In order to investigate how age and generation affect luxury expenditure in fully flexible

models that might be more realistic for demographic variables, I try machine learning techniques which are able to search for optimal nonlinearity and interactions based on information in the data. I introduce a simple neural network and explain details on model training process. The best models are selected based their out-of-sample performances after the overfitting concern is removed. The same procedures of counterfactual predictions carried out using results from OLS regression apply to the selected models to pin down the pure age and generation effects. While predicting generation specific age profiles, I always take the whole data set to keep the values of other control variables the same for each generation from 21 to 80, and calculate the means of predictions. For both log and share of luxury expenditure, the results are not really diverging from the patterns derived from linear setting that seems not only very straightforward, but also absolutely reliable.

In the end, I compare the economically defined luxury in this paper with “classic” luxury perceived by common sense, and the other related topic—conspicuous consumption, by listing some categories analyzed in the literature. Notwithstanding some overlaps, luxury goods in this paper, based on total expenditure elasticity, are not subsets of either of them. Furthermore, I run the same regressions for specific categories to see how idiosyncratic the findings are. There are some deviates behind the overall generation and age effects, but from those categories that are also considered as “classic” luxury according to common sense, I find stably compatible results saying that Millennials are consuming less of them. Correspondingly, relating to the categories that are also supposed to be conspicuous consumption, the effects of household characteristics are both consistent and complementary to findings in the literature.

This paper makes several contributions to the existing literature. On one hand, my findings contradict the stereotyped impression of Millennials as (potential) growth engine of luxury industry (see, e.g., Panteva, 2011; Rubin, 2011; Jay, 2012; Danziger, 2015) because the pure generation effect reveals their sobriety. This corresponds to the theory of Martin and Turley (2004) and McCrindle (2007) who consider Millennials as rational and suspicious because they’ve already seen through all the manipulated fanciness in the market. I find the received idea of Millennials’ purchasing power actually comes from pure age effect that leads to monotonically decreasing luxury expenditure over life cycle, and I provide quantitative evidences on the argument of age as an essential predictor of consumer behavior (see, e.g., Kapferer and Bastien, 2009; Nye, 2011; Halpert, 2012; Danziger, 2015).

One the other hand, I fill the literature gap in four aspects. Firstly, luxury is a novel topic of consumer expenditure. Some of the standard literature focus on (non)durable expenditure (see, e.g., Fernández-Villaverde and Krueger, 2007; Aguiar and Hurst, 2013), while others only take selected categories into consideration. For instance, Blundell et al. (1994) choose seven broad commodities including food, alcohol, fuel, clothing, transport, services and other goods; more specifically, alcohol consumption, tourism behavior and medical expenditure have also been investigated (see, e.g., Aristei et al., 2008; Bernini and Cracolici, 2015; Banks et al., 2019). One of the very related topics is conspicuous consumption studied by, e.g., Charles et al. (2009), Heffetz (2011), Friehe and Mechtel (2014) and Heffetz (2018). However, as compared in Section 8.2, luxury and visibility are essentially not equivalent to each other. The lack of awareness of luxury might be due to the difficulties in embodying such an abstract concept.

For example, the arbitrary classification by Paulin and Riordon (1998) founded on common sense is lacking academic objectivity. To derive a reliable measure, I refer to microeconomic definition of luxury as being highly elastic, and therefore estimate total expenditure elasticity. This economic measure of luxury constitutes the second aspects of filling research gap.

Thirdly, this paper introduces the methodology of decomposing age and generation effects to luxury related research. Cross-generational study on such topic usually depends on one-time market surveys which couldn't keep age and generation effects separated because of the lack of information on dynamic aging process. For example, Kapferer and Michaut (2019) recruit 3217 luxury buyers between the age 18 and 75 to see how different generations define luxury, but the generational grouping is justy based on age; similar approach is taken by Eastman and Liu (2012) in analyzing the impact of generational cohorts on status consumption, where the 220 adult consumers in the sample are divided into three generations, Baby Boomers, Generation X and Millennials according to age. Although Gurău (2012) conducts life-stage analysis of Generation X and Millennial consumers,² age effect is not directly or systematically examined. With data collected across multiple years, household expenditure surveys work better in this scenario, but few research using such data could strategically achieve this goal. Norum (2003) only employs data from 1998 CE of the U.S., thus still categorizing age groups based on generational definitions. Paulin and Riordon (1998) investigate income and expenditure patterns of people aged from 18 to 29 using data from the CE program in three periods, 1972–1973, 1984–1985 and 1994–1995, but they only focus on Baby Boomers and Generation X. To estimate age and generation effects simultaneously, I exploit the dynamics of long-term expenditure survey data which persistently keep track of consumers of all generations.

At last, this paper provides a nice example of using machine learning techniques in empirical economics analysis. While most of traditional econometric approaches are based on specific functional forms that require lots of statistical assumptions, machine learning techniques flexibly search for the optimal models that fit data the best, which especially works well in my case when demographic variables are highly interactive and nonlinear. This advantage has been noticed and utilized by more and more economists (see, e.g., Varian, 2014; Mullainathan and Spiess, 2017; Athey, 2018; Athey and Imbens, 2019). However, there is not doubt that machine learning mainly deals with prediction instead of estimation and inference, so it is complementing, rather than substituting empirical econometrics, and as a consequence, the applications of machine learning techniques have been so far mainly restricted to the financial market (see, e.g., Gu et al., 2020; Peng et al., 2021; Nosratabadi et al., 2020) where prediction is the major issue. Notwithstanding, in this paper, I could precisely trace out the desired age and generation effects while still making use of the advantage of model flexibility. Hence, by providing new and powerful tools, machine learning shows tremendous potential in economics to be fulfilled.

The remainder of this paper is structured as follows. Section 2 introduces the setting of generational segments and the data. Section 3 classifies the expenditure categories in the CE program into luxury and necessity based on estimated total expenditure elasticity. Section 4

²Millennials are divided into three categories: college students, young single professionals and young married professionals; Generation X are divided into two categories: single professional adults and married professional adults.

and Section 5 presents the descriptive and regression analysis respectively. Section 6 shows the robustness of the regression results. Section 7 confirms the results using one of the most popular machine learning techniques—neural network. After Section 8 discusses the results and intuition, Section 9 concludes.

2 Setting and Data

2.1 Generational Segments

Labeling generations started from Baby Boomers due to their special demographic characteristics (McCrindle, 2007). Now it has been a general consensus that a generation consists of people born in a specific time period, so they share life stages through the same macro environment and develop common value systems, attitudes and behaviors (Howe and Strauss, 2000; McCrindle, 2007). Over life cycle, the external events during late adolescent or early adulthood years, the period when people are “coming of age”, have the deepest influences, named “defining moments” by Schewe et al. (2000).

Although disagreement about the specific periods of birth years arises with respect to defining generations (see, e.g., Strauss and Howe, 1991; Smith et al., 1997; Norum, 2003), people born in the twentieth century are divided into six groups, the Greatest Generation, the Silent Generation, Baby Boomers, Generation X, Generation Y which is also called Millennials, and Generation Z. This paper refers to the generational segments developed by the Pew Research Center, a nonpartisan fact tank that provides information on the U.S. social and demographic trends, summarized in Table 1. To empirically explain “defining moments”, the Pew Research Center conducted a survey called “Americans Name the 10 Most Significant Historic Events of Their Lifetimes” (Deane et al., 2016), and Table A.1 shows that the lists vary across generations.

The Greatest Generation was working during the worst economic times, the Great Depression, thus being indoctrinated with conservative values of financial security (Schewe et al., 2000). At the same time, as the main participants of the World War II, the Greatest Generation also experienced the extreme political turmoil, where they developed the ability to delay gratification (Schewe et al., 2000). Influenced by economic hardship and wartime experiences, the Greatest Generation had been willing to sacrifice personal satisfaction for the sake of a better society, reflected in the Inaugural Address of John F. Kennedy in 1961, “ask not what your country can do for you—ask what you can do for your country” (Norum, 2003). Consequently, fighting for the country rather than personal fame or recognition became the “right thing to do”, and the Greatest Generation ultimately achieved remarkable accomplishments, such as the Interstate Highway System and Medicare program, which made the U.S. a better place to live in (Brokaw, 1998).

The Silent Generation experienced a relatively long time of economic growth and social stability. Economically, they hold less conservative attitudes towards saving and spending (Schewe et al., 2000). Nevertheless, when coming of age after the World War II, they cautiously kept heads down and worked hard in the new social order that they never had motivation or courage to change, and this was where the “silent” label came from (Howe, 2014). Locating between the Greatest Generation who had been fighting and sacrificing, and Baby Boomers

who created shock waves afterwards, the Silent Generation stays in an awkward situation like a sandwich (Howe, 2014), therefore refraining from individual expression (Schewe et al., 2000).

Owing to their enormous numbers, Baby Boomers had been dominating all aspects of American society (Schewe et al., 2000). Opposite to the war years, this period was symbolized by unmatched economic prosperity, ample educational opportunities and extraordinary technological advancement (Strauss and Howe, 1991; McCrindle, 2007). Growing up in such a booming environment, Baby Boomers value independence and individualism (Eastman and Liu, 2012), so they attach more importance to personal achievements than contribution to the society (Smith et al., 1997). In contrast to previous generations characterized by humility and modesty, they started defying established social orders and questioning the nature, and for this reason, Russell (1993) call them “free agent”. At the same time, full employment encouraged and fostered their financial confidence and consequent spending habits (Eastman and Liu, 2012). Therefore, austerity was left behind, and instead, “buy now, pay late” became their new consumption philosophy (Schewe et al., 2000).

Generation X grew up in a less optimal environment created by the individualism and self-fulfillment of their boomer parents who shifted the focus of the society from children to adults (Howe and Strauss, 1993). The increasing divorce rate and female labor force participation of Baby Boomers left Generation X unsupervised after school, and this was where the name the “latchkey generation” came from (Shamma, 2011; Blakemore, 2015). When Generation X was coming of age, the economic recession in 1980s made them conscious and pessimistic (Eastman and Liu, 2012). Meanwhile, turbulent political conditions caused their uncertainty and disillusionment (Smith et al., 1997). All of these unfortunate experiences shaped Generation X negatively, aimless, bleak, and cynical (Paulin and Riordon, 1998), portrayed by Richard Link later in a 1990 American comedy-drama film *Slackers*.

By the end of economic recession and political instability experienced by Generation X, Millennials appeared on the scene. Having been living through the era of digital revolution, globalization and environmentalism (Schewe et al., 2000; McCrindle, 2007), Millennials are always considered as distinguished from previous generations in all aspects, which are discussed in details as follows.

2.2 Millennials

Millennials have been attracting attentions due to their distinguishability and uniqueness. Two most distinct features of Millennials are probably increased education levels (Frey, 2018) and familiarity with new technology (Valentine and Powers, 2013). Demographically, the Pew Research Center estimated that by 2019, Millennials (with a number of 72.1 million) had passed Baby Boomers (with a number of 71.6 million) and become the largest living adult generation in the U.S, thanks to the dynamics of mortality and immigration (Fry, 2020). And as a much more racially and ethnically diverse generation, Millennials perform the function of the demographic “bridge” to America’s diverse future (Fromm and Garton, 2013; Frey, 2018).

The stereotype of Millennials is formed by the fact that Millennials grew up in a time of accumulated materialism (Valentine and Powers, 2013) and are well protected by the society and government safety regulations (Tucker, 2006). As such an indulged and spoiled generation,

Millennials are too impatient to delay gratification, indicating their possible active participation in luxury market. However, such modern environment could have been shaping Millennials in an opposite manner. Exposed to explosive information and massive technological innovation, Millennials have actually developed sophistication and suspicion (Valentine and Powers, 2013). For example, Martin and Turley (2004) find Millennials objective, rational and goal-oriented during a mall excursion, where they emphasize functional values instead of being motivated by hedonism or marketing tricks.

At the same time, the new era that the Millennials have been living through is also full of unpredictability. First of all, the expected gains from greater educational achievement have been counteracted by accompanying decreasing returns due to overproduction of advanced degrees (Emmons et al., 2019). Secondly, since the Great Recession, other than benefiting the least from the recovery (Smith, 2012), Millennials have been actually facing a worse situation in labor market than did Baby Boomers and Generation X when they were young (Frey, 2018). By examining the effects of the Great Recession on wealth accumulation, Gale et al. (2020) show similar evidences: notwithstanding the wealth decline of all age groups in the short run, compared to other older generations, Millennials have been poorer and poorer in the long run. In addition, the massive size of Millennials results in fierce competition for jobs (Zeihan, 2016). At last, the new trends of artificial intelligence and robotics generate not only new opportunities but also challenges (Zao-Sanders and Palmer, 2019).

Shaped by these revolutionary external events from all sides, Millennials have been evolving differently from the predecessors, reflected in their unique thinking and consumer behaviors. Millennials might be strongly stimulating the American economy (Noble et al., 2009) while having been reaching peak earning and spending years, especially given their exceptional size. However, the complexity of this generation yields ambiguity in luxury market. Therefore, it is hard to ignore this generation not only in marketing, but also in academic research.

2.3 Data

To explore age and generation effects on luxury expenditure patterns, I use data from the Consumer Expenditure Survey (CE), a program to collect data of household expenditures on goods and services in the United States, where basic information on economic and demographic characteristics is also included.

Carried out by the U.S. Bureau of Labor Statistics (BLS), the CE program consists of two separate surveys using different samples: the Quarterly Interview Survey collects data on large and recurring expenditures during the three months prior to the interview, and the Diary Survey is designed for small and frequently purchased items for two consecutive one-week periods. I only use the Quarterly Interview Survey due to its higher data quality.³

The Quarterly Interview Survey is a short rotating panel survey in which approximately 6000 interviews are conducted each calendar quarter.⁴ Each household is interviewed every three months over four consecutive quarters, and is supposed to recall expenditures during

³See Bee et al. (2012) for detailed discussion about this issue.

⁴Here “quarter” means the time period when the interviews, not the purchases occur.

past three months.⁵ After the fourth interview, households are dropped from the sample and replaced by new ones which consist of 25 percent of total sample. Although each household can provide data for a maximum of one year, I treat records of each interview independently without reporting the sum of expenditures across all interviews that one household has participated because of the following reasons: less than 50 percent of the households complete all four surveys; those who participate in all four quarters are biased towards older and richer households and more likely to own their homes.

The annual data collection of the CE program has started since the end of 1979, including expenditures in different levels of details reported by different files. The FMLI files of the Quarterly Interview Survey provide summary level expenditures and other household characteristics. I use data of the FMLI files from 2000 to 2018 for consistent questionnaire design and expenditure categorization, or in other words, the consumption bundle keeps the same in the data since 2000. And in this way, Millennials are also included in all sample years. I aggregate specific expenditure categories in the FMLI files into 32 categories, and Table A.2 reports the details.⁶ Besides expenditures, I also take data on total amount of household income after taxes in the last 12 months and household characteristics from the FMLI files.⁷ All expenditure and income data are deflated to 2007 dollars using Consumer Price Index (CPI). Household characteristics include age, gender, race, marital status and education of household heads, household size, the number of adults, urban residence, information on metropolitan statistical area, region, and interview quarter of the each record. The full sample contains 526828 observations.

3 Defining Luxury Expenditure

The first step is to determine which of the 32 categories listed in the left column of Table A.2 can be treated as luxury. Based on the microeconomic description of luxury on which expenditure increases more than one percent with one percent increases in total expenditure, I estimate the total expenditure elasticity of each category and determine whether it should be treated as luxury or necessity by comparing the value to one. Concerning measurement errors and extreme values, I drop households with negative expenditure of any category and households in the top or bottom one percent of distribution of total expenditure within each year from the 526828 observations in the full sample. For elasticity estimation, I don't consider specific generations or age range as the way to classify expenditure categories into luxury and necessity should be representing the perception of luxury of the whole population.

⁵Before 2015, a preliminary bounding interview was included to minimize telescoping errors. Because of its ineffectiveness and cost, it was stopped at the beginning of 2015 (Elkin, 2012).

⁶The FMLI files also report aggregated expenditure categories, for example, shelter, utilities, fuels and public services, household operations and house furnishings and equipment are all included in a single categories called total housing outlays, but this is too broadly defined and the heterogeneity among individual categories might already be averaged out.

⁷Complete income reporters were the only source of published income data before 2004, since when the CE program started to impute missing values. Estimation of personal taxes was introduced in the second quarter of 2013, which has replaced all reported and missing values. Therefore, collected data with missing incomes are used before 2004, while imputed or collected data are used for the years 2004–2013; after 2013, only estimated taxes are reduced from imputed or collected income data.

Following the approach of Heffetz (2004, 2011, 2018), I conduct nonparametric estimation using the prepared sample. To be specific, I start with estimating the expenditure of each of the 32 categories as a function of total expenditure at 101 total expenditure points, using Fan (1992)'s weighted local linear regression with quartic kernel. Next, the slopes of the 100 lines connecting the estimated 101 points are calculated, and 100 local expenditure elasticities are derived from these slopes. Finally, average elasticity of all households are obtained from these 100 local elasticities weighted by the number of households located in each of the 100 intervals. The same steps are repeated for all of the 32 expenditure categories.

As the perception of luxury depends on subject thinking that cannot change too frequently, I treat total expenditure elasticity as a long-run variable and rely on averages across time. However, because some categories might have the elasticities fluctuating around one, the same estimation is executed in different periods, 2000–2009, 2010–2018 and 2000–2018. The estimation results are shown in Figure 2, where value one is marked by the vertical line as the threshold elasticity. As the results suggest, the elasticities of some categories, like food away from home, alcoholic beverages, shelter, etc., are relatively unstable when estimated during different periods, and also located around one. To avoid any arbitrariness and randomness, I only define the categories with elasticities substantially and consistently larger than one in any periods as luxury, which leads to 15 categories of luxury goods: household operations; house furnishings and equipment; clothing for adults; vehicle purchases; other vehicle expenditures;⁸ public and other transportation; fees and admissions; pets, toys and playground equipment; recreational vehicles; miscellaneous entertainment outlays; education; cash contribution; retirement, pensions, social security; life and other personal insurance; and miscellaneous outlays.⁹ After this, two categories, retirement, pensions social security and life and other insurance are excluded because they belong to consumption transferred into the future. In the end, 13 categories boldfaced in Figure 2 are defined as luxury and luxury expenditure is the sum of expenditures on all of them in the following analysis.

Arguments that whether some categories really belong to luxury must be rising here since the estimation results here might not be in line with all personal opinions. For instance, it is debatable whether education should be treated as investment or expenditure, and the methods of payment for it also involves complex financial issues that are not homogeneous across households or generations. To keep things simple and objective, here I only rely on economic definition of luxury instead of moving to the next step and thinking about the rationale behind it. Alternately, I also show the results from specific categories in Section 8.1, especially those that are agreeably considered as “classic” luxury. As discussed in Section 8.2, results from such categories are consistent with the main findings.

4 Descriptive Analysis

This section provides descriptive analysis of luxury expenditure. I summarize some descriptive statistics after refining the full sample with 526828 observations; then, I graph (generation

⁸Other vehicle expenditures include vehicle rental, leases, licenses, and other charges. See Table A.2 for details.

⁹Miscellaneous outlays specifically include checking account fees and other bank service charges, credit card memberships, accounting fees, funerals, union dues, etc.. See Table A.2 for details.

specific) sample means over life cycle and across time to show overall patterns of luxury expenditure (for each generation).

4.1 Sample Selection and Summary Statistics

Among the 526828 observations, I exclude Generation Z since there are very few observations in the sample and most of them probably haven't finished education yet, which might distort their expenditure structure. Next, I restrict the attention to households whose heads are aged 21–80 for the facts that an insignificant amount of old households were surveyed,¹⁰ and people younger than 21 don't legally have access to some expenditure categories in the U.S. such as alcoholic beverages and tobacco and smoking supplies.¹¹ On top of that, I drop the ones with negative expenditure in any category and negative income (before and after taxes) from the sample. For the data before 2004, I drop incomplete income reporters. Finally, to control for the impacts of extreme values, I drop households in the top or bottom one percent of distribution of both total expenditure and income (before and after taxes) within each year. The resulting sample contains 443497 observations, which are used in the descriptive and regression analysis.

For the reason that much less households of old generations are included in the survey and Millennials are the focus of this paper, I combine the two oldest generations, the Greatest Generation and the Silent Generation, together into one single generation in the main specification. McCrindle (2007) calls them Builders because they have transformed an agrarian economy into an industrialized one by building the infrastructure and organizations of the new postwar society. Figure 1 graphs the size of each generation in the sample across time, which are not equally distributed, but definitely not distorted.

Both the log and share of luxury expenditure are the main variables for analysis. Table 2 lists summary statistics for the refined sample. On average, households spend \$2591.561 per quarter (in 2007 dollars) on luxury, accounting for around 18.3 percent of total expenditure. Probably because Millennials are just at the beginning of career path and receive relatively low income, they buy the least amount of luxury in terms of absolute level, followed by the Builder, and these two generations also have the lowest total expenditure. However, Millennials on average have the largest share of luxury expenditure among all generations, which to some extent agrees with the established social impression of Millennials as excelling at purchasing luxury, but the average figure is not enough for this conclusion yet as it is also related to age. Besides, the reason why the mean of total expenditure is only one fifth of average income after taxes is that expenditure data are quarterly based while income data are for the last 12 month.

Regarding demographics, the average age in the sample is 48, which is driven by the a little overrepresented Baby Boomers and Generation X in the survey as the oldest Millennials are just 37 in 2018. Slightly more than half of household heads are women, and households with married heads make up 54.5 percent. High school graduate is the largest group of education level, accounting for 46.1 percent, and 81.5 percent the household heads are Whites. The spatial distribution of households is uneven as most of them locate in urban and metropolitan

¹⁰There are consistently more than 3000 observations of each age group of household heads younger than 81, but for households older than 80, the number of observations fluctuates between 4972 and 0.

¹¹Actually this age condition could also rule out most of members of Generation Z.

statistical area, and the largest number of surveys happened in the South. The four calendar quarters are weighted relatively equally in the survey.

Some attentions should be paid to the adjustment of household size due to the economies of scale in consumption. Different choices of scales are discussed in the literature, all of which have advantages and drawbacks (see, e.g., Fernández-Villaverde and Krueger, 2007; Aguiar and Hurst, 2013). In the main specification, I use the “OECD equivalence scale”, also called “Oxford scale”, which assigns a value of 1 to the first household member (which is household head in this case), a value of 0.7 to each additional adult and 0.5 to each child.¹² Alternatively, “OECD-modified scale” and “square root scale” are employed in robustness checks,¹³ which deliver almost the same results. It is also noted that from some of the given household characteristics such as household size, the number of adults, age and marital status, more information about household structure could actually be inferred, so I don’t include redundant variables here.

4.2 Age Profiles

I firstly present the average log level and share of luxury expenditure by age. I pool observations of all sample years and calculate the averages conditional on age. Figure 3 shows the resulting age profiles. On average, the level of life-cycle luxury expenditure is characterized by a “hump” in Figure 3(a), peaking around age 40, corresponding to the dynamics of earning years over life cycle. Nonetheless, Figure 3(b) reveals uninterrupted declining of the share of luxury expenditure over life cycle. After falling drastically from slightly below 22 percent at age 21 to around 18 percent at age 40, it stays on a stable decrease until it sharply drops again from age 60. The key takeaway from Figure 3 is that age is an active factor affecting luxury expenditure in terms of both level and share, and young people are in general doing very well in consuming luxury. Although Millenials are the youngest generation in the sample, Figure 3 only shows means of each age among all generations, so the specific behaviors of Millennials couldn’t be revealed from the average numbers which are also based on expenditure of Generation X at the same age.

As the generation heterogeneity behind Figure 3 is still puzzling, I further provide information on the evolution of average luxury expenditure over life cycle for each generation, as Figure 4 plots, with expenditure level and share shown in Figure 4(a) and Figure 4(b) respectively. Each connected line represents the expenditure behavior of a specific generation over the 19-year sample period. Different generations are observed through different life stages, with some overlaps among age brackets which could be used for comparing neighboring generations. The vertical distances between lines present the existence of generation effect, though it is still contaminated by other effects at this preliminary step.

The overall “hump” shaped age profiles of expenditure level and declining age profiles of expenditure share still remain, while differences between generations are obvious as well. At the

¹²See <http://www.oecd.org/economy/growth/OECD-Note-EquivalenceScales.pdf> (accessed 9 September 2021) for details.

¹³“OECD-modified scale” assigns a value of 1 to the household head, a value of 0.5 to each additional adult and 0.3 to each child. “Square root scale” uses the square root of the total number of household members. See <http://www.oecd.org/economy/growth/OECD-Note-EquivalenceScales.pdf> (accessed 9 September 2021) for details.

same age, younger generations tend to spend less on luxury in terms of both expenditure level and share, and Figure 4(b) shows that the differences are especially substantial in expenditure share. Even though there are noises accompanying the data of the oldest Generation X and the youngest Baby Boomers, Millennials have been consistently consuming less luxury than Generation X at any given age from 21 to 37, through which both generations are traced in the data. However, the average expenditure patterns cannot tell to what extent the results in Figure 4 is driven by other effects. Therefore, more strategic regression analysis is employed for clarifying these confusions.

4.3 Time Trends

Following age profiles, I turn to look at luxury expenditure across time to have an overall perception of how period effect works. Figure 5 presents the results. Clearly, the level and share of luxury expenditure follow the same time trend, declining from early 2000s until 2014 and then starting to recover. The lowest expenditure in 2014 reflects the long-term lasting influences of the recession.

Subsequently, I switch to analyzing generation specific time trends, which is plotted in Figure 6 with Figure 6(a) and Figure 6(b) showing expenditure level and share respectively. As absolute luxury expenditure level is directly related to total expenditure or income, Generation X and Baby Boomers are always at the top positions because they are still closer to peak earning ages over life cycle and have highest total expenditure as Table 2 shows. Naturally, Baby Boomers are replaced by Generation X as the leading purchaser around 2010 when gradually approaching retirement. In Figure 6(a), the expenditure level of Millennials diverges from that of other generations and also the general picture, as it is continuously increasing across time, consistent with the observation that Millennials are highlighted in luxury market. The generation differences in Figure 6(b) reflect average statistics in Table 2, where Millennials consistently have the largest luxury expenditure share from 2000 to 2018.

An important feature of Figure 6 is that time trends of luxury expenditure are basically synchronizing among all generations, implying that every generation faces more or less similar period effect. This feature empirically supports the separability of period effect from generation effect, on which my main specification is based, whereas some sensitivity tests present additional results in the end.

5 Regression Analysis

More than the descriptive analysis that provides evidences on average luxury expenditure over life cycle and across time, the following econometric model identifies age and generation effects from the overall trend and quantitatively measures them.

5.1 Identification Strategy

With log level and share of luxury expenditure as dependent variables, I take full vectors of age dummies and generation dummies for estimation. However, when time control is also

included, collinearity problem arises because age is the difference between calendar time and birth year which determines generation. To avoid it, I use proxy variable approach suggested by Dohmen et al. (2017), substituting for period effect with GDP growth rate which captures the cyclical pattern of expenditure variations across time.¹⁴ On top of that, seeing the enduring influences of GDP growth rate on luxury expenditure, like the long-lasting consequences of the recession shown in Figure 5, lagged GDP growth rate is also taken into consideration.

To find the best proxy variable, I scrutinize multiple choices of length as lag periods. I check the coefficients and significance levels of the correlations between average luxury expenditure of each year and lagged GDP growth rates, from one to six years of lags in Table A.3. The correlations between current-year GDP growth rate and the log or share of luxury expenditure are actually economically weak and statistically insignificant, but both the coefficients and significance levels increase with more years of lags. The highest coefficients, together with lowest p-values, come from the correlations between 5-year lagged GDP growth rate and luxury expenditure in terms of both level and share. Therefore, persistent long-term lagged time effect does exist, which has been increasing and peaks after five years, so 5-year lagged GDP growth rate would work best as the proxy. To further corroborate this approach, Figure A.1 plots 5-year lagged GDP growth rate and average luxury expenditure of each year, and there appears to be strong positive relationships between them. Figure A.1 also illustrates that the cyclical patterns of luxury expenditure can be epitomized by GDP growth to some degree, so linear time trend probably wouldn't work very well in this case.

The main specification is built on the separability assumption which states that there are no interactions among control variables. In descriptive analysis empirically displays that period effect is separable from generation effect, but the absence of interaction terms between age and generation dummies is assumed here to explore each individual effect, and also to make the regression table shorter and easily presented. So I estimate the following regression:

$$L_{it} = \alpha_0 + \beta_a D_{it}^a + \beta_g D_i^g + \alpha_1 \text{Period}_t + \alpha_2 \ln(\text{income})_{it} + \beta_h X_{it} + \varepsilon_{it}, \quad (1)$$

where L_{it} is either the log of luxury expenditure or the share of luxury expenditure of household i during the last 3 months in year t ; D_{it}^a is a vector of age dummies for ages from 21 to 80, with age 40 as the base group; likewise, D_i^g is a vector of generation dummies for Millennials, Baby Boomers and Builders, where Generation X is the base group; Period_t stands for 5-year lagged GDP growth rate as the proxy for period effect; $\ln(\text{income})$ is the log of total amount of household income after taxes in the last 12 months and X_{it} is a vector of control variables of household characteristics specified in Table 2, including household demographics, size, location and information on interview quarter, which follows the selection of controls in related literature (see, e.g., Charles et al., 2009; Friehe and Mechtel, 2014).

5.2 Main Results

To start with, I exclude age dummies in a naïve regression model to see what happens when looking at generational variations of luxury expenditure without thinking about age. Next, I

¹⁴Data on GDP growth rate are taken from the World Bank, available at <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2019&locations=US&start=1961> (accessed 9 September 2021).

include age dummies, generation dummies, period effect and income in the baseline model which shows the preliminary pure generation effect independent of age. Furthermore, I run the preferred regression including full controls for household characteristics X_{it} , where region (Northeast, Midwest, South and West) rather than specific state is controlled because of two reasons. First of all, the sample period is too long to rule out the considerable influences from large-scale migration across state, meaning that state fixed effect gets obscure in the sample as expenditure preference geographically moves with people. But region is a large area, across which the migration frequency is supposed to be much lower, and hence region fixed effect is comparatively stable; secondly, there are a significant number of missing values of state information in the data. For the same reasons, I cluster standard errors at household level instead of state level that literature using short-term data usually does. Nevertheless, I still check the results when both region and state fixed effects are included.

Estimation results are presented in Table 3. For both log and share of luxury expenditure as dependent variables, Column (1) and Column (5) display the results of the naïve models. Without controlling for age, the estimated coefficients on generation dummies are decreasing (except for expenditure share of Builders), which coincides with the established impression of Millennials' high spending power in luxury market. However, in the baseline model including age dummies, generation effect immediately switches direction, as shown in Column (2) and Column (4). Earlier born generations tend to consume more luxury than the amount of later born ones, conditional on age, time period and income level. This striking finding is further confirmed by the preferred regressions in Column (3) and Column (6) which controls for household characteristics additionally. At last, coefficients almost don't change when state fixed effect are counted in Column (4) and Column (8). In all specifications with age controls, generation effect appears to be solid and significant. And the magnitudes of these estimators keep relatively stable. Corresponding to the overview of generation specific age profiles in Figure 4, the pure generation effect from the regression works the same but more precisely: younger generations actually spend less on luxury.

Millennials are consuming less luxury than Generation X so in terms of both level and share. Quantitatively, Column (2) reads that when controlling for age, income and time period, Millennials spend 7.35 percent less than Generation X spend on luxury, and this number increases to 8.72 percent in Column (3) when household characteristics are further controlled for. Based on the average luxury expenditure of Generation X, i.e., \$2727.530 per quarter in Table 2, the estimation results in generation differences from \$200 to \$238 per quarter. At the same time, Column (6) and Column (7) show that with and without controls of household characteristics, the share of luxury expenditure of Millennials is 1.39 percent and 1.56 percent less than that of Generation X. Given that the average share of luxury expenditure of Generation X in the sample is only 18.6 percent from Table 2, the generation difference is not trivial at all. Considering the monotone increase of luxury expenditure across generations, Millennials behave even more conservatively when compared with Baby Boomers and Builders. The effects of household characteristics are quite intuitive as well. Conditional on the same household size, the negative effect of the number of adults implies the existence of altruism, so parents are more willing to purchasing luxury for children. Referring to education, when high school graduate

is taken as the base group for its largest share, the estimation suggests a positive correlation between luxury expenditure and education level, so luxury might actually be requiring certain amount of knowledge from education to understand and appreciate it.

Figure 7 portrays age effect on luxury expenditure, where the solid lines plot the coefficients on age dummies from preferred model with shade demarcating 95 percent confidence intervals. The horizontal zero lines mark reference age 40. Conditional on other variables, luxury expenditure monotonically decreases over life cycle, with respect to both expenditure level and share. So people become less and less interested in luxury as they age. And the received idea of Millennials' excellence in luxury expenditure seems to arise out of the fact that generatlyly they are still young in the sample, and this has nothing to do with the effect of their special generation identity.

5.3 Counterfactual Predictions

To give a visual representation of age and generation effects I make use of the regression results to construct counterfactual age profiles of luxury expenditure for all generations. The estimators from the preferred models in Column (3) and Column (7) in Table 3 are used to predict values of the dependent variables. For each specific generation g , instead of only using sample of generation g for prediction, I take the whole data set and calculate the means.¹⁵ Specifically, for each generation g at age a , the predicted values here are explained as the average luxury expenditure of all households when they were treated as generation g at age a . The life-cycle luxury expenditure of generation g is completed after the same exercise are repeated from age 21 to 80. In this way, for each generation at all ages, values of control variables in the whole data set are plugged into preferred models for predictions, so the obtained counterfactual patterns exactly delineate pure age and generation effects conditional on all other controls. Figure 8 plots the predictions for all generations, with log level in Figure 8(a) and share in Figure 8(b), where vertical distances between lines indicate generation differences at the same age.

Comparing the predicted values to real values in Figure 4 in descriptive analysis, while Figure 8(b) presents a pattern of expenditure share accordant with Figure 4(b), Figure 8(a) completely diverges from the "hump" shaped age profile of expenditure level in Figure 4(a) which evolves from aggregate effects. The main findings are confirmed by observations in Figure 8: firstly, for all generations, conditional on other controls, decreasing life-cycle luxury expenditure is predicted from the model; secondly, at all ages between 21 and 80, younger generations spend less on luxury than do older generations, so Millennials have been consuming the least at all ages. Indeed, older generations are active in luxury market, even more than younger ones (Amatulli et al., 2015). An argument by McCrindle (2007) provides the logic behind this finding: older generations have finally started indulgent consumption to realize their long-delayed dreams after decades of hard work, which is even enforced by their greater wealth and longer life expectancy.

¹⁵When only samples of individual generations are taken for predicting the life-cycle expenditure, there is an implicit assumption that values of other control variables are not only different across generations, which contaminates the predictions by integrating variations of other controls besides age and generation effects, but also unchanged over life cycle, which is not very realistic.

Additionally, Figure 8 graphically explains how the stereotype actually came to the fore: currently Millennials are still in early stages of life, so when comparing twenty-something Millennials to middle-aged or elderly Generation X, Baby Boomers and Builders without thinking about what Millennials would have done when they get old, it is easy to mistakenly believe Millennials to spend more on luxury. Similarly, how seniors had behaved at young age is always ignored as well. This model fills this gap by speculating that older generations would have had higher luxury expenditure if they were twenty-something. In a nutshell, it is important to focus on the same life stages when plumbing generation effect, in order to isolate it from age effect and keep the results clean.

5.4 Heterogeneous Effects

The main regression models are based on the separability assumption, which doesn't reckon with any interaction terms. However, age and period might be executing heterogeneous effects on different generations, therefore questioning the uniformity of life-cycle patterns and time trends across generations. Following Fitzenberger et al. (2019), I develop the more general models including interaction terms between generation dummies and age or period controls. The meticulous procedures of regression and sensitivity tests are elucidated in Appendix B, as reported by which, period effect is separable, but generation effect cannot be disentangled from age effect. In fact, the independence of period effect is already evidenced by the synchronization of luxury expenditure of all generations in Figure 6. But apropos of age effect, unfortunately, the main results are now questionable as they shouldn't follow the uniform trend due to the entanglement of generation effect with age effect. This conduces to an ideal regression model

$$L_{it} = \alpha_0 + \beta_{ga} D_{it}^g \cdot D_{it}^a + \alpha_1 Period_t + \alpha_2 \ln(Income)_{it} + \beta_h X_{it} + \varepsilon_{it}, \quad (2)$$

which includes interaction terms $\beta_{ga} D_{it}^g \cdot D_{it}^a$. In preference to discrete pure age effect $\beta_a D_{it}^a$ and pure generation effect $\beta_g D_{it}^g$, and other controls stay unchanged.

Figure 9 shows the generation specific age effect on luxury expenditure by representing the estimated coefficients $\hat{\beta}_{ga}$. The declining life-cycle pattern still follows the main age effect in Figure 7, and differences among generations are also consistent with generation effect in Table 3, so older generations differ from younger ones at the same age by consuming more luxury. For each generation, the estimation is only possible at existent values of the interaction terms, so Figure 9 can only plot the results within the age range where there are observations in the data. In spite of this incompleteness, similar patterns to those of main results in Table 3 are clearly appearing here: generation effect gives rise to less luxury expenditure of Millennials versus all predecessors at the same age. There are some weird nonmonotone parts, e.g., the seemingly increasing trend of old Millennials, but most of these deviating estimates are not significant enough to question the main findings. I also visualize age and generation effects by conducting the same counterfactual analysis as how to construct Figure 8 and present the predicted values in Figure A.2 in Appendix A.

6 Robustness

Several robustness checks are conducted in this section to look at the stability of the main results. I begin with alternative model specifications concerning generation specific classification of expenditure categories into luxury and necessity, generation effect within the same age range, and symmetric treatment of age and generation by controlling for either grouped or individual values of both of them at the same time. And then I check if some adjustments of other control variables than age and generation dummies affect the results.

6.1 Alternative Model Specifications

Generation specific definition of luxury expenditure categories. As individual generations might perceive and define luxury differently, the elasticity estimation based on the overall sample may not fit every individual generations. Therefore, I estimate elasticities using data of each generation following the same procedures in Section 3. Because total expenditure of one single generation is distributed too scarcely at the very top and bottom values, sometimes leaving zero observations between two of the 101 total expenditure points when estimating, I trim households of each generation in the same way as sample selection procedures in Section 4.1: for each generation, I exclude households in the top or bottom one percent of distribution of total expenditure. Besides, generation specific elasticities are only estimated for the whole sample period from 2000 to 2018 given the fact that generation specific ways of defining luxury might be varying nonuniformly across time, so overall average works the best in more equally treating generations.¹⁶

The estimated elasticities are shown in Figure A.4. Based on the same threshold of being luxury, a generation defines a category as luxury good if the estimated elasticity is higher than one using sample of this generation. The overall classification style, on which the main specification is based, are shown by the boldfaced categories. The classification indeed differs across generations, but most of the luxury categories defined by the overall sample are also acknowledged by all generations. Millennials have the most parsimonious selection of luxury. For example, they don't really consider education and clothing for adults as luxury, partially corresponding to the argument that Millennials view luxury as must-haves (Halpert, 2012; Giovannini et al., 2015). Moreover, the estimated elasticity of recreational vehicles is substantially negative, which could be either distorted results from lots of zero expenditure on it, or the fact that Millennials are extremely not interested in it. By contrast, Builders and Baby Boomers view most of the categories as luxury.

I use classification by each generation to construct the dependent variables and run the same regression based on the preferred model (1) including full controls. Table 4 presents the results. Generation effect keeps qualitatively stable and statistically significant. Regardless of the fact that the effect seems weaker in comparison with the main results in Table 3, it is reasonable since none of the definitions of luxury could represent all households in the sample now, which is basically weakening the effect.

¹⁶As an example, Millennials had been gradually coming of age from 2000 to 2018, so their perception of luxury was not as stable as that of Baby Boomer during the same period, and the estimation based on the whole sample period could to some extent average out the instabilities across time.

Common age range. As each generation is only observed through certain life stages during the sample period from 2000 to 2018, the comparison is imprecise when households of different generations don't share common age range in the data.¹⁷ Therefore, I run the same regressions for only two neighboring generations every time, and just focus on households within their common overlapping age range.

Three groups are analyzed separately based on age range of each generation in the sample. Specifically, I compare Millennials and Generation X from age 21 to 37, Generation X and Baby Boomers from age 36 to 53, and Baby Boomers and Builders from age 55 to 72. Table 5 shows generation effect. Each column presents results based on the sample of two generations, with the older one always being the base group. The negative and significant coefficients on generation dummies implies the robustness of the main results: conditional on the same age, younger generations consume less luxury. What's more, the magnitudes of the coefficients are also similar to those of the main estimates: Millennials have about 8 percent less luxury expenditure than Generation X, and the difference in the share is about 1.5 percent. So the lack of common age range among multiple generations in the data is not a big concern for generation effect.

Symmetric treatment of age and generation. As generation is essentially bunched cohorts, but age is taken as individual dummies in the regression, the results might be some coincides of such asymmetric treatment of generation and age. To make sure that generation effect is not just a broad age group effect, I use cohort, defined by specific birth year, as proxy for generation, to check whether the overall cohort trend follows the monotonic generation effect from the main results in Table 3, while age dummies are controlled in the same way.

Figure 10 plots the continuous cohort effect with 1960 as the reference birth year. The results are qualitatively the same when either log or share of luxury expenditure is the dependent variable, and also quantitatively comparable to generation differences in Table 3. So without being grouped into generations, individual cohorts vary in luxury expenditure analogously. Conditional on age, younger cohort monotonically spends less and less on luxury. The behaviors of the oldest and youngest groups, cohorts born in 1920s and 1990s, seem erratic seeing that the effect is a bit fluctuating, but the abnormalities are too insignificant to be informative or interesting. The underlying declining pattern certainly gets more and more stable when moving towards the middle. Likewise, Figure 11 plots age effect in the same way as does Figure 7. Conditional on cohort and other controls, the same age effect persists as we see not only declining life-cycle luxury expenditure, but also quantitatively almost identical magnitudes of the estimators.

Apart from this, strategy based on cohort fixed effect also speaks to the concern about the size of each generation. As shown by Figure 1, the two middle generations, Baby Boomers and Generation X are a bit overrepresented in the sample, which might be distorting the results. But Figure 10 manifests that when generations are equally disaggregated into cohorts, the original generation effect is basically replicated by differences among cohorts, so relative size

¹⁷Builders are tracked from the age 55, which is the age of those born in 1945 and surveyed in 2000, but the oldest members of Generation X, who were born in 1965, were only 53 in 2018, let alone Millennials who come even later.

of each generation doesn't create real troubles for the main findings to remain intact.

To further confirm that the asymmetric treatment of age and generation doesn't really matter to the results, I try an alternative approach, controlling for generation fixed effect in the same way as does the main identification but bunching age into groups, and Figure A.5 and Figure A.6 in Appendix A present very consistent evidences of monotonic age group and generation effects.¹⁸

6.2 Adjustment of Controls

IV estimation. The first concern comes from the fact that income data of the CE program are of poor quality, especially at the beginning of the sample years when income data only depended on reporters. Permanent income hypothesis tells that total expenditure could be a proxy for income, and the data quality of total expenditure is much higher. However, Charles et al. (2009) point out two possible problems of proxy variable approach: endogeneity and measurement error in total expenditure data.¹⁹ Luckily, Charles et al. (2009) also provide a solution: controlling for total expenditure and using income as an instrument for it. Following the same identification of the preferred model, I use both simple OLS estimation controlling for total expenditure, and the IV approach. It can be seen from Table A.6 that generation effects are similar to that of main results, while magnitudes of coefficients from OLS estimation in Column (1) and (3) are slightly lower. Additionally, all values of R^2 in Table A.6 actually increase remarkably compared to main results, on account of the fact that total expenditure are explaining lots of variations and does trigger endogeneity problem.

Different household scales. Secondly I check if the results stay the same when different household scales are applied. Aguiar and Hurst (2013) argue that results based on consumer expenditure survey are usually sensitive to the choice of household scales, both across and within categories. For instance, a teenager and a baby are both viewed as children but they might not be deserving the same weight, and the economies of scale in education must also be much weaker than those in household operations. So, I try other choices of household scales to see if the results could stay robust. I replace "OECD equivalence scale" used in the main specification with "OECD-modified scale" and "squared root" scale respectively.²⁰ And generation effect in Table A.7 is basically replicating those of the main results.

More disaggregated generational segments. Thirdly I try a more disaggregated generational segments. In the main specification, I combine the Greatest Generation and the Silent Generation together and call them "Builders", therefore dividing households in the sample into four generations excluding the youngest Generation Z.²¹ Now I keep the oldest two generations separately as how they are originally defined in Table 1. Besides, I follow Kapferer

¹⁸As reported by Figure A.6, generation differences are decaying conditional on age group, but still significant.

¹⁹According to Charles et al. (2009), all expenditure categories are jointly determined in a consumption model, which makes total expenditure endogenous in the regression with one of the categories as dependent variable; and measurement error in any of the categories could contaminate total expenditure, which is just the sum of expenditures on all individual categories in the original data of the CE program.

²⁰See Section 4.1 and Footnote 13 for details.

²¹See Section 4.1 for details of the generation setting in the main specification.

and Michaut (2019) who divide Millennials into two subgroups because of the concerns that Millennials might be too widely defined and lacking homogeneity. Therefore, I run the alternative regression model with six generations: the Greatest Generation (1902–1927), the Silent Generation (1928–1949), Baby Boomers (1946–1964), Generation X (1965–1980), Millennials I (1981–1989) and Millennials II (1990–1996). Column (1) and (3) of Table A.8 present the results, where Generation X is still taken as the base group. The estimated coefficients on the new generation dummies are consistent with the main results in Table 3: in addition to the direction of generation effect, the estimates of two subgroups of Millennials are similar, and the Greatest Generation are not behaving too differently from the Silent Generation, suggesting that aggregated setting in the main specification is actually reasonable.

Deaton (1997) for the collinearity problem. At last, I use an alternative approach to solve the collinearity problem. I follow the standard normalization of Deaton (1997) who uses period effect for cyclical fluctuations, thus restricting period effect to average zero over the sample period and be orthogonal to a time trend, so that all growth of luxury expenditure is attributed to age and generation effects. Specifically, I use year dummies instead of the proxy variable, and drop the first two of them in the regression.²² Column (2) and Column (4) of Table A.8 shows the estimated coefficients. The resulting generation effect, albeit quantitatively weaker, still corroborates earlier findings.

7 Model Flexibility: Results from Machine Learning

In spite of the robust findings, linear model might still be too restrictive because the demographic variables are usually highly nonlinear and interactive. So in this section I use a simple supervised machine learning method—neural network—to investigate the effects of age and generation in more flexible model setting.

7.1 Machine Learning in This Setting

As new emerging economic methodologies, machine learning techniques have been extensively discussed in literature, including reviews of both popular methods and comprehensive empirical economic applications (see, e.g., Varian, 2014; Mullainathan and Spiess, 2017; Athey, 2018; Athey and Imbens, 2019; Nosratabadi et al., 2020). Compared to traditional economic approaches, three distinctive attributes of machine learning should be noticed. First, while traditional empirical economics focuses on parameter estimation, machine learning is invented mainly for prediction, so the attention is given to \hat{y} instead of $\hat{\beta}$. \hat{y} sure is an old economic problem, but machine learning provides new tools for it (Mullainathan and Spiess, 2017). Second, as $\hat{\beta}$ is not interested any more, we have the freedom of developing more flexible and complex models, even without relying on strong statistical assumptions, which suggests the greatest advantage of machine learning: data-driven model selection. Instead of picking up arbitrary functional forms, e.g., the linear model, we resort to information in data to find out the most suitable model based on some criteria (Athey, 2018). Third, different from most

²²The coefficients on the first two year dummies can be recovered from the two restrictions.

econometric approaches that tries to measure goodness of fit within the same sample for estimation, machine learning underscores out-of-sample prediction. Notwithstanding that better data fitting implies poor out-of-sample performances as noises are also explained, lots of regularization procedures could help to balance the trade-off between representativeness and overfitting so that a nice out-of-sample prediction ability is usually guaranteed.²³

When interactions terms are added in model (2), the regression results in Figure 9 reveals the heterogeneous age effect across generations. But are there more interactions? Clearly, a fixed linear model with arbitrarily set interaction terms might be far from capturing the true variable relationships that could be very complicated because demographic characteristics are intensively intertwined with each other. As the desired solution here, machine learning is able to break free from those constraints imposed in linear model by automatically searching for nonlinearity and interactions. Additionally, as machine learning provides better techniques for manipulating big data, the large-scale sample size in this paper works perfectly for machine learning algorithms to find intricate patterns through strict regularization process.

However, estimating age and generation effects using machine learning is tricky. On one hand, when the model gets complicated, there might not be separate coefficients that exactly measure such marginal effects, like $\hat{\beta}$. On the other hand, even they are estimable, machine learning couldn't guarantee some necessary properties—e.g., unbiasedness and consistency—simply because it specializes in prediction. Nevertheless, a nice solution lies in the idea behind the counterfactual predictions using OLS results in Figure 8: with the most suitable model derived through proper training process, the counterfactual predictions are nice visual representations of individual variables' effects. Specifically, using the whole data set, if I only manipulate age and generation information while keeping all other variables untouched, the averages of predicted output values will pin down the differences between each age-generation combination, which is exactly the generation specific age effect shown in Figure 8 and Figure A.2.

7.2 Neural Network Training

In this paper I train standard *fully connected neural network*, the basic idea of which is briefly introduced in Appendix C.1. Appendix C.2 describes details of model selection—i.e., the selection of the activation function and hyperparameters. `scikit-learn` library in Python is applied to implement model training and results prediction.

The exact structure of the neural network, specifically the number of layers and number of nodes per layer, plays an particularly crucial role in both convergence process and final prediction performances. Farrell et al. (2021) have already discussed about this issue in the literature where there are no agreed optimal choices. After all, models are data-driven. Therefore, following the normal machine learning procedure, I randomly split the whole data set into two parts, 70 percent as training set and 30 percent as testing set. I try different combinations of the number of layers and nodes to train the model (or to basically estimate weights w and biases b as explained in Appendix C.2) using training set, the results of which are saved as trained models. Then, I input data from testing set into those trained models to

²³See Mullainathan and Spiess (2017) for details on regularization.

get predicted output variables, and compare them to the real data. The goodness of fit (R^2) of these predictions determines the best models. As model training only depends on information in training set, the out-of-sample performances in testing set show how well the trained models could capture the real patterns out of interruptive noises.

The input variables are the same as the independent variables in the preferred model of OLS regression, and I use log and share of luxury expenditure separately as outputs. Besides transforming all categorical variables into 0-1 dummies, I use min-max normalization to normalize the continuous input variables in the training set as

$$\tilde{X}_i = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)}$$

so that all inputs range from 0 to 1 to make the training process more stable. Likewise, I also normalize input variables in testing set, through the normalization built in training set to prevent information in testing set from leaking out. For both log level and share of luxury expenditure being the output variables, I start training the model from only one hidden layer, and try different numbers of nodes from 5 to 200 in steps of 5 or 10.²⁴ Next, I move to two and three hidden layers. While searching for the optimal number of nodes from 5 to 200 as well, I keep the number of nodes per hidden layer the same for simplicity.²⁵

Figure 12 shows performances of all trained models in testing set by plotting the the goodness of fit (R^2) of these predictions from different models, with log of luxury expenditure as the output variable on the left and share on the right. The horizontal lines represent the goodness of fit of OLS out-of-sample predictions, where the same procedures including data set splitting, model training and testing are adopted for the results to be more comparable. Intuitively, a very simple neural network doesn't work very well in learning deep information in the data. With more complex structure, neural network fits training data better, until at some point the trained model moves towards overfitting by learning more and more noises as the structure gets too complex, leading to worse and worse prediction performances in testing set whose information is completely unknown during training process. Figure 12 clearly shows this process: with both single-layer and multiple-layer neural network, in the beginning, the goodness of fit in testing set increases with the number of nodes per hidden layer, and then it starts to decrease with more and more nodes after reaching a peak. When too many nodes are included, neural network even works worse than simple OLS. The results regarding expenditure share seem a bit unstable, but the intrinsic trend is still clear. What's more interesting is the comparison among different numbers of hidden layers in Figure 12(a). As each additional hidden layer accelerates the complexity of the model, more hidden layers make the the overfitting problem appear faster and earlier.

Lastly, I want to comment on one more issue that the relatively low R^2 in neural network means that the fitting is far from being perfect. As a subjective human behavior, expenditure is not possible to be accurately predicted by some demographic and economic variables. Nonetheless, the focus of this paper is not to precisely reproduce the output variables, but

²⁴Several steps of 5 are only tried around the optimal choices to be more precise, and for other parts that are obviously not optimal, I only use steps of 10.

²⁵The choices here are indeed a bit arbitrary, but I can always adjust it if the results show abnormal patterns.

to uncover how different generations differ from each other in spending money on luxury, even just qualitatively. In this sense, a simple OLS framework is already enough to deliver the desired results. But beyond it, neural network could meet this needs while allowing variables to interact with each other flexibly, which is more realistic.

7.3 Age and Generation Effects from Neural Network

I consider the goodness of fit shown in Figure 12 to determine the best models, or the optimal numbers of nodes. It is worth noting that using my data set, the neural network with multiple hidden layers is not substantially better than the simple single-layer one, despite of much more computation cost. This observation corresponds to the *universal approximation theorem* with bounded number of hidden layers, proved by Hornik et al. (1989), saying that even neural network with only one hidden layer could be a universal approximator given sufficiently many nodes. In my case, with a single hidden layer, the optimal numbers of nodes is 20 and 40, with output variables being log and share of luxury expenditure respectively, so I load these two trained models for predictions. It is worth mentioning that predictions conducted using the whole data set because the splitted training and testing data sets are only required for model selection.

The idea is the same as that of counterfactual predictions using results from OLS regression in Figure 8. For each generation, I take the whole data set and treat all households as aged 21 when inputting them in the best trained models for predicted log and share of luxury expenditure. Then, average predicted log and share of luxury expenditure are stored as counterfactual predictions of this generation at 21. This procedure applies to all generations at all ages from 21 to 80, always with the whole data set being used. In such manner, when values of other control variables in the data set are equally added to all generations at all ages, variations only due to age and generation differences are sucked out, and Figure 13 plots the final results predicted using model with one hidden layer.

Even with flexibly nonlinear and interactive functional forms, similar findings still exist. There is a clear declining trend of luxury expenditure over life cycle, with younger generations consuming less. The differences in expenditure level in Figure 13(a) between Millennials and Generation X become somewhat invisible since age 30, but Millennials still consistently have less expenditure share. Overall, the averages of predictions in Figure 13 are in essence not so different from the smooth counterfactual results based on simple linear models. So in fact, predictions from the main results with separable age and generation effects in Figure 8 are more straightforward in disclosing the intrinsic general trend where more complex models are actually converging. Therefore, instead of oversimplifying the variables relationships, linear regression model is sufficient enough for delivering the main findings.

The results from best trained models with two and three hidden layers are presented in Figure 14 and Figure 15, where the general findings—i.e., luxury expenditure decreases over life cycle, and younger generations consume less—keep consistent, though the specific point prediction is not always strictly monotone and slightly varies according to different neural network structures. With more hidden layers, it also becomes more prominent that Millennials have lower luxury expenditure level that do Generation X, while the monotone change of

expenditure share across generations is always stable.

8 Discussion

Luxury goods defined by elasticity overall might not be congruous with what people think as luxury, but overlaps could exist among individual categories, so in this section I analyze luxury categories individually to see what is happening to these “classic” luxury. Moreover, I also relate the disaggregated results to the studies of conspicuous consumption in the literature. At last, I discuss the intuition behind the findings.

8.1 Evidences on Specific Categories

According to the classification in Section 3, luxury consists of 13 different expenditure categories. I combine several closely related categories together into aggregated ones: vehicle purchases and other vehicle expenditures as vehicles; fees and admissions, pets, toys and playground equipment, recreational vehicles and miscellaneous entertainment outlays as entertainment, leading to 9 categories, and Table A.9 reports summary statistics of them. I run the same regression based on the preferred model for each of the 9 individual categories, and present the results in Table 6. Generation effects seem pretty heterogeneous in terms of both magnitudes and significance levels, but mostly still monotone and significant. Millennials tend to spend significantly less on the majority of the categories except for household operations and education, and the expenditure gaps on clothing for adults, vehicles and public and other transportation in Column (4) and (5) are also fairly large between them compared to the main results. Across all generations, I find the strongest increasing coefficients when estimating the effects on clothing for adults in Column (3), on which Builders spend 62 percent more than Generation X. Two outliers are Column (1) and Column (7) where household operations and education have opposite but also almost significant generation effect, so younger generations are obviously more interested in it. In addition, for the last two categories, cash contribution and miscellaneous outlays, the estimates are also monotone across generations but mostly not significant, and also economically weak.

Age effects are presented in Figure A.3. While older generations tend to spend less on household operations, the expenditure on it is increasing over life cycle. Age profiles of expenditures on cash contribution and miscellaneous outlays also diverge from the decreasing age effects in the main results in Figure 7, which is mainly driven by the categories in Figure A.3(b) that show a declining trend, especially clothing for adults and vehicles, on which age effect is even strong enough to cancel out the divergent age profiles of expenditures on the rest ones. The cyclical age effect on education could be caused by the intermittent education period of oneself and one’s children.

8.2 Relating to “Classic” Luxury and Conspicuous Consumption

To see the how luxury goods defined by elasticity are different from the “classic” luxury goods that are arbitrarily categorized based on common sensed criteria, Table 7 compares the

13 categories defined in Section 3 to luxury mentioned by Paulin and Riordon (1998) who divide expenditure categories in CE data into basic goods and services, and luxury goods, mainly recreation related expenditures, from their personal points of view. Overlaps does exists to some degree, as entertainment, vehicles and transportation are considered as luxury by both classification styles, but others, like household related expenditures, clothing for adults, education, cash contribution and miscellaneous outlays, don't seem like luxury without economic measurement. In addition, food away from home actually doesn't pass the threshold of elasticity although Paulin and Riordon (1998) see it as "classic" luxury.

Another related concept is conspicuous consumption, firstly introduced by Veblen (1899). Veblen effect refers to the observation that people buy visible goods to signal wealth, and this is supposed to be achieved through expensiveness, suggesting an upward-sloping demand curve (see, e.g., Leibenstein, 1950; Bagwell and Bernheim, 1996). Empirical research that focus on conspicuous consumption have pretty consistent choices of visible goods by either surveys or simple introspection (see, e.g., Charles et al., 2009; Friehe and Mechtel, 2014; Heffetz, 2011). The categories of Charles et al. (2009) and Heffetz (2011), both of which also use CE data, and Friehe and Mechtel (2014) based on German income and expenditure sample, are shown in the last column of Table 7. In like manner, apart from a few overlaps, neither conspicuous expenditure or luxury defined by elasticity is a subset of the other.

Following that, I investigate the effects on categories that also belong to "classic" luxury or conspicuous consumption discussed in Section 3. As shown in Table 7, within the 9 disaggregated categories, entertainment, vehicles and transportation are also considered as luxury by Paulin and Riordon (1998), on which generation effect shows less expenditure of Millennials in Table 6. So the findings based on the economically defined luxury are representative enough to apply to what people think as luxury according to general common sense, and are thus cogent evidences against the argument that Millenials are growth engine of luxury. Likewise, results from these categories that are "conspicuous" also correspond to findings in the literature. Charles et al. (2009) show that Blacks spend more on visible goods—i.e., clothing/jewelry, personal care and vehicles, than do Whites conditional other controls. As clothing for adults and vehicles are also luxury goods according to total expenditure elasticity, the race fixed effects with Whites being the base group shown in the full regression table Table A.4 confirms this finding. Regarding the effect of education as already discussed in the main results in Table 3, Table A.4 and Table A.5 further demonstrate the positive correlation between luxury expenditure and education level (except for vehicles). This finding to some extent contradicts to the conclusion of Friehe and Mechtel (2014), who find households with higher education level tend to spend less on visible goods that also includes some categories defined as luxury in this paper, such as household furnishings and equipment and clothing. This can be explained by the increasing education level of new generations, meaning that the negative education effect found by Friehe and Mechtel (2014) results from the omission of generation dummies, so within generation, education effect is still positive.

8.3 What Do We learn?

Several theories from both economic and sociological perspectives might explain these findings. Firstly, introduced in Section 2.2, Millennials have been facing lots of obstacle in current economic environment. As the previous generations, by whom everything in the society has already been well built and organized, are still dominating the market, there are not many good opportunities left. Millennials have always been benefiting the least and suffering the more in macro business cycles (see, e.g., Smith, 2012; Gale et al., 2020), and the situation is deteriorating even more from the increasing peer competition (see, e.g., Emmons et al., 2019; Zeihan, 2016). Not surprising, Millennials are always struggling with crises like unemployment (Halpert, 2012), and as a consequence, they have been postponing marriage, housing and fertility plans, let alone a luxury lifestyle (Danziger, 2015).

Secondly, this finding actually corresponds to the statement of McCrindle (2007) who calls Millennials “new puritans”: having grown bored of prepackaged spiels, Millennials see through all the contrived messages, so they become more circumspect, critical and savvy when being marketed. Therefore, contrary to the stereotype of being spoiled and consumption-oriented, Millennials are more likely to be objectively rather than socially motivated to spend money (Martin and Turley, 2004). In addition, as for older generations, the results also support some arguments in the literature. For example, Paulin and Riordon (1998) show that compared to Baby boomers, Generation X consume less luxury goods and more necessities. Opposite to Baby boomers who stress self-achievement and personal success, Generation X are more disillusioned and skeptical due to both economic and societal uncertainty that they grew up with (Eastman and Liu, 2012).

Both external social pressure and internal personality together generate Millennials’ abstention and discretion. Worry about extravagance is fortunately unneeded, but there are other open issues. From the perspective of luxury industry, it is essential to comprehend more unbiased information from surface evidences for better strategies in the future, so more efforts are needed to conduct deeper market research on long-run demographics. The findings also shed lights on the context of social welfare. Apparently, the situation of Millennials is not as promising as thought. In current steady state of the economy that is mainly governed by previous generations, not much space is left for Millennials to actually play a role in. Plus lots of other challenges of contemporary society, all disadvantages bring Millennials into overwhelmedness and anxiousness, and thus, more social care should be given to this generation.

9 Conclusion

Having grown up in a time of prosperity and materialism, Millennials are stereotyped as a protected and indulged generation with an unprecedented purchasing power in luxury market. Distinguishing between age and generation effects on luxury expenditure is not a new topic, as Rudy Wilson, former vice president of marketing and brand leader of Frito-Lay, once said “everyone feels like they can market to Millennials because they were a teen at one time, but this teen is very different” (Fromm and Garton, 2013). However, without strategic identification,

it is uncertain whether this generation is really different or the uniqueness of them just results from their current young age. This paper fills the literature gap by identifying generation specific characteristics separately from those that change with life stages.

After classifying expenditure categories in the Consumer Expenditure Survey of the U.S. into luxury and necessity based on economic definition of luxury as having total expenditure elasticity higher than one, I show average expenditure on luxury over life cycle and across time in descriptive analysis. Following that, I extend the textbook methodology of decomposing age, generation and period effects to luxury expenditure, and also take heterogeneous effects into account by adding interaction terms. To make the results more convincing, I use one of the most popular machine learning techniques, i.e., neural network, to derive the most suitable models with full flexibility. Finally, I compare the results from specific categories with related topics—“classic” luxury and conspicuous consumption—and discuss the intuition in a more general sense.

The OLS regression results show a decreasing trend of luxury expenditure over life cycle for all generations, while generation effect works oppositely: younger generations tend to consume less luxury than do older generations conditional on age. Quantitatively, Millennials spend around 8 percent less on luxury than Generation X, compared to whom Baby Boomers have around 9 percent more luxury expenditure, and Builders have around 18 percent more. The results keep robust to alternative model specifications and adjustment of controls. Moreover, the models trained from neural network exhibits the same patterns across generations and over life cycle. Therefore, instead of acting as an indulged generation, Millennials are conveying attitudes of abstinence, consciousness and rationality, just like “new puritans” (McCrindle, 2007). And their remarkable ability of shopping luxury is actually the result of strong age effect being predominating.

This stimulating finding refreshes the conventional points of view, and brings new challenges to marketers who target Millennials as well. As America’s largest generation, Millennials have been gradually prevailing over the market. Nevertheless, Millennials’ lack of interest in luxury may suggest potential crisis in this industry, especially as they age. Therefore, understanding the underlying mechanisms driving generation effect helps marketers to discern the intricacies of Millennials, on which future work could focus more. As another future research direction, it is also interesting to test the results using data from other countries to see if this is an international phenomenon. With regard to policy implications, as discussed in Section 8.3, Millennials’ asceticism to certain extent signals their inauspicious situation in the contemporary society, which calls for social care for the improvement of their well-being.

References

- Aguiar, M. and Hurst, E. (2013). Deconstructing Life Cycle Expenditure. *Journal of Political Economy*, 121(3):437–492.
- Amatulli, C., Guido, G., and Natarajan, R. (2015). Luxury purchasing among older consumers: Exploring inferences about cognitive Age, status, and style motivations. *Journal of Business Research*, 68(9):1945–1952.
- Aristei, D., Perali, F., and Pieroni, L. (2008). Cohort, age and time effects in alcohol consumption by Italian households: A double-hurdle approach. *Empirical Economics*, 35(1):29–61.
- Athey, S. (2018). The Impact of Machine Learning on Economics. In *The Economics of Artificial Intelligence: An Agenda*, pages 507–547. University of Chicago Press.
- Athey, S. and Imbens, G. W. (2019). Machine Learning Methods That Economists Should Know About. *Annual Review of Economics*, 11(1):685–725.
- Bagwell, L. S. and Bernheim, B. D. (1996). Veblen Effects in a Theory of Conspicuous Consumption. *The American Economic Review*, 86(3):349–373.
- Banks, J., Blundell, R., Levell, P., and Smith, J. P. (2019). Life-Cycle Consumption Patterns at Older Ages in the United States and the United Kingdom: Can Medical Expenditures Explain the Difference? *American Economic Journal: Economic Policy*, 11(3):27–54.
- Bee, A., Meyer, B. D., and Sullivan, J. X. (2012). The Validity of Consumption Data: Are the Consumer Expenditure Interview and Diary Surveys Informative? NBER Working Paper w18308, National Bureau of Economic Research.
- Bernini, C. and Cracolici, M. F. (2015). Demographic change, tourism expenditure and life cycle behaviour. *Tourism Management*, 47:191–205.
- Blakemore, E. (2015). The Latchkey Generation: How Bad Was It? Available at: <https://daily.jstor.org/latchkey-generation-bad/> (accessed 9 September 2021).
- Blundell, R., Browning, M., and Meghir, C. (1994). Consumer Demand and the Life-Cycle Allocation of Household Expenditures. *The Review of Economic Studies*, 61(1):57–80.
- Brokaw, T. (1998). *The Greatest Generation*. Random House, New York.
- Charles, K. K., Hurst, E., and Roussanov, N. (2009). Conspicuous Consumption and Race. *The Quarterly Journal of Economics*, 124(2):425–467.
- Danziger, P. (2015). Millennials & Their Luxury Aspirations. Available at: <https://unitymarketingonline.com/millennials-their-luxury-aspirations/> (accessed 9 September 2021).
- Deane, C., Duggan, M., and Morin, R. (2016). Americans Name the 10 Most Significant Historic Events of Their Lifetimes. Available at: <https://www.pewresearch.org/politics/2016/12/15/americans-name-the-10-most-significant-historic-events-of-their-lifetimes/> (accessed 9 September 2021).

- Deaton, A. (1997). *The analysis of household surveys: a microeconomic approach to development policy*. Published for the World Bank [by] Johns Hopkins University Press, Baltimore, MD.
- Dimock, M. (2019). Defining generations: Where Millennials end and Generation Z begins. Available at: <https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/> (accessed 9 September 2021).
- Dohmen, T., Falk, A., Golsteyn, B. H. H., Huffman, D., and Sunde, U. (2017). Risk Attitudes Across The Life Course. *The Economic Journal*, 127(605):F95–F116.
- Eastman, J. K. and Liu, J. (2012). The impact of generational cohorts on status consumption: An exploratory look at generational cohort and demographics on status consumption. *Journal of Consumer Marketing*, 29(2):93–102.
- Elkin, I. (2012). Recommendation regarding the use of a CE bounding interview. Bounding interview project unpublished paper, US Bureau of Labor Statistics.
- Emmons, W. R., Kent, A. H., and Ricketts, L. (2019). Is College Still Worth it? The New Calculus of Falling Returns. *Federal Reserve Bank of St. Louis Review*, 101(4):297–329.
- Fan, J. (1992). Design-adaptive Nonparametric Regression. *Journal of the American Statistical Association*, 87(420):998–1004.
- Farrell, M. H., Liang, T., and Misra, S. (2021). Deep Neural Networks for Estimation and Inference. *Econometrica*, 89(1):181–213.
- Fernández-Villaverde, J. and Krueger, D. (2007). Consumption over the Life Cycle: Facts from Consumer Expenditure Survey Data. *The Review of Economics and Statistics*, 89(3):552–565.
- Fitzenberger, B., Mena, G., Nimczik, J., and Sunde, U. (2019). Personality Traits Across the Life Cycle: Disentangling Age, Period, and Cohort Effects. Discussion Paper 214, Collaborative Research Center TRR 190.
- Frey, W. H. (2018). The millennial generation: A demographic bridge to America’s diverse future. Metropolitan Policy Program, Brookings.
- Friehe, T. and Mechtel, M. (2014). Conspicuous consumption and political regimes: Evidence from East and West Germany. *European Economic Review*, 67:62–81.
- Fromm, J. and Garton, C. (2013). *Marketing to millennials: reach the largest and most influential generation of consumers ever*. AMACOM, American Management Association, New York.
- Fry, R. (2020). Millennials overtake Baby Boomers as America’s largest generation. Available at: <https://www.pewresearch.org/fact-tank/2020/04/28/millennials-overtake-baby-boomers-as-americas-largest-generation/> (accessed 9 September 2021).
- Gale, W., Gelfond, H., Fichtner, J. J., and Harris, B. H. (2020). The Wealth of Generations, With Special Attention to the Millennials. NBER Working Paper 27123, National Bureau of Economic Research.

- Giovannini, S., Xu, Y., and Thomas, J. (2015). Luxury fashion consumption and Generation Y consumers: Self, brand consciousness, and consumption motivations. *Journal of Fashion Marketing and Management*, 19(1):22–40.
- Gu, S., Kelly, B., and Xiu, D. (2020). Empirical Asset Pricing via Machine Learning. *The Review of Financial Studies*, 33(5):2223–2273.
- Gurău, C. (2012). A life-stage analysis of consumer loyalty profile: Comparing Generation X and Millennial consumers. *Journal of Consumer Marketing*, 29(2):103–113.
- Halpert, J. (2012). Millennials: Young, Broke, and Spending on Luxury. Available at: <https://www.thefiscaltimes.com/Articles/2012/05/15/Millennials-Young-Broke-and-Spending-on-Luxury> (accessed 9 September 2021).
- Heffetz, O. (2004). Conspicuous Consumption and the Visibility of Consumer Expenditures. Working Paper, Princeton University.
- Heffetz, O. (2011). A Test of Conspicuous Consumption: Visibility and Income Elasticities. *The Review of Economics and Statistics*, 93(4):1101–1117.
- Heffetz, O. (2018). Expenditure Visibility and Consumer Behavior: New Evidence. NBER Working Paper w25161, National Bureau of Economic Research.
- Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5):359–366.
- Howe, N. (2014). The Silent Generation, "The Lucky Few" (Part 3 of 7). Available at: <https://www.forbes.com/sites/neilhowe/2014/08/13/the-silent-generation-the-lucky-few-part-3-of-7/> (accessed 9 September 2021).
- Howe, N. and Strauss, W. (1993). *13th Gen: Abort, Retry, Ignore, Fail?* Vintage Books, New York.
- Howe, N. and Strauss, W. (2000). *Millennials Rising: The next Great Generation*. Vintage Books, New York.
- Jay, E. (2012). New breed of consumer shakes up luxury fashion. Available at: <https://www.mobilemarketer.com/ex/mobilemarketer/cms/opinion/columns/12361.html> (accessed 9 September 2021).
- Kapferer, J.-N. and Bastien, V. (2009). The specificity of luxury management: Turning marketing upside down. *Journal of Brand Management*, 16(5-6):311–322.
- Kapferer, J.-N. and Michaut, A. (2019). Are Millennials really redefining luxury? A cross-generational analysis of perceptions of luxury from six countries. *Journal of Brand Strategy*, 8(3):250–264.
- Kiefer, J. and Wolfowitz, J. (1952). Stochastic Estimation of the Maximum of a Regression Function. *The Annals of Mathematical Statistics*, 23(3):462–466.
- Kingma, D. P. and Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

- Lafayette, J. (2011). Marketers Targeting Generation of Millennials. Available at: <https://www.nexttv.com/news/marketers-targeting-generation-millennials-52582> (accessed 9 September 2021).
- Leibenstein, H. (1950). Bandwagon, Snob, and Veblen Effects in the Theory of Consumers' Demand. *The Quarterly Journal of Economics*, 64(2):183–207.
- Martin, C. A. and Turley, L. (2004). Malls and consumption motivation: An exploratory examination of older Generation Y consumers. *International Journal of Retail & Distribution Management*, 32(10):464–475.
- McCrindle, M. (2007). Seriously cool: Marketing and communicating with diverse generations. Technical report, McCrindle Research.
- Mullainathan, S. and Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives*, 31(2):87–106.
- Nair, V. and Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th International Conference on International Conference on Machine Learning, ICML'10*, pages 807–814. Omnipress.
- Noble, S. M., Haytko, D. L., and Phillips, J. (2009). What drives college-age Generation Y consumers? *Journal of Business Research*, 62(6):617–628.
- Norum, P. S. (2003). Examination of Generational Differences in Household Apparel Expenditures. *Family and Consumer Sciences Research Journal*, 32(1):52–75.
- Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S. S., Reuter, U., Gama, J., and Gandomi, A. H. (2020). Data Science in Economics: Comprehensive Review of Advanced Machine Learning and Deep Learning Methods. *Mathematics*, 8(10):1799.
- Nye, J. S. (2011). *The Future of Power*. PublicAffairs, New York.
- Panteva, N. (2011). Luxury spending drives recovery. Available at: <https://seekingalpha.com/instablog/924011-ibisworld/172276-luxury-spending-drives-recovery> (accessed 9 September 2021).
- Paulin, G. and Riordon, B. (1998). Making it on their own: The baby boom meets Generation X. *Monthly Labor Review*, 121(2):10–21.
- Peng, Y., Albuquerque, P. H. M., Kimura, H., and Saavedra, C. A. P. B. (2021). Feature selection and deep neural networks for stock price direction forecasting using technical analysis indicators. *Machine Learning with Applications*, 5:100060.
- Robbins, H. and Monro, S. (1951). A Stochastic Approximation Method. *The Annals of Mathematical Statistics*, 22(3):400–407.
- Rubin, C. (2011). Why You Should Focus on Generation Y. Available at: <https://www.inc.com/news/articles/201107/why-you-should-market-to-generation-y.html> (accessed 9 September 2021).
- Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, 323(6088):533–536.

- Russell, C. (1993). *The Master Trend: How the Baby Boom Generation Is Remaking America*. Plenum Press, New York.
- Schewe, C. D., Meredith, G. E., and Noble, S. M. (2000). Defining moments: Segmenting by cohorts. *Marketing Management*, 9(3):48–53.
- Shamma, T. (2011). What's The Defining Moment Of Your Generation? Available at: <https://www.npr.org/2011/11/02/141930849/whats-the-defining-moment-of-your-generation> (accessed 9 September 2021).
- Smith, E. B. (2012). American Dream Fades for Generation Y Professionals. Available at: <https://www.bloomberg.com/news/articles/2012-12-21/american-dream-fades-for-generation-y-professionals> (accessed 9 September 2021).
- Smith, J. W., Clurman, A., and Yankelovich Partners (1997). *Rocking the Ages: The Yankelovich Report on Generational Marketing*. HarperBusiness, New York, NY.
- Strauss, W. and Howe, N. (1991). *Generations: The History of America's Future, 1584 to 2069*. William Morrow, New York.
- Tucker, P. (2006). Teaching the Millennial Generation. *The Futurist*, 40(3):7.
- Valentine, D. B. and Powers, T. L. (2013). Generation Y values and lifestyle segments. *Journal of Consumer Marketing*, 30(7):597–606.
- Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives*, 28(2):3–28.
- Veblen, T. (1899). *The Theory of the Leisure Class: An Economic Study in the Evolution of Institutions*. Macmillan.
- Zao-Sanders, M. and Palmer, K. (2019). Why Even New Grads Need to Reskill for the Future. Available at: <https://hbr.org/2019/09/why-even-new-grads-need-to-reskill-for-the-future> (accessed 9 September 2021).
- Zeihan, P. (2016). *The Absent Superpower: The Shale Revolution and a World without America*. Zeihan on Geopolitics.
- Zhang, Q., Yang, L. T., Chen, Z., and Li, P. (2018). A survey on deep learning for big data. *Information Fusion*, 42:146–157.

Figures and Tables

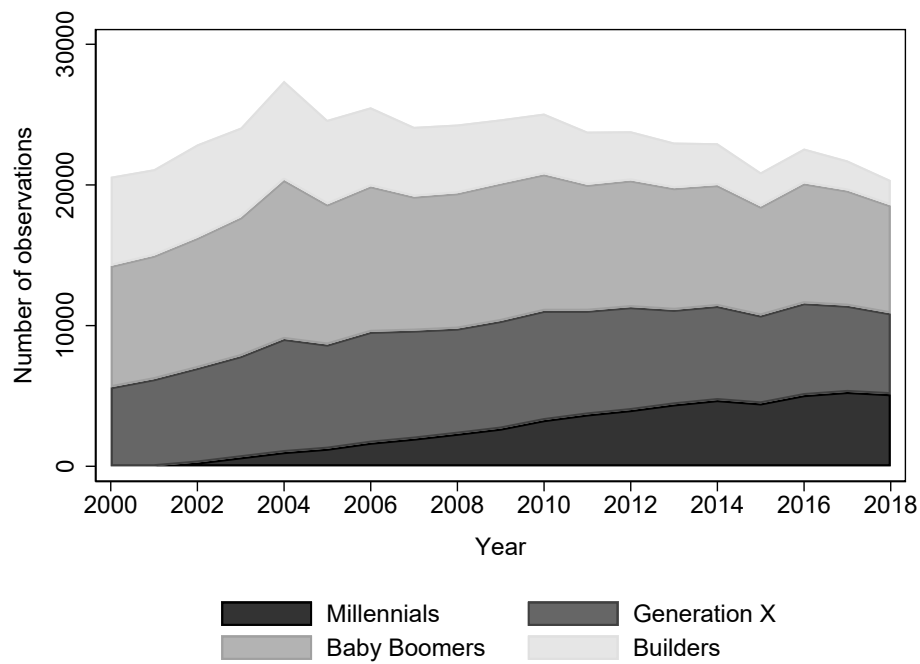


Figure 1: *The Size of Each Generation 2000–2018*

Notes: The figure reports the size of each generation across time in the refined sample (including 443,497 observations) for descriptive and regression analysis. Different from the earliest birth year of the Greatest Generation 1902 defined in Table 1, 1906 is the earliest birth year of Builders in the refined sample. Age range of each generation in the sample is: Millennials (21–37); Generation X (21–53); Baby Boomers (36–72); Builders (55–80).

Sources: Consumer Expenditure Survey (CE) 2000–2018

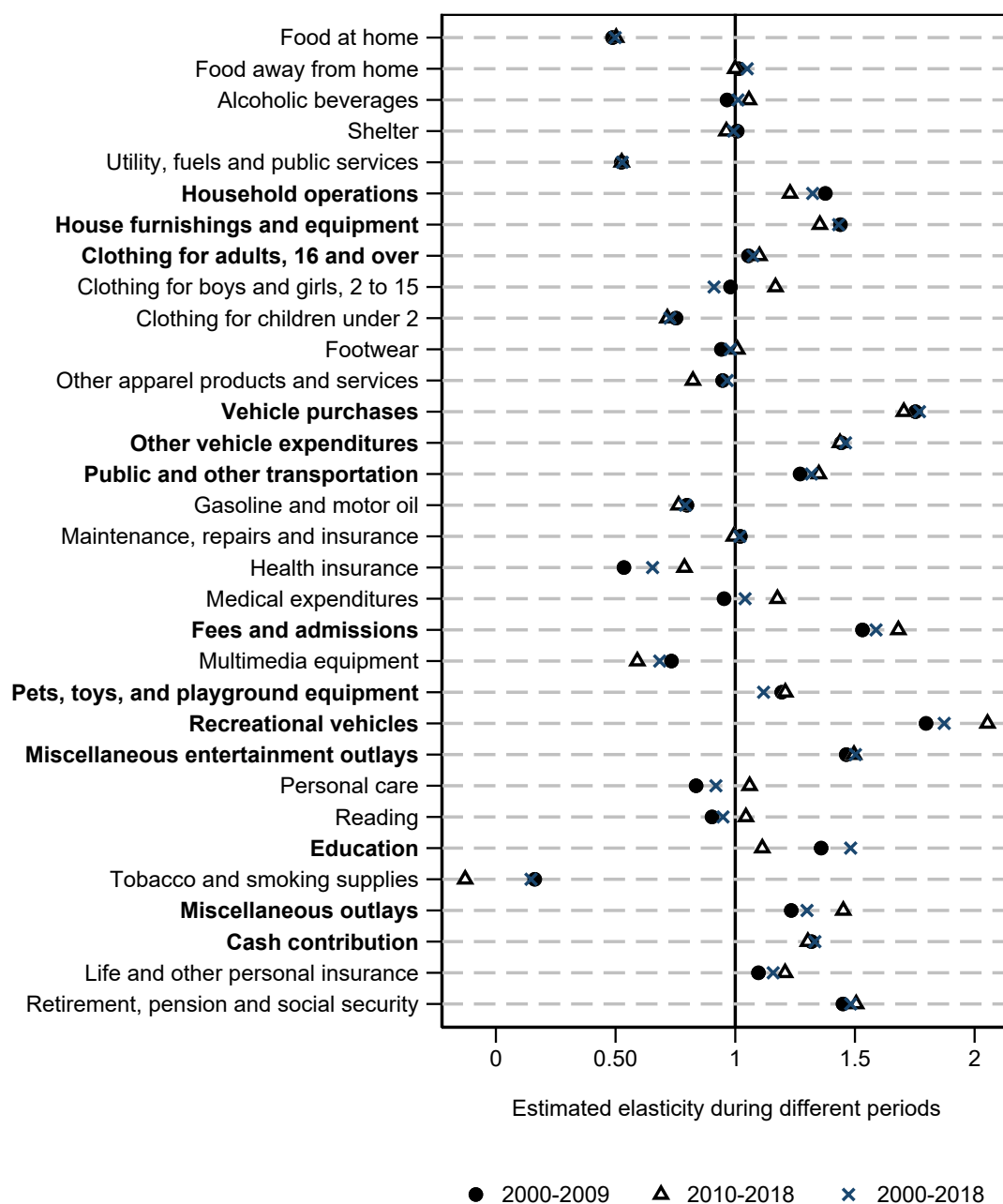
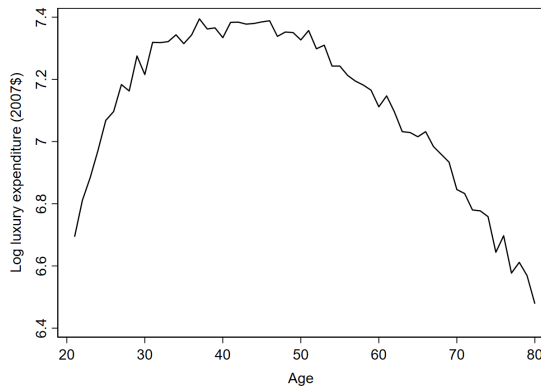
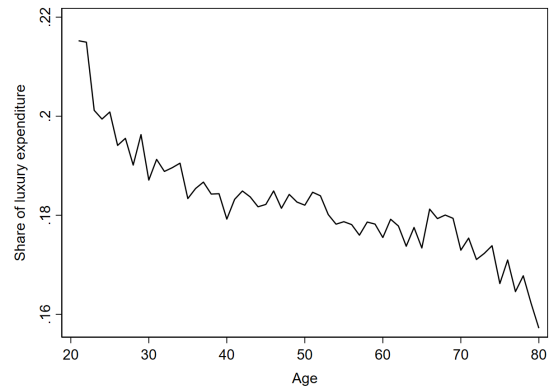


Figure 2: Total Expenditure Elasticity

Notes: This figure reports the estimated total expenditure elasticity of each of the 32 categories listed in the left column of Table A.2, into which I aggregate the original expenditure categories in the FMLI files. The same estimation procedure was conducted during different time periods to keep results consistent and stable. The final resulting luxury goods are the boldfaced 13 ones.



(a) Log Level

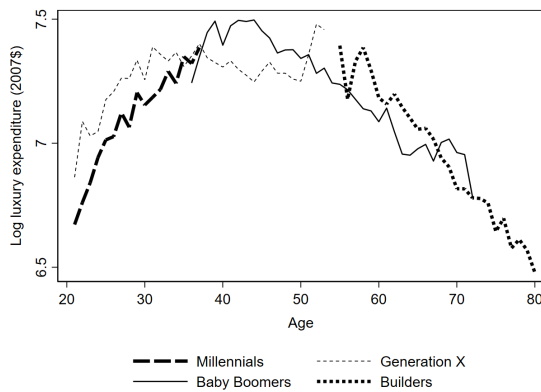


(b) Share

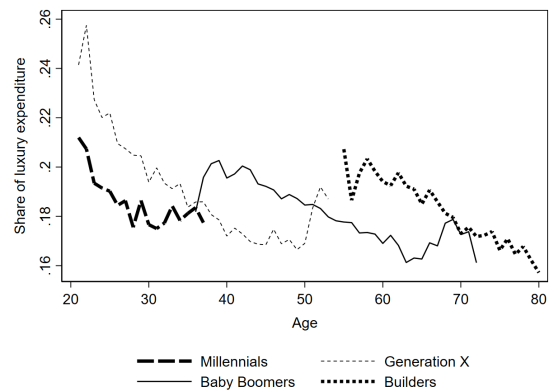
Figure 3: Luxury Expenditure by Age

Notes: Values are in US 2007 dollars. Both figures plot means at each age from 21 to 80, with Figure 3(a) showing the log level of luxury expenditure and Figure 3(b) showing the share of luxury expenditure.

Sources: Own calculations based on Consumer Expenditure Survey (CE) 2000–2018



(a) Log Level

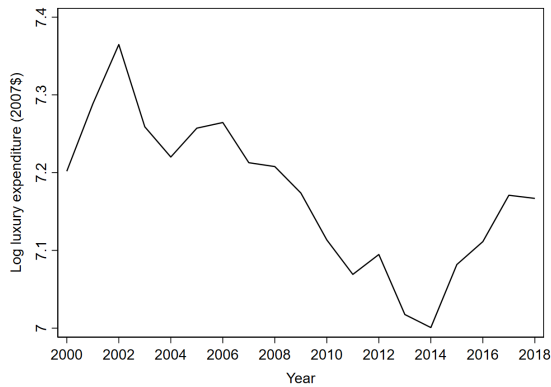


(b) Share

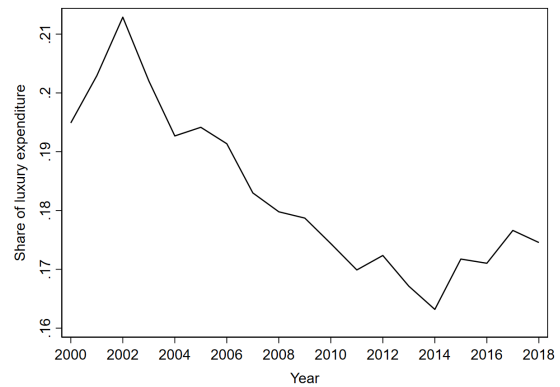
Figure 4: Generation Specific Luxury Expenditure by Age

Notes: Values are in US 2007 dollars. Both figures plot means at each age from 21 to 80 for each generation, with Figure 4(a) showing the log level of luxury expenditure and Figure 4(b) showing the share of luxury expenditure.

Sources: Own calculations based on Consumer Expenditure Survey (CE) 2000–2018



(a) Log Level

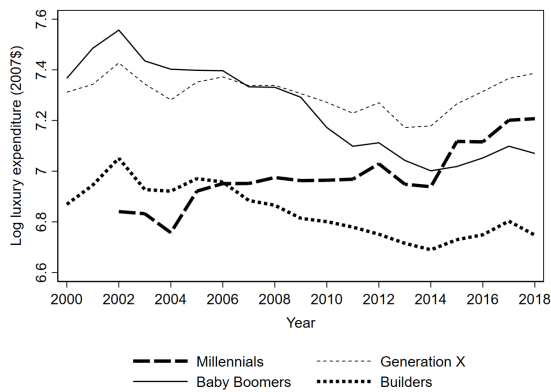


(b) Share

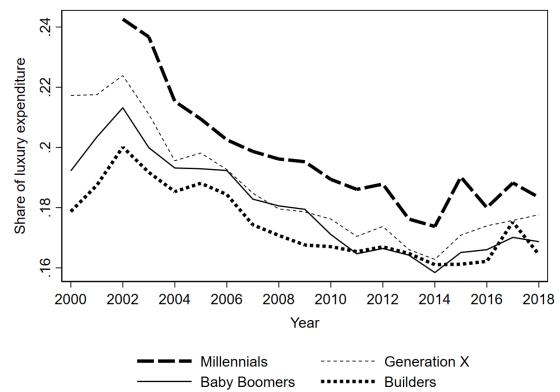
Figure 5: Luxury Expenditure by Year

Notes: Values are in US 2007 dollars. Both figures plot means in each year from 2000 to 2018, with Figure 5(a) showing the log level of luxury expenditure and Figure 5(b) showing the share of luxury expenditure.

Sources: Own calculations based on Consumer Expenditure Survey (CE) 2000–2018



(a) Log Level



(b) Share

Figure 6: Generation Specific Luxury Expenditure by Year

Notes: Values are in US 2007 dollars. Both figures plot means in each year from 2000 to 2018 for each generation, , with Figure 6(a) showing the log level of luxury expenditure and Figure 6(b) showing the share of luxury expenditure.

Sources: Own calculations based on Consumer Expenditure Survey (CE) 2000–2018

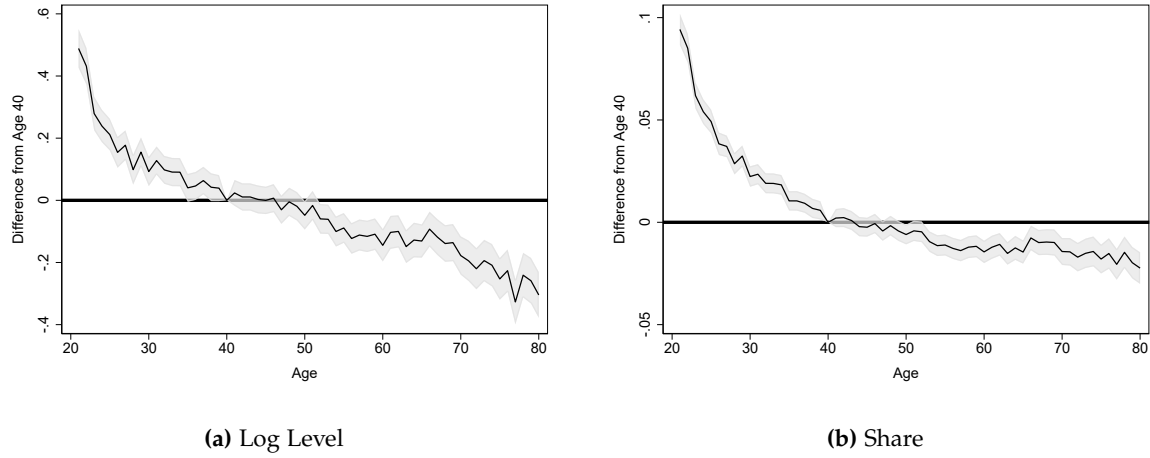


Figure 7: Main Results: Age Effect on Luxury Expenditure

Notes: Both figures show the estimated coefficients on age dummies from Column (3) and Column (7) in Table 3, including 95% confidence intervals, with Figure 7(a) showing the effect on log level of luxury expenditure and Figure 7(b) showing the effect on share of luxury expenditure. Coefficients are relative to reference age 40, which is marked as the horizontal zero lines.

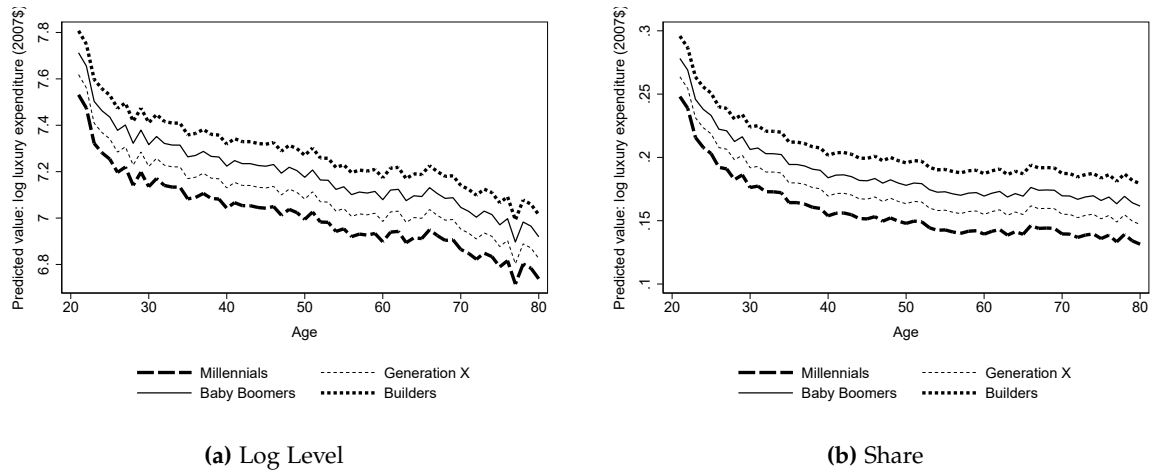
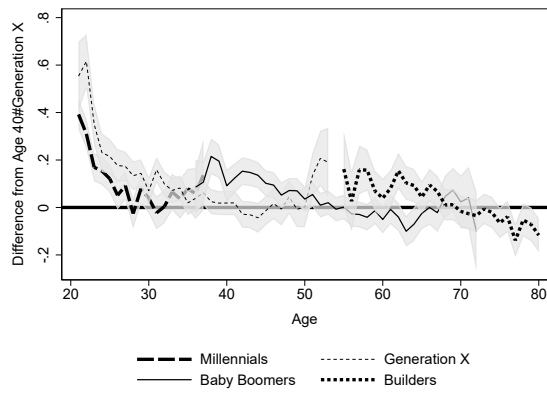
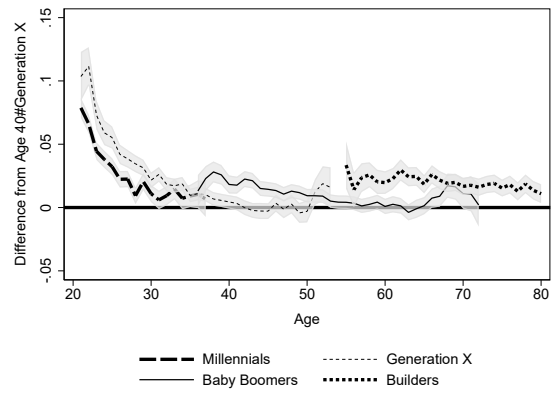


Figure 8: Main Results: Predicted Generation Specific Luxury Expenditure by Age

Notes: Values are in US 2007 dollars. Both figures plot predicted means at each age from 21 to 80 for each generation using the estimated coefficients on age dummies from Column (3) and Column (7) in Table 3, with Figure 8(a) showing the log level of luxury expenditure and Figure 8(b) showing the share of luxury expenditure. Predictions are always conducted using the whole data set to pin down pure age and generation effects while giving other controls the same values.



(a) Log Level



(b) Share

Figure 9: *Heterogeneous Effects: Generation Specific Age Effects on Luxury Expenditure*

Notes: Both figures show the estimated coefficients on the interaction terms in (2), including 95% confidence intervals, with Figure 9(a) showing the effect on log level of luxury expenditure and Figure 9(b) showing the effect on share of luxury expenditure. Coefficients are relative to 40-year-old Generation X, which is marked as the horizontal zero line.

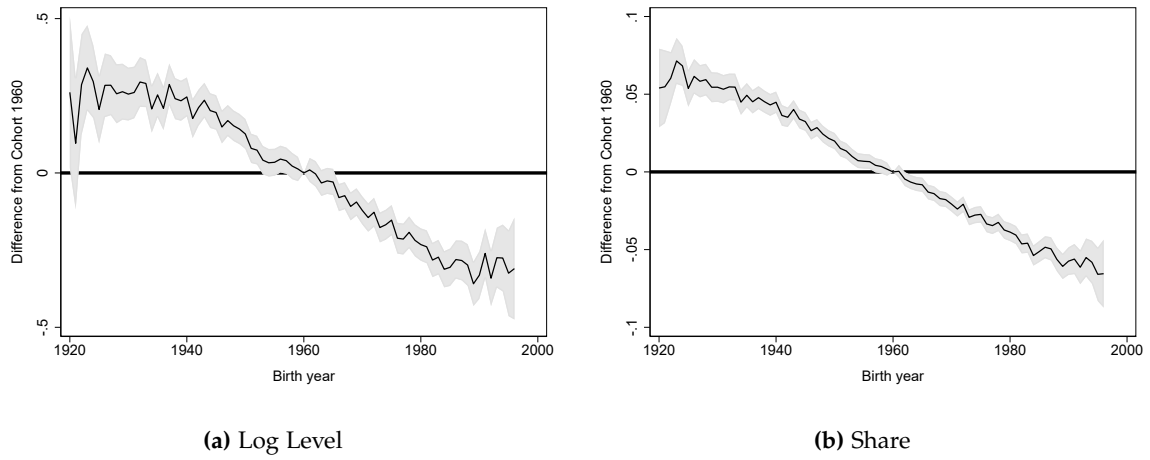


Figure 10: Controlling for Birth Year: Generation Effect on Luxury Expenditure

Notes: Both figures show the estimated coefficients on cohort dummies, including 95% confidence intervals, with Figure 10(a) showing the effect on log level of luxury expenditure and Figure 10(b) showing the effect on share of luxury expenditure. Cohort is defined by the specific birth year, and coefficients are relative to reference cohort 1960, which is marked as the horizontal zero line.

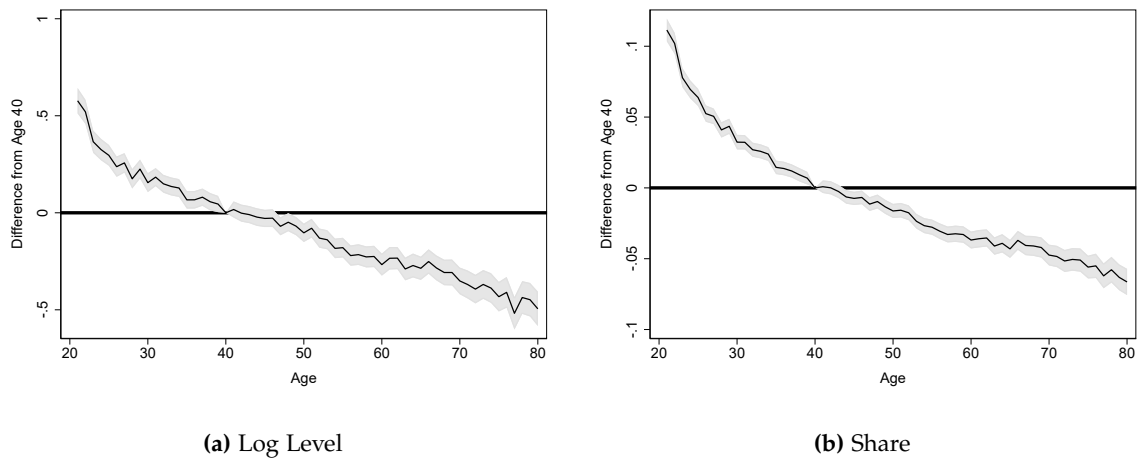


Figure 11: Controlling for Birth Year: Age Effect on Luxury Expenditure

Notes: Both figures show the estimated coefficients on age dummies, including 95% confidence intervals, with Figure 11(a) showing the effect on log level of luxury expenditure and Figure 11(b) showing the effect on share of luxury expenditure. Coefficients are relative to reference age 40, which is marked as the horizontal zero line.

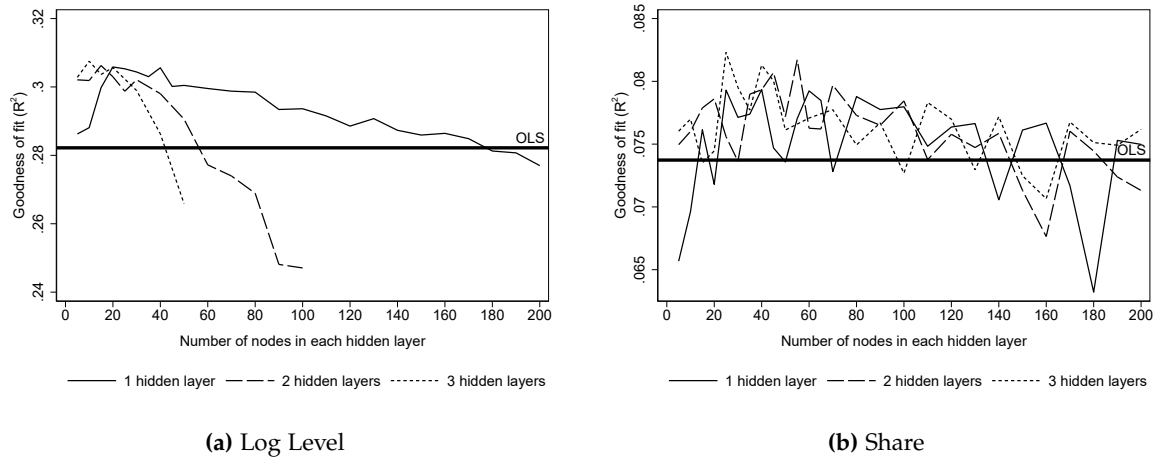


Figure 12: *Neural Network Model Selection: Testing the Goodness of Fit*

Notes: Both figures plot the goodness of fit of predictions (R^2) in the testing set, with Figure 12(a) showing the results in log level of luxury expenditure and Figure 12(b) showing the results in the share of luxury expenditure. Models of different structures—different numbers of layers and nodes—are trained using data from the training set. The goodness of fit of OLS regression, where parameters are estimated using the training data and R^2 is calculated from test in the same way that the neural network predictions are conducted, is marked by the horizontal lines.

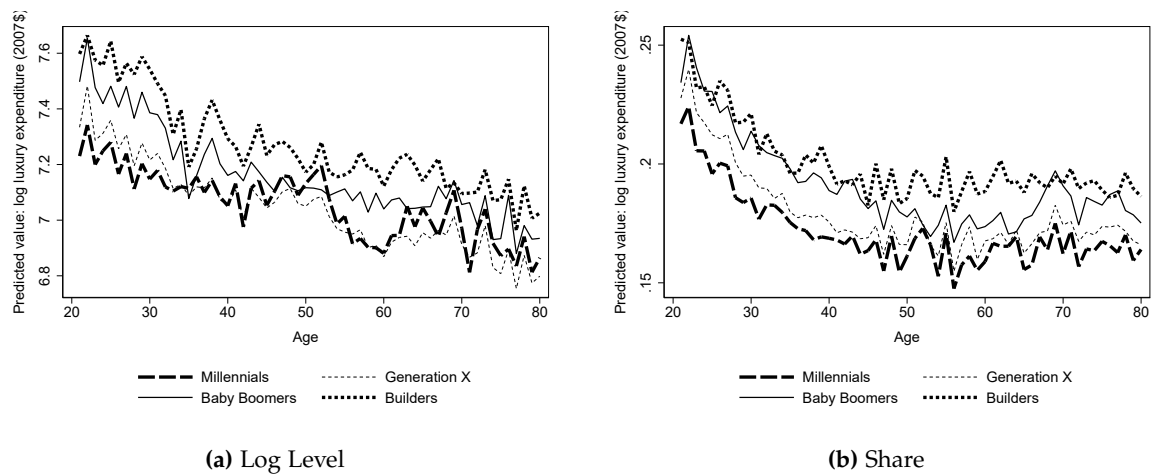


Figure 13: *Neural Network: Predicted Generation Specific Luxury Expenditure by Age (One Layer)*

Notes: Values are in US 2007 dollars. Both figures plot predicted means at each age from 21 to 80 for each generation using the best one-layer neural network models, with Figure 13(a) showing the log level of luxury expenditure and Figure 13(b) showing the share of luxury expenditure. The optimal numbers of nodes in the hidden layer are 20 and 40 when log and share of luxury expenditure are output variables respectively.

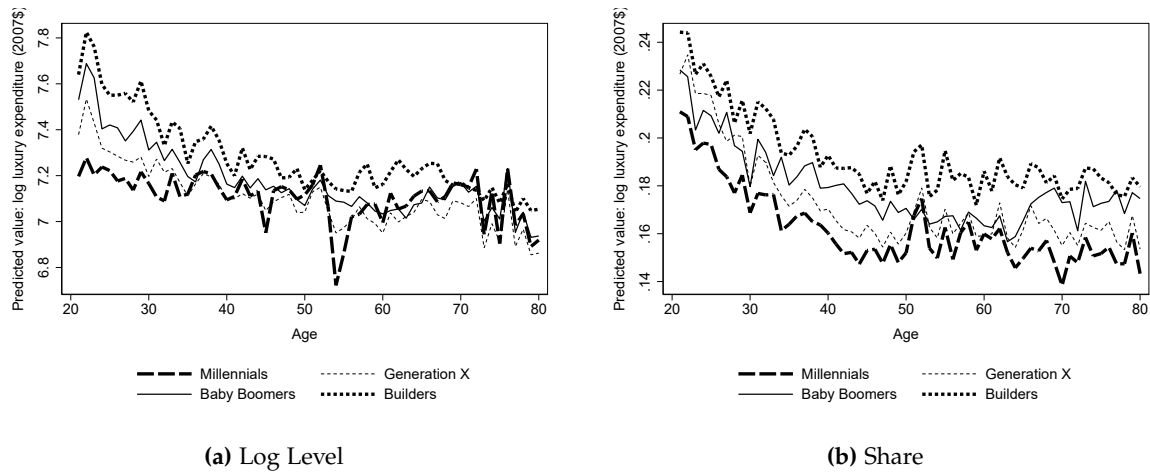


Figure 14: Neural Network: Predicted Generation Specific Luxury Expenditure by Age (Two Layers)

Notes: Values are in US 2007 dollars. Both figures plot predicted means at each age from 21 to 80 for each generation using the best two-layer neural network models, with Figure 14(a) showing the log level of luxury expenditure and Figure 14(b) showing the share of luxury expenditure. The optimal numbers of nodes in both of the hidden layers are 15 and 55 when log and share of luxury expenditure are output variables respectively.

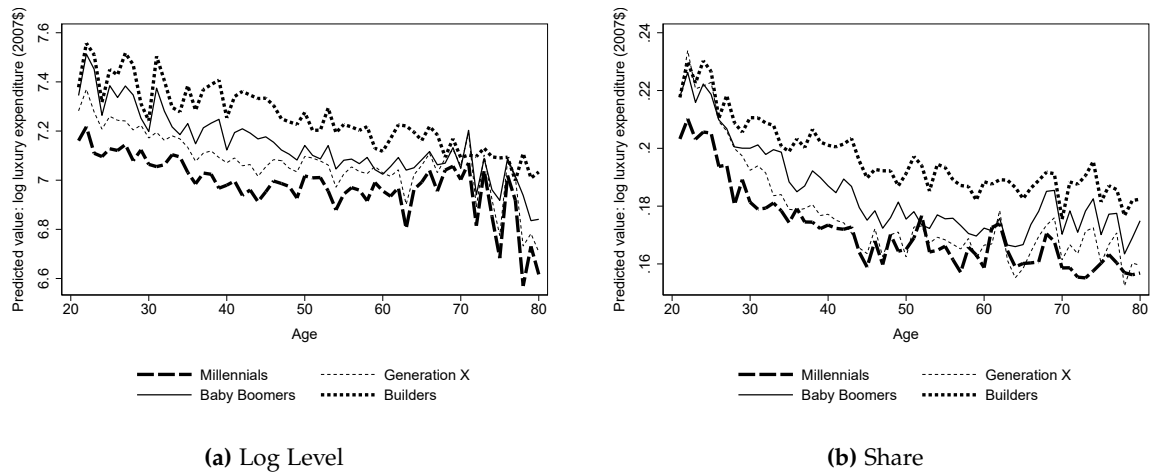


Figure 15: Neural Network: Predicted Generation Specific Luxury Expenditure by Age (Three Layers)

Notes: Values are in US 2007 dollars. Both figures plot predicted means at each age from 21 to 80 for each generation using the best three-layer neural network models, with Figure 15(a) showing the log level of luxury expenditure and Figure 15(b) showing the share of luxury expenditure. The optimal numbers of nodes in all of the hidden layers are 10 and 25 when log and share of luxury expenditure are output variables respectively.

Table 1: *Generational Segments*

	Birth Year	Age in 2021
The Greatest Generation	1902–1927	94–119
The Silent Generation	1928–1945	76–93
Baby Boomers	1946–1964	57–75
Generation X	1965–1980	41–56
Generation Y (Millennials)	1981–1996	25–40
Generation Z	From 1997	younger than 25

Sources: The Pew Research Center, available at <https://web.archive.org/web/20170216215337/http://www.pewresearch.org/methodology/demographic-research/definitions/> (accessed 9 September 2021); Dimock (2019)

Table 2: Summary Statistics

Dependent variables	N	Mean	SD	Min	Max
Luxury expenditure (overall)	443497	2591.561	3425.366	0	42948.560
Millennials	51797	2126.423	2812.116	0	39564.710
Generation X	132364	2727.530	3214.430	0	40640.740
Baby Boomers	174083	2825.222	3653.385	0	40824.000
Builders	85253	2185.931	3535.532	0	42948.560
Share of luxury expenditure (overall)	443497	0.183	0.141	0	0.989
Millennials	51797	0.188	0.148	0	0.989
Generation X	132364	0.186	0.134	0	0.959
Baby Boomers	174083	0.181	0.137	0	0.976
Builders	85253	0.178	0.153	0	0.944
Income and total expenditure	N	Mean	SD	Min	Max
Income after taxes	443249	56637.610	45088.500	831.476	310994.200
Total expenditure	443497	11615.090	7624.983	1501.618	51922.450
Millennials	51797	9564.919	5807.893	1507.523	51754.86
Generation X	132364	12426.74	7430.917	1511.897	51827.42
Baby Boomers	174083	12699.76	8205.196	1501.618	51922.45
Builders	85253	9385.696	6914.062	1517.802	51794.45
Demographics of household head	N	Mean	SD	Min	Max
Age	443497	48.460	15.469	21	80
Male	443497	0.487	0.500	0	1
Married	443497	0.545	0.498	0	1
Below 9th grade	443497	0.048	0.213	0	1
High school, no diploma	443497	0.083	0.276	0	1
High school graduate	443497	0.461	0.498	0	1
College graduate	443497	0.299	0.458	0	1
Masters degree and above	443497	0.109	0.312	0	1
White	443497	0.815	0.388	0	1
Black	443497	0.119	0.324	0	1
Native American	443497	0.006	0.078	0	1
Asian or Pacific Islander	443497	0.049	0.216	0	1
Other races	443497	0.011	0.104	0	1
Household size	N	Mean	SD	Min	Max
Number of household members	443497	2.590	1.507	1	21
Number of adults	443497	1.985	0.926	1	13
Household scale (equivalence)	443497	1.992	0.899	1	12.6
Household location	N	Mean	SD	Min	Max
Urban	443497	0.933	0.251	0	1
Metropolitan statistical area	443497	0.871	0.336	0	1
Northeast	438897	0.177	0.382	0	1
Midwest	438897	0.224	0.417	0	1
South	438897	0.355	0.479	0	1
West	438897	0.243	0.429	0	1
Interview quarter	N	Mean	SD	Min	Max
Quarter 1	443497	0.245	0.430	0	1
Quarter 2	443497	0.254	0.436	0	1
Quarter 3	443497	0.251	0.433	0	1
Quarter 4	443497	0.250	0.433	0	1

Notes: The table reports summary statistics of the refined sample (including 443497 observations) for the descriptive and regression analysis. Different numbers of observations come from missing values of corresponding variables. Expenditure data are quarterly based while income after taxes is measured as total amount of household income after taxes in the last 12 months.

Table 3: Main Results

	Log luxury expenditure				Share of luxury expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Millennials	0.0545*** (0.0087)	-0.0735*** (0.0110)	-0.0872*** (0.0109)	-0.0823*** (0.0114)	0.0180*** (0.0010)	-0.0139*** (0.0013)	-0.0156*** (0.0012)	-0.0148*** (0.0013)
Baby Boomers	-0.0533*** (0.0062)	0.0780*** (0.0099)	0.0939*** (0.0098)	0.0955*** (0.0102)	-0.0054*** (0.0007)	0.0136*** (0.0011)	0.0145*** (0.0011)	0.0150*** (0.0011)
Builders	-0.1019*** (0.0083)	0.1350*** (0.0167)	0.1887*** (0.0164)	0.2044*** (0.0173)	0.0044*** (0.0009)	0.0286*** (0.0018)	0.0322*** (0.0018)	0.0353*** (0.0019)
Period	0.0292*** (0.0015)	0.0177*** (0.0016)	0.0198*** (0.0016)	0.0181*** (0.0017)	0.0050*** (0.0002)	0.0033*** (0.0002)	0.0033*** (0.0002)	0.0032*** (0.0002)
ln(income)	0.8016*** (0.0035)	0.8066*** (0.0037)	0.6409*** (0.0042)	0.6453*** (0.0045)	0.0331*** (0.0003)	0.0352*** (0.0003)	0.0273*** (0.0004)	0.0280*** (0.0004)
Household scale (equivalence)			0.0568*** (0.0058)	0.0513*** (0.0062)			-0.0031*** (0.0006)	-0.0038*** (0.0006)
Number of adults			-0.0177*** (0.0055)	-0.0098* (0.0058)			-0.0025*** (0.0006)	-0.0015** (0.0006)
Male			-0.0182*** (0.0054)	-0.0262*** (0.0057)			-0.0014** (0.0006)	-0.0025*** (0.0006)
Married			0.2594*** (0.0067)	0.2488*** (0.0071)			0.0149*** (0.0007)	0.0134*** (0.0007)
Below 9th grade			-0.4844*** (0.0148)	-0.4914*** (0.0162)			-0.0318*** (0.0014)	-0.0316*** (0.0015)
High school, diploma			-0.3767*** (0.0114)	-0.3738*** (0.0122)			-0.0281*** (0.0010)	-0.0274*** (0.0011)
College graduate			0.2415*** (0.0062)	0.2363*** (0.0065)			0.0162*** (0.0007)	0.0157*** (0.0007)
Masters degree and above			0.4004*** (0.0085)	0.3948*** (0.0089)			0.0286*** (0.0010)	0.0283*** (0.0010)
Black			-0.1588*** (0.0090)	-0.1418*** (0.0094)			-0.0118*** (0.0009)	-0.0088*** (0.0009)
Native American			-0.0980*** (0.0360)	-0.1250*** (0.0395)			0.0013 (0.0036)	-0.0053 (0.0039)
Asian or Pacific Islander			-0.2095*** (0.0128)	-0.1683*** (0.0134)			-0.0145*** (0.0014)	-0.0086*** (0.0015)
Other races			0.0280 (0.0232)	0.0386 (0.0243)			0.0035 (0.0026)	0.0060** (0.0027)
Urban			-0.0256* (0.0145)	0.0400 (0.0443)			-0.0031* (0.0016)	-0.0005 (0.0048)
Metropolitan statistical area			0.0517*** (0.0114)	0.0233 (0.0353)			-0.0104*** (0.0012)	-0.0099*** (0.0038)
Age		✓	✓	✓		✓	✓	✓
Region			✓	✓			✓	✓
Quarter			✓	✓			✓	✓
State				✓				✓
Observations	426498	426498	422145	373198	443249	443249	438658	387495
R ²	0.2499	0.2521	0.2854	0.2926	0.0456	0.0529	0.0721	0.0832

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months. High school graduate is the base group of education, and White is the base group of race.

Table 4: Robustness: Generation Specific Definition of Luxury

	Log luxury expenditure			
	Millennials	Generation X	Baby Boomers	Builders
	(1)	(2)	(3)	(4)
Millennials	-0.0537*** (0.0109)	-0.0098 (0.0089)	-0.0200** (0.0086)	-0.0176** (0.0080)
Baby Boomers	0.0731*** (0.0098)	0.0425*** (0.0083)	0.0514*** (0.0080)	0.0507*** (0.0075)
Builders	0.1648*** (0.0161)	0.1238*** (0.0139)	0.1381*** (0.0136)	0.1188*** (0.0127)
Period	0.0183*** (0.0015)	0.0101*** (0.0013)	0.0100*** (0.0013)	0.0114*** (0.0012)
ln(income)	0.6272*** (0.0041)	0.6015*** (0.0037)	0.5961*** (0.0036)	0.5697*** (0.0034)
Age	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓
Observations	422529	432265	434048	434796
R ²	0.2791	0.3315	0.3394	0.3504
	Share of luxury expenditure			
	Millennials	Generation X	Baby Boomers	Builders
	(1)	(2)	(3)	(4)
Millennials	-0.0097*** (0.0012)	-0.0054*** (0.0013)	-0.0073*** (0.0013)	-0.0073*** (0.0014)
Baby Boomers	0.0105*** (0.0010)	0.0099*** (0.0011)	0.0121*** (0.0012)	0.0121*** (0.0012)
Builders	0.0290*** (0.0018)	0.0311*** (0.0019)	0.0348*** (0.0020)	0.0326*** (0.0020)
Period	0.0031*** (0.0002)	0.0029*** (0.0002)	0.0032*** (0.0002)	0.0038*** (0.0002)
ln(income)	0.0261*** (0.0004)	0.0293*** (0.0005)	0.0304*** (0.0005)	0.0286*** (0.0005)
Age	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓
Observations	438658	438658	438658	438658
R ²	0.0723	0.0834	0.0827	0.0781

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months. The dependent variables are either log or share of luxury expenditure defined by each generation according to estimated total expenditure elasticity using sample of each generation in Figure A.4.

Table 5: Robustness: Common Age Range

	Log luxury expenditure		
	Millennials & Generation X 21-37	Generation X & Baby Boomers 36-53	Baby Boomers & Builders 55-72
	(1)	(2)	(3)
Millennials	-0.0796*** (0.0115)		
Generation X		-0.0896*** (0.0102)	
Baby Boomers			-0.1020*** (0.0133)
Period	0.0233*** (0.0028)	0.0199*** (0.0025)	0.0177*** (0.0031)
ln(income)	0.5882*** (0.0076)	0.7302*** (0.0072)	0.6100*** (0.0078)
Age	✓	✓	✓
Household characteristics	✓	✓	✓
Observations	119607	157620	119759
R ²	0.2317	0.3103	0.2806
	Share of luxury expenditure		
	Millennials & Generation X 21-37	Generation X & Baby Boomers 36-53	Baby Boomers & Builders 55-72
	(1)	(2)	(3)
Millennials	-0.0146*** (0.0013)		
Generation X		-0.0143*** (0.0011)	
Baby Boomers			-0.0184*** (0.0014)
Period	0.0037*** (0.0003)	0.0032*** (0.0003)	0.0031*** (0.0003)
ln(income)	0.0184*** (0.0008)	0.0333*** (0.0007)	0.0284*** (0.0007)
Age	✓	✓	✓
Household characteristics	✓	✓	✓
Observations	123806	162682	124983
R ²	0.0563	0.0828	0.0750

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months.

Table 6: Results from Specific Categories

	Log luxury expenditure								
	Household operations	House furnishings and equipment	Clothing for adults	Vehicles	Public and other transportation	Entertainment	Education	Cash contribution	Miscellaneous outlays
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Millennials	0.1959*** (0.0142)	-0.0319** (0.0147)	-0.2867*** (0.0114)	-0.1900*** (0.0193)	-0.1384*** (0.0217)	-0.0389*** (0.0122)	0.1190*** (0.0325)	-0.0190 (0.0241)	-0.0529*** (0.0190)
Baby Boomers	-0.2051*** (0.0111)	0.0600*** (0.0131)	0.2742*** (0.0104)	0.0994*** (0.0179)	0.0105 (0.0197)	0.0248** (0.0114)	-0.0331 (0.0269)	0.0195 (0.0185)	0.0027 (0.0169)
Builders	-0.4324*** (0.0172)	0.1370*** (0.0212)	0.6169*** (0.0170)	0.1603*** (0.0300)	0.0799** (0.0326)	0.0689*** (0.0196)	-0.2285*** (0.0591)	0.0435 (0.0274)	0.0491* (0.0275)
Period	-0.0284*** (0.0016)	0.0042** (0.0021)	0.0526*** (0.0016)	0.0341*** (0.0029)	-0.0080** (0.0031)	0.0006 (0.0018)	-0.0063 (0.0047)	-0.0115*** (0.0026)	0.0020 (0.0027)
ln(income)	0.3593*** (0.0043)	0.3984*** (0.0053)	0.3583*** (0.0043)	0.4225*** (0.0072)	0.3810*** (0.0073)	0.4745*** (0.0049)	0.3603*** (0.0119)	0.4286*** (0.0069)	0.2930*** (0.0070)
Age	(0.0535)	(0.0625)	(0.0501)	(0.0876)	(0.0910)	(0.0552)	(0.1295)	(0.0928)	(0.0819)
Household characteristics	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	302213	249698	249599	273465	93028	298734	67974	214811	183118
R ²	0.1438	0.0748	0.1428	0.0868	0.1197	0.1729	0.1563	0.1028	0.0460

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months.

Table 7: *Luxury Defined by Elasticity and Related Categories*

Luxury defined by elasticity	"Classic "luxury	Visible (conspicuous) goods
Household operations	Paulin and Riordon (1998)	Charles et al. (2009)
House furnishings and equipment	<i>Food away from home</i>	<i>Clothing/jewelry</i>
clothing for adults, 16 and over	<i>Entertainment</i>	<i>Personal care</i>
Vehicle purchases	<i>Reading</i>	<i>Vehicles</i>
Other vehicle expenditures	<i>Lodging except for shelter</i>	
Public and other transportation	<i>Vehicles</i>	Heffetz (2011)
Fees and admissions	<i>Transportation</i>	(Top lists based on visibility index)
Pets, toys, and playground equipment		<i>Cigarettes</i>
Recreational vehicles		<i>Cars</i>
Miscellaneous entertainment outlays		<i>Clothes, jewelry</i>
Education		<i>Furniture, appliances</i>
Miscellaneous outlays		<i>Recreational equipment</i>
Cash contribution		Friehe and Mechtel (2014)
		<i>Motor vehicles</i>
		<i>Shoes, apparel (adults, children, babies)</i>
		<i>Jewelry, watches, headpieces</i>
		<i>Skin and body care</i>
		<i>Dental treatments, prostheses</i>
		<i>Furniture, Household appliances</i>
		<i>Phones, TVs, Radio sets, Cameras</i>

Notes: This table lists luxury goods defined by the estimation measurement in this paper, categories that are arbitrarily considered as luxury based on common sense, or "class" luxury, and visible goods defined in the literature based on Veblen (1899)'s conspicuous consumption theory. Heffetz (2011) develops visibility index for each category based on surveys, and here I only show the 10 goods with the highest visibility indices. Friehe and Mechtel (2014) extend the definition of conspicuous consumption by Charles et al. (2009) and Heffetz (2011) by adding some categories that are usually noticed within closer groups such as colleagues and friends.

A Additional Figures and Tables

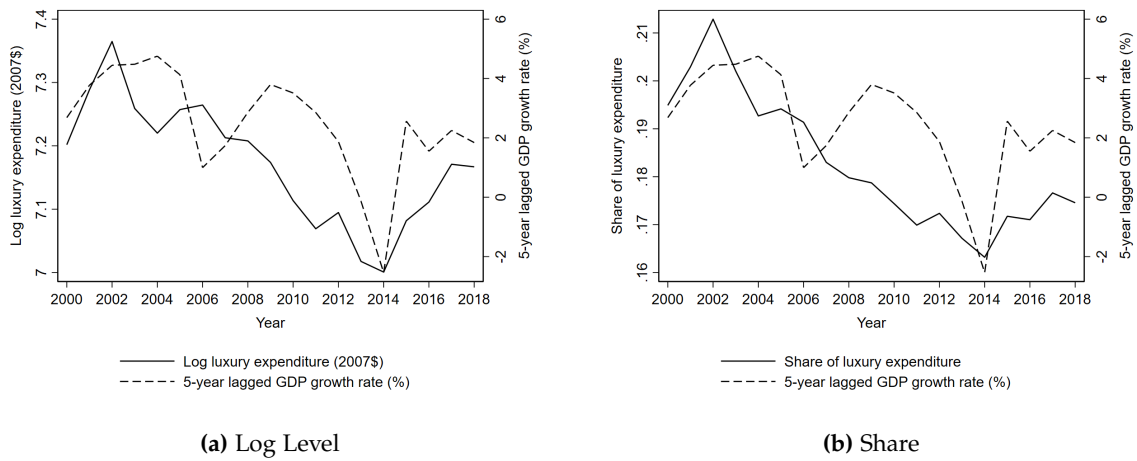


Figure A.1: *Luxury Expenditure and 5-year Lagged GDP Growth Rate*

Notes: Both figures show 5-year lagged GDP growth rates and average luxury expenditure over the sample period, with Figure A.1(a) showing the log level of luxury expenditure level and Figure A.1(b) showing the share of luxury expenditure.

Sources: The World Bank; Consumer Expenditure Survey (CE) 2000–2018

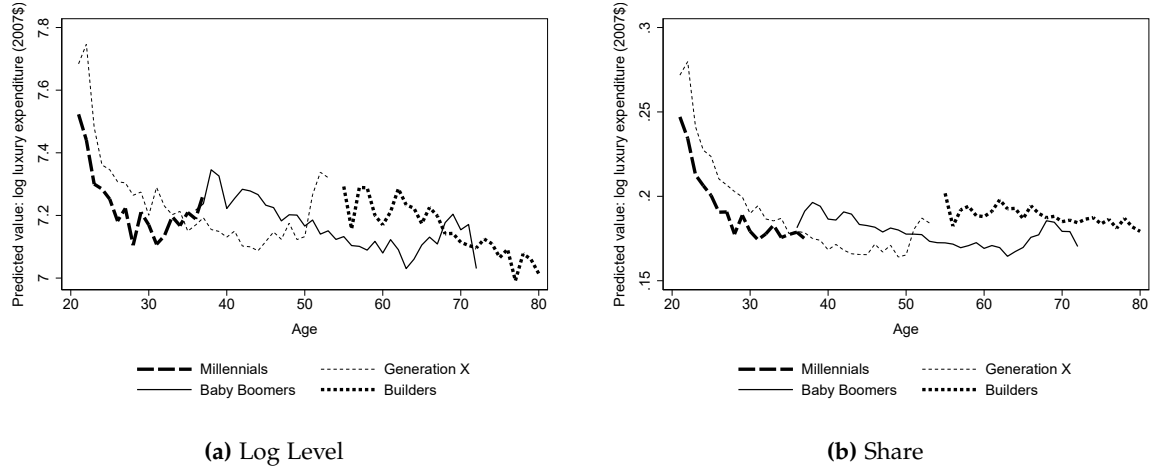


Figure A.2: Heterogeneous Effects: Predicted Generation Specific Luxury Expenditure by Age

Notes: Values are in US 2007 dollars. Both figures plot predicted means at each age from 21 to 80 for each generation using the estimated coefficients on age dummies from (2), with Figure A.2(a) showing the log level of luxury expenditure and Figure A.2(b) showing the share of luxury expenditure. Predictions are always conducted using the whole data set to pin down pure age and generation effects while giving other controls the same values.

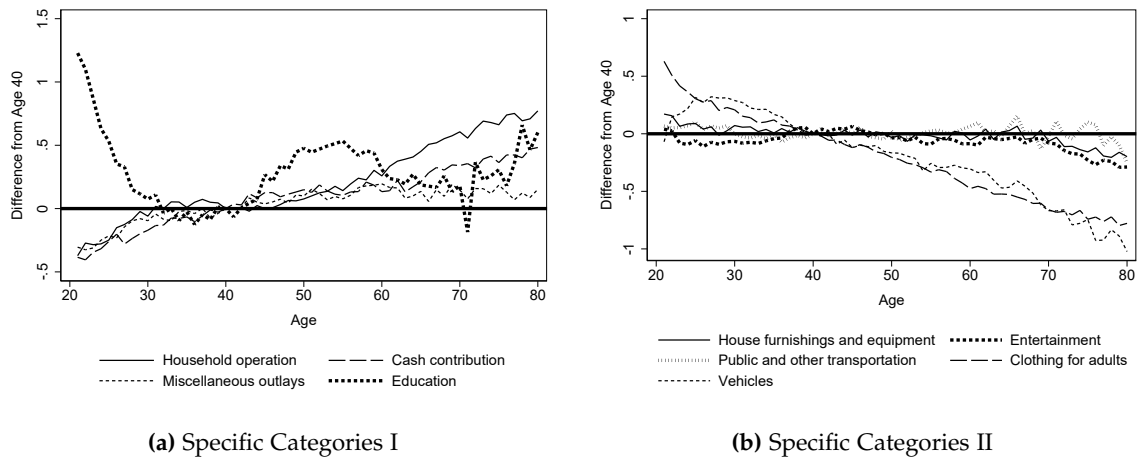


Figure A.3: Specific Categories: Age Effect on Luxury Expenditure

Notes: Both figure show estimated coefficients on age dummies based on the preferred model (1), with log expenditure of different luxury categories being dependent variables. Coefficients are relative to reference age 40, which is marked as the horizontal zero line.

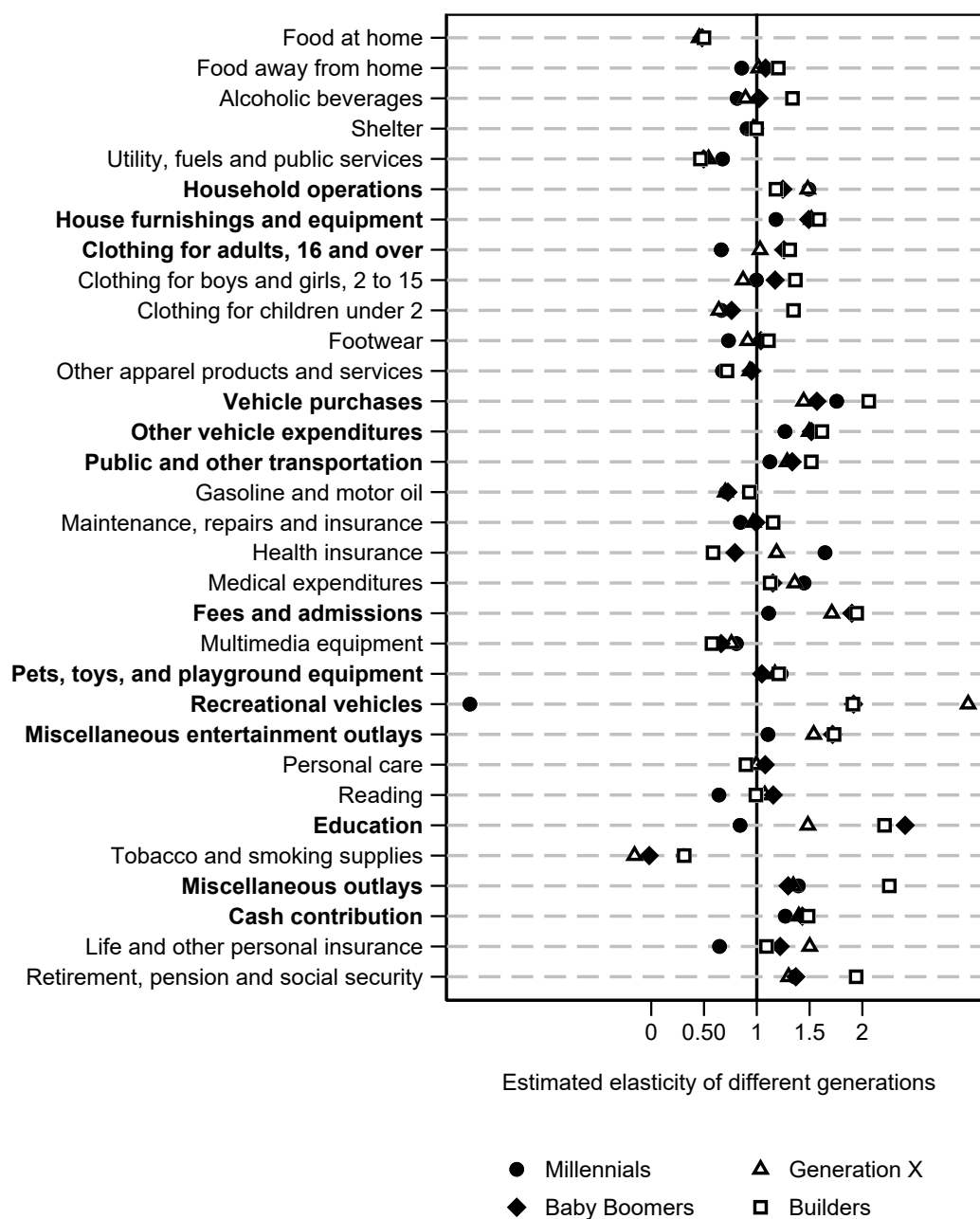
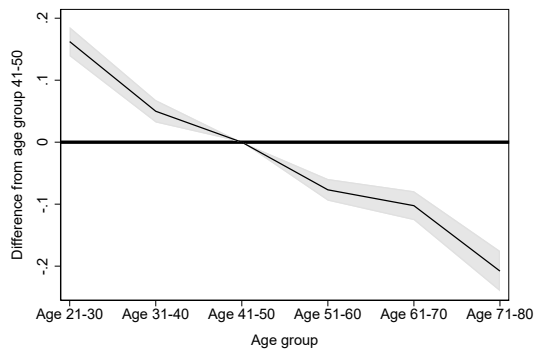
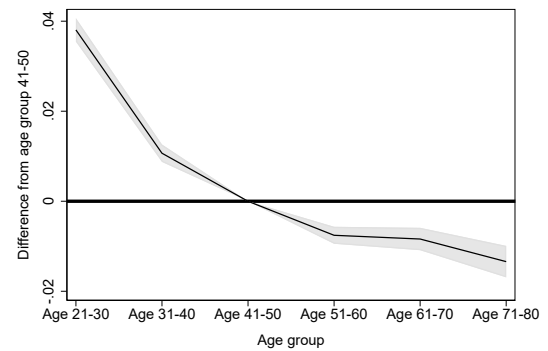


Figure A.4: *Generation Specific Total Expenditure Elasticity*

Notes: The figure reports how different generations classify the 32 expenditure categories into luxury and necessity, and the 13 categories that are classified by the overall sample households in the main specification is boldfaced. Estimations are only conduct for the whole sample period 2000–2019 using sample of each generation. Health insurance, which Millennials and Generation X consider as luxury, are excluded for the same reason why I drop life and other personal insurance and retirement, pensions social security from Figure 2 as they belong to the consumption transferred to the future.



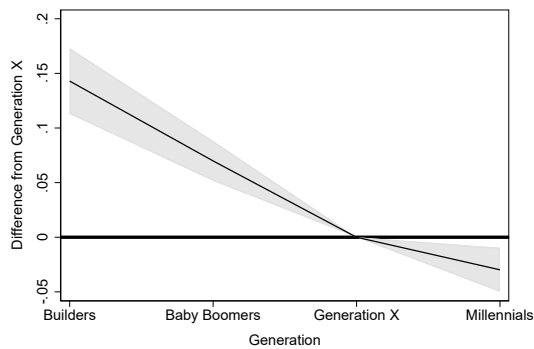
(a) Log Level



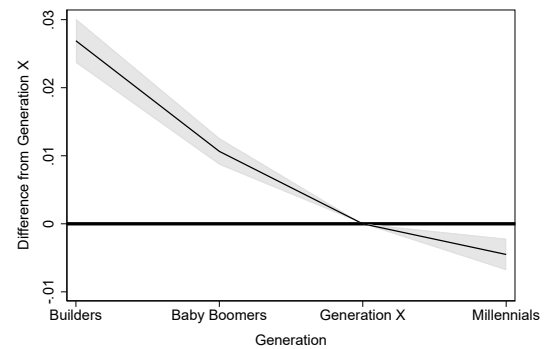
(b) Share

Figure A.5: Controlling for Age Group: Age Effect on Luxury Expenditure

Notes: Both figures show the estimated coefficients on age group dummies, including 95% confidence intervals, with Figure A.5(a) showing the effect on log level of luxury expenditure and Figure A.5(b) showing the effect on share of luxury expenditure. Coefficients are relative to reference age group 41–50, which is marked as the horizontal zero line.



(a) Log Level



(b) Share

Figure A.6: Controlling for Age Group: Generation Effect on Luxury Expenditure

Notes: Both figures show the estimated coefficients on generation dummies, including 95% confidence intervals, with Figure A.6(a) showing the effect on log level of luxury expenditure and Figure A.6(b) showing the effect on share of luxury expenditure. Coefficients are relative to reference Generation X, which is marked as the horizontal zero line.

Table A.1: Historic Events by Generation

Millennials	Ranking	Frequency
Sept.11	1	86%
Obama election	2	47%
Irap/Afghanistan wars	3	24%
Gay marriage	4	19%
The tech revolution	5	18%
Orlando shooting	6	17%
Hurricane Katrina	7	11%
Columbine shooting	8	10%
Bin laden	9	10%
Sandy Hook	10	7%
Generation X	Ranking	Frequency
Sept.11	1	79%
Obama election	2	40%
Fall of Berlin Wall/End of Cold War	3	21%
The tech revolution	4	20%
Irap/Afghanistan wars	5	18%
Gulf War	6	15%
Challenger disaster	7	14%
Gay marriage	8	10%
Hurricane Katrina	9	10%
Columbine shooting	10	9%
Baby Boomers	Ranking	Frequency
Sept.11	1	70%
JFK assassination	2	45%
Vietnam War	3	41%
Obama election	4	38%
Moon landing	5	35%
The tech revolution	6	26%
Civil rights movement	7	18%
Fall of Berlin Wall/End of Cold War	8	16%
MLK assassination	9	15%
Irap/Afghanistan wars	10	11%
The Silent Generation	Ranking	Frequency
Sept.11	1	59%
WWII	2	44%
JFK assassination	3	41%
Vietnam War	4	37%
Moon landing	5	29%
Obama election	6	28%
The tech revolution	7	27%
Civil rights movement	8	18%
Korean War	9	18%
Irap/Afghanistan wars	10	14%

Notes: Shown are results of a survey question “Please name the 10 historic events that occurred in your lifetime that you think have had the greatest impact on the country. This could be one specific event, a series of related events or any other historic development or change that had an important on the nation”. The survey was called “Americans Name the 10 Most Significant Historic Events of Their Lifetimes”, conducted in 2016 by the Pew Research Center (Deane et al., 2016), available at <https://www.pewresearch.org/politics/2016/12/15/americans-name-the-10-most-significant-historic-events-of-their-lifetimes/> (accessed 9 September 2021).

Table A.2: Categorization of the FMLI Files

My Expenditure Categories	Corresponding FMLI Expenditure Categories
Food at home	<i>Food at home</i>
Food away from home	<i>Food excluding meals as pay; Meals as pay</i>
Alcoholic beverages	<i>Alcoholic beverages</i>
Shelter	<i>Owned home outlays including mortgage principal and interest, property taxes, maintenance, insurance, and other expenses; Rented dwelling; Outlays for other lodging such as owned vacation home including mortgage principal and interest, property taxes, maintenance, insurance, and other expenses</i>
Utilities, fuels and public services	<i>Natural gas, electricity, fuel oil and other fuels; Telephone services; Water and other public services</i>
Household operations	<i>Domestic services; Other household expenses</i>
House furnishings and equipment	<i>Household textiles; Furniture; Floor coverings; Major appliances; Small appliances, miscellaneous housewares; Miscellaneous household equipment</i>
Clothing for adults, 16 and over	<i>Clothing for men, 16 and over; Clothing for women, 16 and over</i>
Clothing for children, 2 to 15	<i>Clothing for boys, 2 to 15; Clothing for girls, 2 to 15</i>
Clothing for children under 2	<i>Clothing for children under 2</i>
Footwear	<i>Footwear</i>
Other apparel products and services	<i>Other apparel products and services</i>
Vehicle purchases	<i>New vehicle purchases including down payment, principal and interest paid on loans, or if not financed, purchase amount; Used vehicles purchases including down payment, principal and interest paid on loans, or if not financed, purchase amount; Other vehicle purchases including down payment, principal and interest paid on loans, or if not financed, purchase amount</i>
Other vehicle expenditures	<i>Vehicle rental, leases, licenses, and other charges</i>
Public and other transportation	<i>Public and other transportation on trips; Public and other transportation, excluding trips</i>
Gasoline and motor oil	<i>Gasoline and motor oil</i>
Maintenance, repairs and insurance	<i>Maintenance, repairs and insurance on transportation</i>
Health insurance	<i>Health insurance</i>
Medical expenditures	<i>Medical services, prescription drugs and medical supplies</i>
Fees and admissions	<i>Fees and admissions for entertainment events</i>
Multimedia equipment	<i>Televisions, radios, and sound equipment</i>
Pets, toys, and playground equipment	<i>Pets, toys, and playground equipment</i>
Recreational vehicles	<i>Motored and non-motored recreational vehicles</i>
Miscellaneous entertainment outlays	<i>Photographic and sports equipment and boat and RV rentals</i>
Personal care	<i>Personal care products and services</i>
Reading	<i>Reading</i>
Education	<i>Education</i>
Tobacco and smoking supplies	<i>Tobacco and smoking supplies</i>
Miscellaneous outlays	<i>Safety deposit box rental, checking account fees and other bank service charges, credit card memberships, legal fees, accounting fees, funerals, cemetery lots, union dues, occupational expenses, expenses for other properties, and finance charges other than those for mortgages and vehicles</i>
Cash contribution	<i>Cash contribution</i>
Life and other personal insurance	<i>Life and other personal insurance</i>
Retirement, pensions society security	<i>Retirement, pensions society security</i>

Notes: The right column lists the original specific expenditure categories in the FMLI files, and I aggregate them into 32 categories shown in the left column. The FMLI files also report aggregated expenditure categories, for example, shelter, utilities, fules and public services, household operations and house furnishings and equipment are all included in a single categories called total housing outlays, but this is too broadly defined and the heterogeneity among individual categories might already be averaged out.

Table A.3: *Correlation between Luxury Expenditure and GDP Growth Rates*

	Log luxury Expenditure		Share of Luxury Expenditure		N
	Correlation Coefficient	P-value	Correlation Coefficient	P-value	
Current-year GDP growth rate	0.0227	0.9266	0.1598	0.5134	19
1-year lagged GDP growth rate	0.2195	0.3665	0.2785	0.2482	19
2-year lagged GDP growth rate	0.5463	0.0155	0.5132	0.0246	19
3-year lagged GDP growth rate	0.5821	0.0089	0.5794	0.0093	19
4-year lagged GDP growth rate	0.6198	0.0047	0.6055	0.0060	19
5-year lagged GDP growth rate	0.6750	0.0015	0.6649	0.0019	19
6-year lagged GDP growth rate	0.5215	0.0220	0.5612	0.0124	19

Notes: The table reports the correlations between (the average log level and share of) luxury expenditure of each year from 2000 to 2018 and the (lagged) GDP growth rate.

Sources: The World Bank; Consumer Expenditure Survey (CE) 2000–2018

Table A.4: Results from Specific Categories (Full Table: Part 1)

	Log luxury expenditure				
	Household operations	House furnishings and equipment	Clothing for adults	Vehicles	Public and other transportation
	(1)	(2)	(3)	(4)	(5)
Millennials	0.1959*** (0.0142)	-0.0319** (0.0147)	-0.2867*** (0.0114)	-0.1900*** (0.0193)	-0.1384*** (0.0217)
Baby Boomers	-0.2051*** (0.0111)	0.0600*** (0.0131)	0.2742*** (0.0104)	0.0994*** (0.0179)	0.0105 (0.0197)
Builders	-0.4324*** (0.0172)	0.1370*** (0.0212)	0.6169*** (0.0170)	0.1603*** (0.0300)	0.0799** (0.0326)
Period	-0.0284*** (0.0016)	0.0042** (0.0021)	0.0526*** (0.0016)	0.0341*** (0.0029)	-0.0080** (0.0031)
ln(income)	0.3593*** (0.0043)	0.3984*** (0.0053)	0.3583*** (0.0043)	0.4225*** (0.0072)	0.3810*** (0.0073)
Household scale (equivalence)	0.3790*** (0.0072)	0.0274*** (0.0076)	-0.1928*** (0.0064)	0.0342*** (0.0105)	-0.0504*** (0.0118)
Number of adults	-0.3300*** (0.0063)	-0.0067 (0.0071)	0.2334*** (0.0059)	0.1197*** (0.0097)	0.0356*** (0.0108)
Male	-0.0861*** (0.0059)	0.0321*** (0.0068)	-0.0655*** (0.0055)	0.0150 (0.0096)	-0.0180* (0.0105)
Below 9th grade	-0.3155*** (0.0180)	-0.1689*** (0.0186)	-0.0963*** (0.0149)	-0.1125*** (0.0289)	-0.1513*** (0.0257)
High school, no diploma	-0.1862*** (0.0129)	-0.0981*** (0.0146)	-0.1035*** (0.0116)	-0.0324 (0.0201)	-0.1946*** (0.0228)
College graduate	0.1377*** (0.0067)	0.1091*** (0.0079)	0.1340*** (0.0064)	-0.1378*** (0.0110)	0.1338*** (0.0128)
Masters degree and above	0.3040*** (0.0097)	0.1540*** (0.0111)	0.2368*** (0.0090)	-0.3056*** (0.0160)	0.2295*** (0.0161)
Urban	0.0078 (0.0153)	-0.0335* (0.0182)	0.1377*** (0.0150)	-0.1579*** (0.0251)	-0.1492*** (0.0388)
Married	0.0935*** (0.0069)	0.1739*** (0.0085)	0.0507*** (0.0069)	0.1656*** (0.0116)	0.2796*** (0.0131)
Metropolitan statistical area	0.1318*** (0.0120)	0.0882*** (0.0141)	0.0703*** (0.0114)	-0.0358* (0.0198)	0.0237 (0.0291)
Black	-0.0227** (0.0098)	-0.0381*** (0.0121)	0.1007*** (0.0095)	0.1593*** (0.0160)	-0.0527*** (0.0154)
Native American	-0.0870** (0.0381)	0.0216 (0.0437)	-0.0283 (0.0334)	0.1049* (0.0605)	-0.1676*** (0.0625)
Asian or Pacific Islander	-0.1455*** (0.0136)	-0.1366*** (0.0163)	-0.0559*** (0.0126)	-0.2373*** (0.0229)	0.2045*** (0.0201)
Other races	-0.0210 (0.0260)	0.0014 (0.0310)	-0.0588** (0.0263)	-0.0142 (0.0438)	-0.1373*** (0.0447)
Age	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Quarter	✓	✓	✓	✓	✓
Observations	302213	249698	249599	273465	93028
R ²	0.1438	0.0748	0.1428	0.0868	0.1197

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months. High school graduate is the base group of education, and White is the base group of race.

Table A.5: Results from Specific Categories (Full Table: Part 2)

	Log luxury expenditure			
	Entertainment	Education	Cash contribution	Miscellaneous outlays
	(6)	(7)	(8)	(9)
Millennials	-0.0389*** (0.0122)	0.1190*** (0.0325)	-0.0190 (0.0241)	-0.0529*** (0.0190)
Baby Boomers	0.0248** (0.0114)	-0.0331 (0.0269)	0.0195 (0.0185)	0.0027 (0.0169)
Builders	0.0689*** (0.0196)	-0.2285*** (0.0591)	0.0435 (0.0274)	0.0491* (0.0275)
Period	0.0006 (0.0018)	-0.0063 (0.0047)	-0.0115*** (0.0026)	0.0020 (0.0027)
ln(income)	0.4745*** (0.0049)	0.3603*** (0.0119)	0.4286*** (0.0069)	0.2930*** (0.0070)
Household scale (equivalence)	0.1697*** (0.0067)	-0.4981*** (0.0162)	-0.0016 (0.0114)	0.0215** (0.0103)
Number of adults	-0.1708*** (0.0062)	0.4187*** (0.0141)	-0.0500*** (0.0102)	-0.0113 (0.0094)
Male	0.0046 (0.0062)	0.1309*** (0.0162)	0.1649*** (0.0094)	0.0311*** (0.0091)
Below 9th grade	-0.4309*** (0.0183)	-0.2168*** (0.0493)	-0.2415*** (0.0253)	-0.1104*** (0.0275)
High school, no diploma	-0.2649*** (0.0131)	-0.4593*** (0.0346)	-0.1364*** (0.0199)	-0.0595*** (0.0191)
College graduate	0.2125*** (0.0072)	0.3288*** (0.0184)	0.1207*** (0.0108)	-0.0127 (0.0104)
Masters degree and above	0.3410*** (0.0101)	0.4646*** (0.0256)	0.2861*** (0.0145)	0.1004*** (0.0151)
Urban	-0.0358** (0.0170)	0.2631*** (0.0441)	-0.0405* (0.0240)	0.0075 (0.0246)
Married	0.1858*** (0.0076)	0.0719*** (0.0201)	0.1801*** (0.0117)	0.0100 (0.0113)
Metropolitan statistical area	0.1000*** (0.0130)	-0.0340 (0.0322)	-0.0176 (0.0187)	0.0683*** (0.0189)
Black	-0.4887*** (0.0106)	-0.0543** (0.0260)	0.2500*** (0.0143)	-0.0152 (0.0150)
Native American	-0.1579*** (0.0391)	-0.0116 (0.0970)	-0.0848 (0.0675)	-0.0230 (0.0584)
Asian or Pacific Islander	-0.3278*** (0.0147)	0.2826*** (0.0331)	-0.1781*** (0.0223)	-0.0625*** (0.0215)
Other races	-0.0474* (0.0282)	-0.0859 (0.0654)	-0.0832* (0.0425)	0.0651* (0.0388)
Age	✓	✓	✓	✓
Region	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Observations	298734	67974	214811	183118
R ²	0.1729	0.1563	0.1028	0.0460

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months. High school graduate is the base group of education, and White is the base group of race.

Table A.6: Robustness: IV Estimation

	Log luxury expenditure		Share of luxury expenditure	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Millennials	-0.0691*** (0.0082)	-0.0741*** (0.0083)	-0.0137*** (0.0011)	-0.0150*** (0.0012)
Baby Boomers	0.0791*** (0.0073)	0.0825*** (0.0074)	0.0131*** (0.0010)	0.0140*** (0.0010)
Builders	0.1787*** (0.0121)	0.1828*** (0.0122)	0.0306*** (0.0016)	0.0319*** (0.0016)
Period	0.0213*** (0.0012)	0.0221*** (0.0012)	0.0032*** (0.0002)	0.0034*** (0.0002)
ln(total expenditure)	1.7814*** (0.0039)	1.5673*** (0.0070)	0.1218*** (0.0006)	0.0657*** (0.0009)
Age	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓
Observations	422382	422145	438897	438658
R^2	0.5904	0.5846	0.2471	0.2062

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Expenditure data are quarterly based. High school graduate is the base group of education, and White is the base group of race.

Table A.7: Robustness: Different Household Scales

	Log luxury expenditure		Share of luxury expenditure	
	Modified	Square root	Modified	Square root
	(1)	(2)	(3)	(4)
Millennials	-0.0872*** (0.0109)	-0.0866*** (0.0108)	-0.0156*** (0.0012)	-0.0156*** (0.0012)
Baby Boomers	0.0939*** (0.0098)	0.0944*** (0.0098)	0.0145*** (0.0011)	0.0145*** (0.0011)
Builders	0.1887*** (0.0164)	0.1894*** (0.0164)	0.0322*** (0.0018)	0.0322*** (0.0018)
Period	0.0198*** (0.0016)	0.0198*** (0.0016)	0.0033*** (0.0002)	0.0033*** (0.0002)
ln(income)	0.6409*** (0.0042)	0.6395*** (0.0042)	0.0273*** (0.0004)	0.0274*** (0.0004)
Household scale (modified)	0.0947*** (0.0097)		-0.0052*** (0.0010)	
Household scale (square root)		0.1354*** (0.0105)		-0.0060*** (0.0011)
Age	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓
Observations	422145	422145	438658	438658
R ²	0.2854	0.2856	0.0721	0.0721

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months. Household scale (modified) represents for “OECD-modified scale”. Household scale (square root) represents for “square root scale”. See Section 4.1 and Footnote 13 for details.

Table A.8: Robustness: More Disaggregated Generational Segments and Orthogonal Period Effect

	Log luxury expenditure		Share of luxury expenditure	
	Different generational segments	Orthogonal period effect	Different generational segments	Orthogonal period effect
	(1)	(2)	(3)	(4)
Millennials I	-0.0821*** (0.0209)		-0.0205*** (0.0026)	
Millennials II	-0.0878*** (0.0110)		-0.0152*** (0.0013)	
Baby Boomers	0.0939*** (0.0098)		0.0147*** (0.0011)	
The Silent Generation	0.1887*** (0.0164)		0.0326*** (0.0018)	
The Greatest Generation	0.1926*** (0.0313)		0.0409*** (0.0033)	
Millennials		-0.0254** (0.0122)		-0.0029** (0.0014)
Baby Boomers		0.0266** (0.0112)		0.0013 (0.0012)
Builders		0.0621*** (0.0197)		0.0065*** (0.0021)
Period	0.0198*** (0.0016)		0.0032*** (0.0002)	
ln(income)	0.6409*** (0.0042)	0.6426*** (0.0042)	0.0273*** (0.0004)	0.0274*** (0.0004)
Year		✓		✓
Age	✓	✓	✓	✓
Household characteristics	✓	✓	✓	✓
Observations	422145	422145	438658	438658
R ²	0.2854	0.2874	0.0722	0.0758

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is always taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months. High school graduate is the base group of education, and the White is the base group of race.

Table A.9: *Summary Statistics of Expenditure on Specific Categories*

	N	Mean	SD	Min	Max
Household operations	443497	232.730	579.208	0	39293.450
House furnishings and equipment	443497	310.795	851.507	0	29116.520
Clothing for adults	443497	135.997	281.978	0	18798.150
Vehicles	443497	801.386	2012.877	0	40613.030
Public and other transportation	443497	124.316	496.074	0	29514.800
Entertainment	443497	319.139	771.349	0	34256.470
Education	443497	190.243	1068.495	0	41309.550
Cash contribution	443497	342.587	997.874	0	38335.280
Miscellaneous outlays	443497	134.369	669.217	0	38520.800

Notes: The table reports summary statistics of expenditure on individual categories that are defined as luxury. All expenditure data are quarterly based.

B Heterogeneous Effects Details

I develop the following two more general models including interaction terms.

Model 1.

$$L_{it} = \alpha_0 + \beta_a D_{it}^a + \beta_g D_i^g + \beta_{gp} D_i^g \cdot \text{Period}_t + \alpha_1 \text{Period}_t + \alpha_2 \ln(\text{income})_{it} + \beta_h X_{it} + \varepsilon_{it}$$

follows the notation of the main specification except that vector β_{gp} denote the coefficients on the interaction terms between generation dummies and 5-year lagged GDP growth rate as proxy for period effect.

Model 2.

$$L_{it} = \alpha_0 + \beta_a D_{it}^a + \beta_g D_i^g + \beta_{ga} D_i^g \cdot D_{it}^a + \alpha_1 \text{Period}_t + \alpha_2 \ln(\text{income})_{it} + \beta_h X_{it} + \varepsilon_{it}$$

includes the interaction terms between generation and age dummies $\beta_{ga} D_i^g \cdot D_{it}^a$. The results of the two models are shown in Table B.1. In Column (1) and Column (2) based on Model 1,

Table B.1: Heterogeneous Effects: Including Interaction Terms

	Model 1		Model 2	
	Log luxury expenditure	Share of luxury expenditure	Log luxury expenditure	Share of luxury expenditure
	(1)	(2)	(3)	(4)
Millennials	-0.0834*** (0.0155)	-0.0150*** (0.0017)	-0.1612** (0.0756)	-0.0247** (0.0102)
Baby Boomers	0.0863*** (0.0136)	0.0137*** (0.0014)	-0.1697** (0.0731)	-0.0108 (0.0080)
Builders	0.1990*** (0.0217)	0.0306*** (0.0023)	-0.1041 (0.1129)	0.0032 (0.0119)
Period	0.0201*** (0.0027)	0.0032*** (0.0003)	0.0189*** (0.0016)	0.0033*** (0.0002)
Period \times Millennials	-0.0020 (0.0049)	-0.0005 (0.0006)		
Period \times Baby Boomers	0.0021 (0.0037)	0.0003 (0.0004)		
Period \times Builders	-0.0045 (0.0049)	0.0005 (0.0005)		
ln(income)	0.6409*** (0.0042)	0.0273*** (0.0004)	0.6413*** (0.0042)	0.0273*** (0.0004)
Age	✓	✓	✓	✓
Age \times Generation			✓	✓
Household characteristics	✓	✓	✓	✓
Observations	422145	438658	422145	438658
R ²	0.2854	0.0721	0.2860	0.0727

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based while ln(income) is the log of total amount of household income after taxes in the last 12 months.

the estimated coefficients on all interaction terms between generation dummies and period effect are insignificant, but pure generation effect remains almost unchanged. Column (3) and Column (4) show the estimated coefficients on pure generation dummies are substantially disrupted as long as interactions between age and generation effects are included.

To further check the results, I conduct two hypothesis tests of the separability assumption to determine the most suitable model. Specifically, I use F tests to see whether the coefficients on interaction terms are jointly zero :

Test 1. *Null:* $\beta_{gp} = 0$;

Test 2. *Null:* $\beta_{ga} = 0$.

The first test is based on Model 1. If this condition holds, the time control, 5-year lagged GDP growth rate is separable from generation dummies, implying that Model 1 converges to the main specification. The second test is based on Model 2, and it tests whether in Model 2 the interaction terms $\beta_{ga}D_i^g \cdot D_{it}^a$ should be included for age effect to vary across generations. Table B.2 shows the results of the hypothesis tests. There are no discrepancies in the results

Table B.2: *Sensitivity Tests (P-values)*

	Log luxury expenditure	Share of luxury expenditure
Model 1: Test 1. <i>Null:</i> $\beta_{gp} = 0$	0.5419	0.3892
Model 2: Test 2. <i>Null:</i> $\beta_{ga} = 0$	0.0000	0.0000

when using either level or share of luxury expenditure as the dependent variable. For Model 1, the null hypothesis that the coefficients β_{gp} are jointly zero cannot be rejected at conventional significance level, meaning that the separability assumption holds for generation effect and period effect. As for Model 2, the results of Test 2 confirm the existence of heterogeneous age effect across generations.

C Neural Network Details

One of the most popular machine learning methods, neural network, is employed in this paper to study the deep information in the data. The mathematical modeling of such biological process dates back to 1940s, but it hadn't been very impactful until recently because of limited computing power, underdeveloped optimization techniques, and a lack of big data support. Not surprisingly, benefiting from theoretical and empirical breakthroughs in 2000s and 2010s, neural network has now been setting the state of the art in machine learning community (Zhang et al., 2018; Farrell et al., 2021).

C.1 Fully Connected Neural Network

Figure C.1 below represents the *fully connected neural network*. The network starts with input

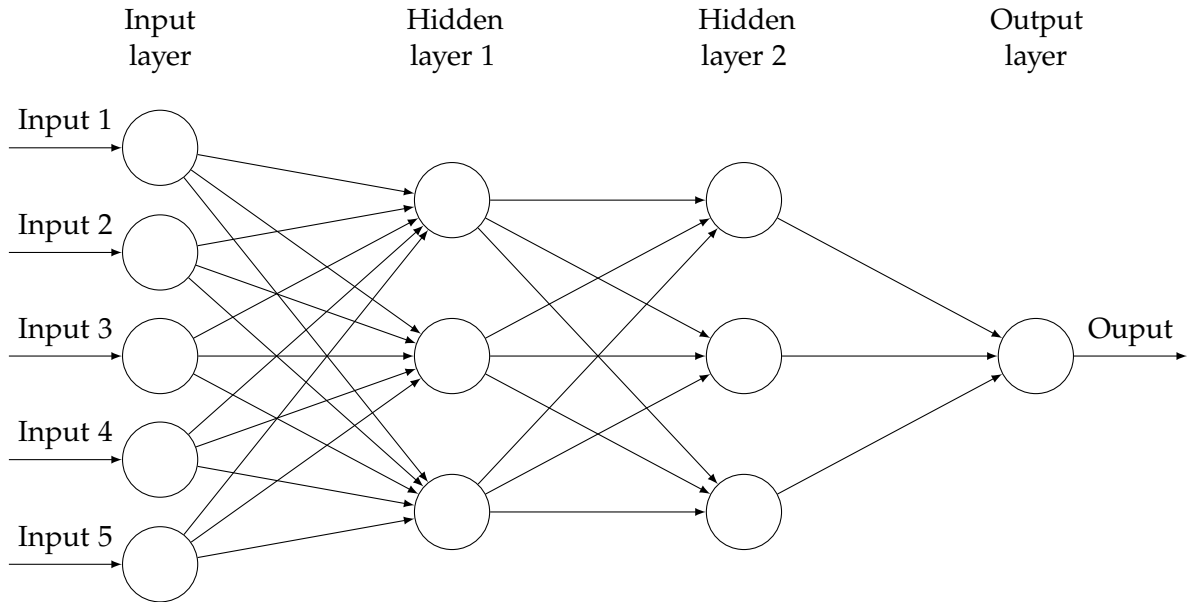


Figure C.1: Illustration of A Full Connected Neural Network

layer, made up of independent variables X , and ends up with output, the dependent variable Y . Input and output layers are connected through hidden layers, each of which consists of hidden nodes, called unobserved variables Z . In a *fully connected neural network*, all nodes in one layer are connected to the nodes in the next layer. Node k of the first hidden layer, $Z_k^{(1)}$ is a linear combination of all inputs X_i as

$$Z_k^{(1)} = \sum_i w_i X_i + b_i,$$

where w_i and b_i are called weight and bias. And then $Z_k^{(1)}$ experiences a nonlinear transformation through an activation function $f(\cdot)$. With only one single hidden layer, the predicted output is

$$\hat{Y} = \sum_k w_k f(Z_k^{(1)}) + b_k.$$

If there are multiple hidden layers, the nonlinearly transformed $f(Z_k^{(1)})$ acts as an input for the next layer and the same process continues until the end.

For any specific structure of neural network, weights w and biases b are estimated by minimizing the loss function, usually the mean squared errors, using stochastic gradient descent, the idea of which was firstly introduced by Robbins and Monro (1951) and Kiefer and Wolfowitz (1952). Different from classic gradient descent which calculates the actual gradient from the whole sample, stochastic gradient descent only uses a randomly drawn subset each time. In this way, each small step is noisy, but the results eventually converge after many times of iterations, with a drastically increased computation speed, especially when the data set is huge. The most common algorithm is *back propagation* (Rumelhart et al., 1986), which computes the gradients of loss function with respect to parameters (weights and biases) backward from the last layer using the chain rule. The super flexible and nonlinear structure of neural network can easily induce overfitting problem, and thus a penal terms is usually added to the loss function. Besides, the activation function and hyperparameters—e.g., learning rate, the number of hidden layers and the number of nodes per hidden layers, also affect the approximation power,

C.2 Model Selection

The rectified linear unit (ReLU),

$$f(x) = \begin{cases} x, & \text{if } x \geq 0; \\ 0, & \text{otherwise,} \end{cases}$$

introduced by Nair and Hinton (2010), is taken as the activation function $f(\cdot)$ for nonlinear transformation in the neural network. ReLU shows more stable performance in convergence than the traditional smooth sigmoid functions such as logistic function or hyperbolic tangent function couldn't reach (Farrell et al., 2021). Concerning regularization for overfitting problems, I use L2 weight decay penalty, by adding a L2 penalty terms to the loss function with shrinkage parameter set to 0.0001 (which is simply the default setting in `scikit-learn`). The batch size, or the number of the randomly draw observations for stochastic gradient descent each time, is set to 200. Given that there are around 400000 observations in the full sample, 2000—equal to $400000 \div 200$ —times of iterations are needed for using up the whole data set, and this is called one epoch. Therefore, I set the maximum number of iterations to 50000 so that at most 25 epochs are required. And I choose adaptive moment estimation (Adam), one of the most famous extension of stochastic gradient descent, as the solver for optimization. Invented by Kingma and Ba (2014), Adam has been excelling in neural network algorithm for its better adaptive learning rate, especially regarding large data set.