Are Millennials Spoiled Kids?
Age and Generation Effects on Luxury Expenditure

Manfei Li*
LMU Munich

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Abstract

Millenials have attracted attention in marketing research because they spend a higher share of their expenses on luxury goods than any preceding generation. However, it remains unclear to which extent this is explained by their young age. In this paper, I study the influence of age and generation effects on luxury expenditure. Using panel data on consumption behavior from the US, I separately identify age and generation effects on luxury expenditure using a variety of different approaches. First, I estimate panel regression models including a full set of age and generation dummies plus a long list of other demographic characteristics. Next, I leverage tools from supervised machine learning, which allow for flexibly non-linear and interactive relationships between the variables. All approaches consistently show that, conditional on age and other demographics, Millenials spend less on luxury goods than the preceding generations, both in absolute terms and as a share of total expenditure. The high luxury expenditure share of Millenials observed in the cross section can be fully attributed to their young age. These results challenge the conventional view of Millenials as a spoiled generation indulging in luxury.

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*Contact information: LMU Munich, Schackstr. 4/IV, 80539 Munich; manfei.li@econ.lmu.de
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1 Introduction

Since the end of the Great Recession in 2009, the American luxury market has grown dramatically (Panteva, 2011; Rubin, 2011). Millennials—those born between 1981 and 1996—are considered as not only the main contributor to this resurgence (Lafayette, 2011; Jay, 2012; Giovannini et al., 2015), but also the target of the luxury market in the future. On one hand, Millennials emerge as a distinct generation with unprecedented population size, extraordinary expenditure power, and a special preference for luxury shopping.[1] On the other hand, it has also been documented extensively that younger consumers typically spend more on luxury compared to older ones.[2] Hence, it remains unclear whether the different consumption pattern of Millennials comes from their younger age, or can be attributed to a generation effect.

In this paper, I address this issue by decomposing age and generation effects on luxury expenditure, to explore whether Millennials behave differently from their predecessors. Specifically, I take the following two steps: First, I estimate age and generation effects based on multiple regression models. Second, I adopt a supervised machine learning approach to pin down the variation in luxury expenditure, that can be explained by age and generation differences. For this purpose, data from the US Consumer Expenditure Survey (CE) 2000 – 2018 is used. I combine generational segments defined by the Pew Research Center and McCrindle (2007), leading to four generations based on their birth year: Builders (1906–1945), Baby Boomers (1946–1964), Generation X (1965–1980), and Millenials or Generation Y (1981–1996).[3]

Luxury is frequently studied in the literature, but it has never been empirically defined from theories. To achieve this, I follow the microeconomic definition of luxury as having a total expenditure elasticity larger than one. I estimate the elasticity of each individual expenditure category in the data, and classify expenditure categories into luxury goods and necessity goods based on the elasticity values. As a result, luxury expenditure is defined as the sum of expenditures over all categories with elasticities larger than one.

To give an overview of luxury expenditure patterns, descriptive age profiles and time trends of the economically defined luxury expenditure are presented. Over the life cycle, the average luxury expenditure is "hump" shaped, peaking at middle adulthood, while the average share of luxury expenditure is declining, especially at young age. Across time, both the level and the share of luxury expenditure had been declining from the first few years of the sample period until 2014 and then started recovering, which can be explained by the persistent influence of the Great Recession. This time trend is similar across all generations.

Although generation-specific age profiles show lower luxury expenditure of younger generations conditional on age, the pure descriptives do not account for the composition of generations in terms of other demographic characteristics such as education level or gender. Therefore, I conduct a regression analysis to detect the variation resulting from age and generation effects,

[1] Fry (2020) reports that Millennials have overtaken their boomer parents and became America's largest generation in 2019. Fromm and Garton (2013) compare purchasing power of Millennials with previous generations. Moreover, Halpert (2012) and Giovannini et al. (2015) illustrate Millennials' unparalleled preferences for shopping, especially luxury items.

[2] For example, Danziger (2015) finds that among all affluents, younger people consistently buy more luxury goods, and Nye (2011) argues that new generations always have the most substantial influence on all markets.

[3] See the website *https://web.archive.org/web/20170216215337/http://www.pewresearch.org/methodology/demographic-research/definitions/* (accessed 9 September 2021) and Dimock (2019) for details on generational segments.

based on full sets of dummies, while controlling for a host of other demographic variables. It is well known that, without parametric restrictions, period, age, and generation effects are colinear and thus not separately identified. The standard practice in the consumption literature assumes that the period effect captures business cycles (Aguiar and Hurst, 2013), so I follow Dohmen et al. (2017) and use GDP growth as a proxy for the period effect.

I find that age and generation effects work in opposite directions: luxury expenditure decreases over the lifetime, yet older generations tend to consume more at the same age, in terms of both expenditure level and share. Millennials actually spend about 8% less on luxury than Generations X conditional on age and other controls, and their share is around 1.5% less than the share of Generation X. Relative to Baby Boomers and Builders, these differences are even larger.

As age and time period might affect different generations non-uniformly, I integrate interaction terms to account for such heterogeneous effects. Following Fitzenberger et al. (2021), I conduct several sensitivity tests to decide which interaction terms should be included in the ideal model. The estimated coefficients show that the main results still remain. Furthermore, the last question about the main specification is if the results are only driven by certain goods categories. The results from specific categories show that there are some deviations from the overall generation and age effects, but Millennials spend less on the majority of individual luxury categories.

Three concerns about the identification are challenging the main findings. First of all, if different generations do not perceive and define luxury in the same way, the employed overall classification will not match the definition of individual generations. Second, it is difficult to compare temporally separated generations due to the lack of overlaps of age ranges in the sample. For example, just comparing Millennials to Baby Boomers based on the main specification is insufficient because the consumption behavior of the latter at younger age were not observed in the survey, and vice versa. Third, age and generation are not treated in symmetric ways. While age is represented by a full set of individual dummies, a generation is a collection of cohorts. Thus, the results can be contaminated by mixing generation and age group effects.

To solve these issues, I show that the results are robust to some alternative model specifications. First, I estimate elasticities using samples of each generation, and derive corresponding luxury definitions. With a generation-specific classification, the main results are still qualitatively stable, though the magnitudes of the effects are smaller.[4] Second, I always use data of two temporally neighboring generations within the common age range, and run multiple regression to complete the comparisons. The direction of the generation effect remains unchanged, as younger generations always consume less luxury. As for the third concern, when grouping individual age dummies or using cohort dummies as proxies for generations, the same luxury expenditure pattern prevails.

So far, every regression analysis is based on a linear model with strict assumptions on functional forms and sample distributions. However, demographic variables are highly interactive and non-linear, which could lead to oversimplified and inaccurate results. In order

[4]It is expected that the effects are weaker because the generation-specific definitions of luxury are not representative of all samples. See Section 6.1 for further details.

to investigate how age and generation affect luxury expenditure in fully flexible models , a machine learning technique based on deep learning is employed. It is able to automatically search for optimal non-linearity and interactions, according to patterns in the data. For this purpose, I use multiple supervised neural networks and explain details on the model training process, where the best models are selected via their validation performance.[5] Using the best models, counterfactual predictions by imposing different age and generation information are carried out.[6] In this way, the predicted results show the variation in luxury expenditure that can be explained by age and generation differences. For both the level and share of luxury expenditure, the results support the patterns uncovered by the linear regression models.

All results are based on the definition of luxury from economic theory which might not necessarily correspond with the definition of luxury from common sense that can be found in related research. Thus, I compare the luxury categories in this paper to luxury classified by Paulin and Riordon (1998) according to their subjective perspectives as an example. The two sets of categories are different, notwithstanding several overlaps. For the overlapping categories the evidences on each category show a similar generation effect as described above, i.e., that Millennials consume less luxury. In addition, luxury is frequently mixed up with conspicuous consumption, so I also discuss literature on conspicuous consumption for comparison. It turns out that conspicuous consumption contains quite different expenditure categories, though some goods indeed belong to both. The resulting effects of household characteristics from the overlapping categories are consistent and complementary to different findings in the literature.

My results challenge the stereotyped impression of Millennials as the (potential) growth engine of luxury industries (see, e.g., Lafayette, 2011; Panteva, 2011; Rubin, 2011; Halpert, 2012; Jay, 2012; Danziger, 2015; Giovannini et al., 2015) because the pure generation effect reveals their sobriety from luxury. The conventional idea of Millennials' purchasing power actually comes from a pure age effect that leads to monotonically decreasing luxury expenditure over the life cycle. Furthermore, 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).

This paper also makes several contributions to the existing literature: Firstly, luxury is a novel topic of economic research on consumer expenditure. Some of the standard literature focuses 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. Moreover, 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 closely related topics is conspicuous consumption studied by, e.g., Charles et al. (2009), Heffetz (2011), Friehe and Mechtel (2014), and Heffetz (2018). However, as shown in Section 8.1, luxury and visibility are essentially not equivalent to each other.

Secondly, I use a theory-based classification to define luxury. The lack of awareness of luxury

[5]Validation performance indicates a models' capability to generalize to new samples from the same distribution. Note that these samples are not used during training to search for the optimal non-linearity.

[6]See Section 7 for details.

in the literature might be due to the difficulties in defining it concretely and quantitatively. Business research often uses questionnaires to examine how consumers perceive luxury as an abstract concept, without specifying the exact categories (see, e.g., Amatulli et al., 2015; Giovannini et al., 2015; Kapferer and Michaut, 2019). Paulin and Riordon (1998) are an exception as they show a list of luxury goods, but their classification is founded on subjective common sense and thus lacks academic objectivity. In this paper, I refer to a microeconomic definition of luxury as being highly elastic, and derive specific luxury categories based on estimated total expenditure elasticities.

Thirdly, this paper introduces the methodology of decomposing age and generation effects to research on luxury. The segmentation of the market by both age and generation has been conceptually pointed out, but it has never been quantitatively analyzed, especially in the context of luxury.[7] So cross-generational studies on this usually depend on one-time market surveys which do not allow for disentangling age and generation effects because of the lack of information on the 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 solely based on age. A 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 according to age: Baby Boomers, Generation X, and Millennials. Although Gurău (2012) conducts a life-stage analysis of Generation X and Millennial consumers, the age effect is not directly or systematically examined.[8] With data collected across multiple years, household expenditure surveys work better in this scenario, but little research using such data could strategically achieve that goal. Norum (2003) only employs data from the 1998 Consumer Expenditure Survey (CE) of the US, thus still categorizing age groups based on generational definitions. Paulin and Riordon (1998) investigate income and expenditure patterns of people from age 18 to 29 using data from the CE program in three periods, 1972–1973, 1984–1985, and 1994–1995, while only focusing on Baby Boomers and Generation X. To estimate age and generation effects simultaneously, I exploit the dynamics of the long-term data from the CE program, which persistently keeps track of consumers of all generations.

Finally, this paper provides an example of using machine learning techniques in empirical economic estimations. While most traditional econometric approaches are based on specific functional forms that require multiple statistical assumptions, machine learning techniques flexibly search for the optimal models that ideally fit data. In my case, this works especially well since demographic variables are highly interactive and non-linear. This advantage has been noticed and is utilized increasingly among economists (see, e.g., Varian, 2014; Mullainathan and Spiess, 2017; Athey, 2018; Athey and Imbens, 2019). However, as machine learning mainly deals with prediction instead of estimation, and consequently, the applications of machine learning techniques have been mostly restricted to the financial market where prediction is the

[7] For example, McCrindle (2007) thinks age alone is inadequate to segment the market because today's teenagers are not comparable to Generation X in the 1980s or to Baby Boomers in the 1960s. In addition, Millennials who are possessed of wealth are not following generations that became affluent before (Danziger, 2015).

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

major issue (see, e.g., Gu et al., 2020; Peng et al., 2021; Nosratabadi et al., 2020). Nevertheless, I trace the desired age and generation effects while still making use of the advantages of a flexible model, that does not require a fixed functional form. Hence, by providing new and powerful tools, machine learning shows a significant potential for future research in economics.

The remainder of this paper is structured as follows: Section 2 introduces the generational segmentation and the data. Section 3 classifies the expenditure categories in the CE program into luxury and necessity, based on estimated total expenditure elasticities. Section 4 presents the sample selection and descriptives. The regression analysis is described in Section 5 for the main specification and Section 6 for the robustness of the regression results. Section 7 confirms the main results using supervised neural networks. Finally, Section 8 discusses the results and intuition and Section 9 concludes.

2 Setting and Data

This section introduces the generational segmentation and the data set used in this paper. The definition and main characteristics of each generation is explained. Afterwards, I briefly introduce the data structure of the US Consumer Expenditure Survey (CE) and how the used samples are selected.

2.1 Generational Segmentation

Although the concept of generation does not have a clear origin, the generation-based demographic segmentation has been widely used in the social science literature since Strauss and Howe (1991) developed the Strauss–Howe generational theory (Chaney et al., 2017). From this perspective, people in the US are divided into different generations based on demographics, political events, and economic environment. These factors are especially important during their coming-of-age years. As a results, each generation develops heterogeneous preferences and behaviors accordingly.

There are no clear, universally defined thresholds of generational segments except for the definition of Baby Boomers.[9] This paper refers to the generational segments developed by the Pew Research Center (a non-partisan fact tank that provides information on the US social and demographic trends), which is summarized in Table 1.[10] The US Census Bureau calls individuals born from 1946 to 1964 “Baby Boomers” because of the drastically rising birth rate during this post-war period (Colby and Ortman, 2014). The predecessors of Baby Boomers, born from 1928 to 1945 during the Great Depression and World War II, are defined as the “Silent Generation”. They are the children of the “Greatest Generation” who played a vital role in dealing with such destructive economic and political events. Following the Baby Boomers, the period of “Generation X” lasted until 1980. Afterwards, the generation of the “Millennials” started, whose oldest members reached young adulthood in the new millennium. The Pew Research Center defines 1996 as the last birth year of Millennials to separate them from the

[9]See, e.g., Norum (2003) for a list of different cutoff points in the literature.

[10]Also see *https://web.archive.org/web/20170216215337/http://www.pewresearch.org/methodology/demographic-research/definitions/* (accessed 9 September 2021) for the segments of the Pew Research Center.

following "Generation Z". Compared to Millennials, Generation Z did not experience key social events such as the 9/11 terrorist attacks and the 2008 election during formative years (Dimock, 2019).

People from the same generation have common value systems, attitudes and behaviors because they share life stages through the same macro environment (Howe and Strauss, 2000; McCrindle, 2007). There is a general consensus that the external events during late adolescence or early adulthood—the coming-of-age period—have the deepest influence on economic and political beliefs. For example, Giuliano and Spilimbergo (2014) empirically prove this psychological theory by showing evidence that an economic recession during these impressionable years significantly shapes preferences for redistribution. To investigate these key political, economic and social factors experienced by each generation when coming of age, the Pew Research Center conducted a survey called "Americans Name the 10 Most Significant Historic Events of Their Lifetimes", and Table A.1 shows that the list varies across generations. In the following, I summarize how generations are shaped by the environment during their formative years.

The Greatest Generation was working during the Great Depression, a harsh economic time, thus being indoctrinated with conservative values of financial security. As the main participants of World War II, they also experienced 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 has been willing to sacrifice personal satisfaction for the sake of a better society. This is 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 a standard, and the Greatest Generation achieved significant accomplishments, such as the Interstate Highway System and Medicare program (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 continuously worked in a new social order and never had the motivation or courage to change it. That is also the origin of the "silent" label (Howe, 2014). Located between the Greatest Generation who had been fighting and sacrificing, and the Baby Boomers who created shock waves afterwards, the Silent Generation stayed in a difficult situation like a sandwich (Howe, 2014), therefore refraining from individual expression (Schewe et al., 2000).

Due to their large population size, Baby Boomers had been dominating all aspects of the American society (Schewe et al., 2000). Opposite to the war years, their period was symbolized by unmatched economic prosperity, ample educational opportunities, and major technological advancements (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 that were characterized by humility and modesty, they started defying established social orders; for this reason, Russell (1993) called them "free agents". At the same time, full employment encouraged and fostered the

Baby Boomers' financial confidence and consequent spending habits (Eastman and Liu, 2012). Therefore, austerity was left behind and "buy now, pay late" became their new consumption philosophy instead (Schewe et al., 2000).

Generation X grew up in a less optimal environment created by the individualism and self-fulfillment of their Baby 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 the Baby Boomers left Generation X unsupervised after school, originating the "latchkey generation" label (Shamma, 2011; Blakemore, 2015). When Generation X was coming of age, the economic recession in the 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 negatively shaped Generation X as aimless, bleak, and cynical (Paulin and Riordon, 1998), portrayed later by Richard Link in the 1990 American comedy-drama film *Slackers*.

By the end of the economic recession and political instabilities experienced by Generation X, Millennials appeared on the scene. Living through the era of digital revolution, globalization, and environmentalism (Schewe et al., 2000; McCrindle, 2007), Millennials are always considered as distinct from previous generations in every aspect, which is discussed in more details in the following.

2.2 Millennials

Millennials have been attracting attention due to their distinguishability and uniqueness. Two most distinct features are a higher relative education level (Frey, 2018) and familiarity with new technology (Valentine and Powers, 2013). Demographically, the Pew Research Center estimated that in 2019, Millennials (with a population of 72.1 million) had passed the Baby Boomers (with a population of 71.6 million) and become the largest living adult generation in the US, thanks to the dynamics of mortality and immigration (Fry, 2020). As a generation with a higher racial and ethnical diversity, Millennials might serve as a demographic "bridge" in America's 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 governmental safety regulations (Tucker, 2006). As a "spoiled" generation, Millennials are too impatient to delay gratification, indicating their possible active participation in the luxury market. However, such a modern environment could shape Millennials in an opposite manner. Exposed to explosive amounts of information and massive technological innovation, Millennials actually developed sophistication and suspicion (Valentine and Powers, 2013). For example, Martin and Turley (2004) find that Millennials were objective, rational, and goal-oriented during a mall excursion, and they emphasize functional values instead of being motivated by hedonism or marketing tricks.

At the same time, the new era of the Millennials is also full of unpredictability. First of all, the expected gains from greater educational achievements have been counteracted by the accompanying decreasing returns due to an overproduction of advanced degrees (Emmons et al., 2019). Since 2000, the college wage premium first started flattening and then disappearing (see, e.g., Beaudry et al., 2014; Valletta, 2018; Ashworth and Ransom, 2019). Secondly Millennials were impact most negatively from the Great Recession. They were benefiting the least from the recovery (Smith, 2012), and are facing a worse situation in the labor market compared to 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 problems: notwithstanding the temporary wealth decline of all age groups, Millennials have become poorer with respect to older generations. Furthermore, the large number 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, Millennials have been evolving differently from their predecessors, reflected in a unique way of thinking and consuming. Millennials might strongly stimulate the American economy (Noble et al., 2009) when reaching their peak earning and spending years, especially given their large number. It is therefore important to understand how their spending pattern differs from previous generations, both from a marketing and a broader economic perspective.

2.3 Data

I use data from the US Consumer Expenditure Survey (CE). Carried out by the US Bureau of Labor Statistics (BLS), CE is a program to collect data of household expenditures on goods and services in the US, where basic information on economic and demographic characteristics is also included. 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. In this paper, I only use the Quarterly Interview Survey due to its higher data quality.[11]

The Quarterly Interview Survey is a short rotating panel survey in which approximately 6000 interviews are conducted each calendar quarter.[12] Each household is interviewed every three months over four consecutive quarters, and is supposed to recall expenditures during the past three months.[13] After the fourth interview, households are dropped from the sample and replaced by new ones which consist of 25% of total sample. Although each household can provide data for a maximum of one year, I treat records of each interview independently. I don't report the sum of expenditures across all interviews that one household has participated because of the following reasons : less than 50% 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.

Among many files report expenditure information in different levels of details since the end of 1979, and I use data of the FMLI files from 2000 to 2018. The FMLI files the Quarterly Interview Survey provide summary level expenditures and other household characteristics.

[11]See Bee et al. (2012) for the detailed discussion about this issue.

[12]Here "quarter" means the time period when the interviews, not the purchases occur.

[13]Before 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).

Since 2000, the questionnaire design and expenditure categorization have been consistent, so that the consumption bundle stays the same during this period. And in this way, Millennials are also included in samples of all years. I aggregate specific expenditure categories in the FMLI files into 32 categories, and Table A.2 reports the details.[14] Besides expenditure, I also take data on total amount of household income after taxes in the last 12 months and household characteristics from the FMLI files.[15] All expenditure and income data are deflated to 2007 dollars using Consumer Price Index (CPI). Household characteristics include demographic information of household head (e.g., age, gender, race, marital status and education), household structure (e.g., size and the number of adults), urban residence, information on metropolitan statistical area, region, and interview quarter of the each record. The pooled 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. The microeconomic definition of luxury says that luxury expenditure increases more than one percent with one percent increases in total expenditure. Based on this definition, 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.

Following the approach of Heffetz (2004, 2011, 2018), I conduct non-parametric 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 elasticites 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.

The estimation is executed using data of different time periods, 2000–2009, 2010–2018 and 2000–2018, for a stable and reliable measure of luxury. Because the perception of luxury depends on subject thinking that cannot change too frequently, I consider total expenditure

[14] 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.

[15] Complete 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.

elasticities as relatively stable across time. However, averages across the whole 19-year sample period might cover some important deviates (e.g., some categories might have the elasticities fluctuating around one when estimated during different periods) and hence make the finial classification imprecise. Therefore, I also estimate elasticities during 2000s and 2010s separately, besides the whole sample period, and only define the categories with elasticities substantially and consistently larger than one in any periods as luxury.

The estimation results are shown in Figure 2, where value one is marked by the vertical line as the threshold elasticity. And the definition above leads to 15 categories of luxury goods: household operations; house furnishings and equipment; clothing for adults; vehicle purchases; other vehicle expenditures;[16] 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.[17] 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 might arise 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 5.5, especially those that are agreeably considered as "classic" luxury. As discussed in Section 8.1, results from such categories are consistent with the main findings.

4 Descriptives

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

Several steps are taken to refine the pooled sample for the following analysis. First, 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 only keep households whose heads are aged 21–80 for the facts that relatively very few old households were surveyed, and people younger than 21 do not

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

[17] Miscellaneous 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.

legally have access to some expenditure categories in the US such as alcoholic beverages and tobacco and smoking supplies.[18] On top of that, I drop the ones with negative expenditure in any category and negative income (before and after taxes) from the sample due to the possible measurement errors. For the data before 2004, I drop incomplete income reporters.[19] 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.

Generation is created as a categorical variable based on the birth year of household heads. 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.

Table 2 lists summary statistics for the refined sample, where both the log and share of luxury expenditure are the main dependent variables for analysis. On average, households spend $2591.561 per quarter (in 2007 dollars) on luxury, accounting for around 18.3% of total expenditure. Probably because Millennials are just at the beginning of career path and receive relatively low income, they exhibit the lowest expenditures on 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 fact that Baby Boomers and Generation X are overrepresented in the survey as the oldest Millennials are just 37 in 2018.[20] Slightly more than half of household heads are women, and households with married heads make up 54.5%. High school graduate is the largest group of education level, accounting for 46.1%, and 81.5% the household heads are Whites. The spatial distribution of households is uneven as most of them locate in urban and metropolitan 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

[18]There 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. And regarding the lower bound of age, actually this condition could also rule out most of members of Generation Z.

[19]See Footnote 15 for detailed information on this.

[20]See Figure 1 for the size of each generation in the sample.

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.[21] Alternatively, "OECD-modified scale" and "square root scale" are employed in robustness checks,[22] 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 the share of luxury expenditure over life cycle. After falling drastically from slightly below 22% at age 21 to around 18% 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 Millennails 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 hidden, I further provide information on the evolution of average luxury expenditure over life cycle for each generation in Figure 4. 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 can 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 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 the data might contain noise for 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 are driven by differences in the demographic composition of generations, such as differences in education levels, household size, or location. To isolate the generation effect from such compositional

[21] See *http://www.oecd.org/economy/growth/OECD-Note-EquivalenceScales.pdf* (accessed 9 September 2021) for details.

[22] "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.

effects, I will turn to regression analysis in Section 5.

4.3 Time Trends

Following age profiles, I move on to examine 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 Great Recession.

Subsequently, I switch to analyzing generation-specific time trends, which are 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 Millennilas 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 synchronized 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 additional identifications present heterogeneous effects.

5 Regression Analysis

In the following, I present econometric models that identify age and generation effects from the descriptive figures and quantitatively measures them. After discussing multiple identifications, I analyze the individual categories to show how the overall results are driven by specific luxury goods.

5.1 Identification Strategy

The main specification is constructed as

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

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. I take full vectors of age dummies $\boldsymbol{D_{it}^a}$ for ages from 21 to 80, with age 40 as the base group; likewise, $\boldsymbol{D_i^g}$ 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. With full sets of both age and generation dummies, time control will induce collinearity problem because age is the difference between calendar time and birth year which determines generation. To avoid this, 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.[23] On top of that, seeing the enduring influences of GDP growth rate on luxury expenditure, like the long-lasting consequences of the Great Recession shown in Figure 5, the lag of the GDP growth rate is also taken into consideration. To find the best proxy variable, I scrutinize multiple choices of length as lag periods, from one to six years of lags, in Table A.3.[24] It turns out that 5-year lagged GDP growth rate works best as the proxy. To further corroborate this approach, Figure A.1 plots both 5-year lagged GDP growth rate and average luxury expenditure across time, showing 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.

$\ln(\text{income})$ is the log of total amount of household income after taxes in the last 12 months and $\boldsymbol{X_{it}}$ 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).

The main specification is built on the separability assumption which states that there are no interactions among control variables. The descriptive time trends empirically support that the period effect is separable from the generation effect. So the absence of interaction terms between age and generation dummies in (1) is assumed here to explore each individual effect, better. But more general specifications are presented later.

5.2 Main Results

Estimation results are presented in Table 3. 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 accounting for age. Next, I include age dummies, generation dummies, 5-year lagged GDP growth rate as a proxy for 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 $\boldsymbol{X_{it}}$.

For both log and share of luxury expenditure as dependent variables, Column (1) and Column (5) display the results of the naïve model. 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 the 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

[23] The standard approach in consumption literature is to assume that time effect captures the cyclical fluctuations, developed by Deaton (1997) (Aguiar and Hurst, 2013). See Section 6.2 in robustness checks for more details on Deaton (1997), which delivers similar results.

[24] Data 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).

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).[25] In all specifications with age controls, generation effect appears to be solid and significant. And the magnitudes of these estimators is 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 the least amount of luxury in terms of both level and share. Quantitatively, Column (2) reads that when controlling for age, income and time period, Millennials spend 7.35% less than Generation X spend on luxury, and this number increases to 8.72% 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 generational 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% and 1.56% less than that of Generation X. Given that the average share of luxury expenditure of Generation X in the sample is only 18.6% 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 people who completed high school are 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 require a certain amount of knowledge.

Figure 7 portrays age effect on luxury expenditure based on the preferred model in Column (3) and Column (7). The solid lines plot the coefficients on estimated age dummies with shade demarcating 95% 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 they are still young in the sample, and this has nothing to do with the effect of their special generation identity.

[25]in the preferred specification, region (Northeast/Midwest/South/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, 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.

5.3 Counterfactual Predictions

To give a visual representation of age and generation effects I construct counterfactual age profiles of luxury expenditure for all generations based on regression results. The estimators from the preferred model 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.[26] Specifically, for 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).

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 Millennials at 20s 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 analysis fills this gap by predicting that Millennials will follow their own age profiles down to their 70s and 80s, which shows lower luxury expenditure over the the whole life cycle. 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 does not 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. (2021), I develop the more general

[26] When 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.

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, I have to adjust the main specification to allow for non-uniform trends due to such entanglement. This conduces to an ideal regression model

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

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

Figure 9 shows the generation specific age effect on luxury expenditure by representing the estimated coefficients $\hat{\boldsymbol{\beta}}_{\boldsymbol{ga}}$. 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 non-monotone parts, e.g., the seemingly increasing trend of old Milennials, 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.

5.5 Evidences on Specific Categories

In this section I analyze the individual categories of luxury goods to see the heterogeneous patterns behind the main results. Among the 13 different expenditure categories of luxury goods according to the classification in Section 3, I combine several closely related categories together into aggregated ones, leading to 9 categories, and Table A.4 reports summary statistics.[27]

I run the same regression based on the preferred model for each of the 9 individual categories, and present the results in Table 4. 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% more than Generation X. Two outliers are Column (1) and Column (7) where household

[27]The new category "vehicles" includes vehicle purchases and other vehicle expenditures. Moreover, fees and admissions, pets, toys and playground equipment, recreational vehicles and miscellaneous entertainment outlays are combined into one single category called entertainment.

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, presented in Figure A.3, are also non-uniform among categories. 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.

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 style, 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 all individual generations alike. Therefore, I estimate elasticities using data of each generation following the same procedures in Section 3. An empirical problem is that 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. To solve this, 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. As generation-specific ways of defining luxury might be varying non-uniformly across time, overall average works the best in more equally treating generations.[28] And the results using sub-samples are also less stable due to larger standard errors.

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

[28] As 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 extend average out the instabilities across time.

specification is based, are shown by the boldfaced category names. The classification indeed differs across generation, but most of the luxury categories defined by the overall sample are also consistent throughout 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 using the sample of Millennials is substantially negative, which could be either distorted results from lots of zero expenditure on it, or the fact that Millenails are not interested in shopping it. By contrast, Builders and Baby Boomers view much more 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 and Table 5 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. And this finding also confirms that even with some extent of misclassification due to measurement error, the main results are still qualitatively robust.

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.[29] Therefore, I run the same regressions for only two neighboring generations every time, and just focus on households within their common overlapping age range.

Table 6 shows generation effect. Three groups are analyzed separately based on age range of each generation in the sample. Specifically, I compare Millenianls 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. 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% less luxury expenditure than Generation X, and the difference in the share is about 1.5%. 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 coincidental because 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

[29] Builders 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 along Milennials who come even later.

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 these parts are too insignificant to affect the results. 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, the 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, even with a generation, so relative size 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 change the results, I use 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.[30]

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 depend 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.[31] Luckily, Charles et al. (2009) also provide a solution: controlling for total expenditure and using income as an instrument variable (IV). 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.7 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.7 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.

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

[31] According 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.

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 check if the results could stay robust to other choices of household scales. I replace "OECD equivalence scale" used in the main specification with "OECD-modified scale" and "squared root" scale respectively.[32] And generation effect in Table A.8 is basically replicating those of the main results.

More disaggregated generational segments. Thirdly I rely on 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.[33] Now I keep the oldest two generations separately as how they are originally defined in Table 1. Besides, I follow Kapferer 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.9 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 additional to the direction of generation effect, the estimators 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.[34] Column (2) and Column (4) of Table A.9 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, the linear model might be too restrictive because the demographic variables are usually highly non-linear and interactive. So in this section I use a machine learning method—supervised neural network—to investigate the effects of age and generation

[32]See Section 4.1 and Footnote 22 for details.

[33]See Section 4.1 for details of the generation setting in the main specification.

[34]The coefficients on the first two year dummies can be recovered from the two restrictions.

in more flexible model setting.

7.1 Machine Learning in This Setting

When interaction terms are added in model (2), the regression results in Figure 9 reveal 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. Because demographic characteristics are intensively intertwined with each other, such variable relationships could be very complicated. As the desired solution here, machine learning is able to break free from those constraints imposed in linear model by automatically searching for non-linearity 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 are no separate coefficients that exactly measure such marginal effects, like $\hat{\beta}$. On the other hand, even if they are estimable, machine learning couldn't guarantee some necessary properties—e.g., unbiasedness and consistency—simply because it is created for prediction.

Here I provide a solution that 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 exactly visual representations of individual variables' effects based on the best model. 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, the same idea as what is shown by the generation specific age effect 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% as training set and 30% as testing set. I check different combinations of the number of layers and nodes to train the model (or to basically estimate weights $\boldsymbol{w}$ and biases $\boldsymbol{b}$ 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 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.

I implement the following steps to search for the best neural network structure. To make the results from neural network comparable to the those of the linear model, 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

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

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.[35] 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.[36]

Figure 12 shows performances of all trained models in the testing set during the searching process, by ploting the goodness of fit (R^2) of these predictions from different models. 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, the 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 to uncover how different generations differ from each other in spending money on luxury,

[35] Several 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.

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

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 noted 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 key part is to derive age and generation effects through prediction. Here the idea is the same as that of counterfactual predictions using results from OLS regression in Figure 8. The results of generation g at age a is conducted as follows: I take the whole data set and treat all households as generation g aged a 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 g at a. 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 predictions, variations only due to age and generation differences are sucked out.

Figure 13 plots the final results predicted using model with one hidden layer. Even with flexibly non-linear and interactive functional forms, similar findings still exist. There is a clear declining trend of luxury expenditure over life cycle for all generations, with later born 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

Categories of luxury goods defined by elasticity might not be congruous with what people think as luxury, so in this section I make use of the evidences on specific categories to compare luxury categories in this paper to these "classic" luxury, and relate to the studies of conspicuous consumption in the literature. At last, I discuss the intuition behind the findings.

8.1 Relating to "Classic" Luxury and Conspicuous Consumption

To start with, I examine how luxury goods defined by elasticity are different from the "classic" luxury goods that are 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 do exist 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.

Following that, I investigate the effects on those economically defined luxury categories that also belong to "classic" luxury. To be specific, I check generation effect from the specific categories in Table 4. 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. So the findings based on the luxury categories classified in Section 3 are representative enough to apply to what people think as luxury according to general common sense. And this provides cogent evidence against the argument that Millenials are a growth engine of luxury products.

Another related concept is conspicuous consumption, firstly introduced by Veblen (1899). The 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.

Likewise, results from these specific 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.5 confirms this finding. Regarding the effect of education as already discussed in the main results in Table 3, Table A.5 and Table A.6 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.

8.2 What Do We learn?

Several theories from both economic and sociological perspectives might explain these findings. Firstly, introduced in Section 2.2, Millennials have being facing lots of obstacles in current economic environment. Compare to preceding generations, 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, members of Generation X consume less luxury goods and more necessities. Opposite to Baby boomers who stress self-achievement and personal success, members of Generation X are more disillusioned and skeptical due to both economic and societal uncertainty that they grew up with (Eastman and Liu, 2012).

9 Conclusion

Having grown up in a time of prosperity and materialism, Millenials are stereotyped as a protected and indulged generation with an unprecedented appetite for luxury. The cross-sectional observation of a high expenditure share on luxuries alone, however, does not necessarily support this view as it confounds age with generation effects. This paper separately identifies age and generation effects on luxury expenditure from a panel of consumption expenditures in the US.

After classifying expenditure categories in the Consumer Expenditure Survey of the US into luxury and necessity based on economic definition of luxury as having total expenditure elasticity higher than one, I show descriptive average expenditure on luxury over the life cycle and across time. Following that, I extend the 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 a state-of-the-art machine learning technique – neural network – to derive the most suitable models with full flexibility. Finally, I compare the results with related topics—"classic" luxury that is subjectively classified in the literature, and conspicuous consumption—and discuss the intuition in a more general sense.

The linear 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% less on luxury than Generation X, 17% less than Baby Boomers, and 26% less than Builders. 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 the life cycle. Therefore, instead of acting as an indulged generation, Millennials are conveying attitudes of abstinence, consciousness and rationality, and their remarkable expenditure on 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, comprehending more unbiased information from surface evidences is essential for better strategies in the future, so more efforts are needed to conduct deeper market research on long-run demographics.

As for future research direction, it is interesting to test the results using data from other countries to see if this is an international phenomenon.

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Figures and Tables

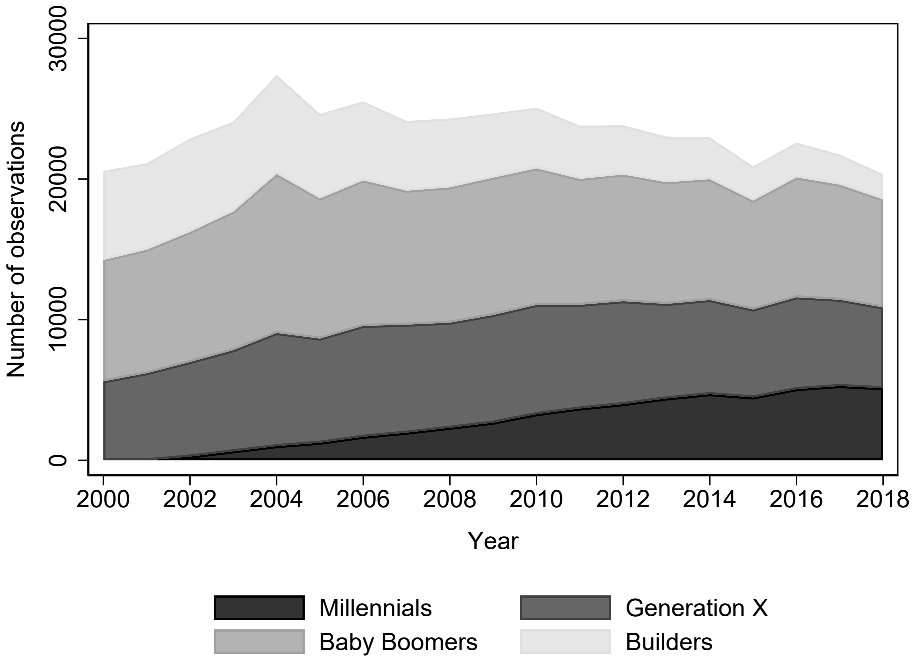


Figure 1: *The Size of Each Generation 2000–2018*

Notes: The figure reports the size of each generation across time in the refined sample (including 443497 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: Millennnails (21–37); Generation X (21–53); Baby Boomers (36–72); Builders (55–80).

Sources: Consumer Expenditure Survey (CE) 2000–2018

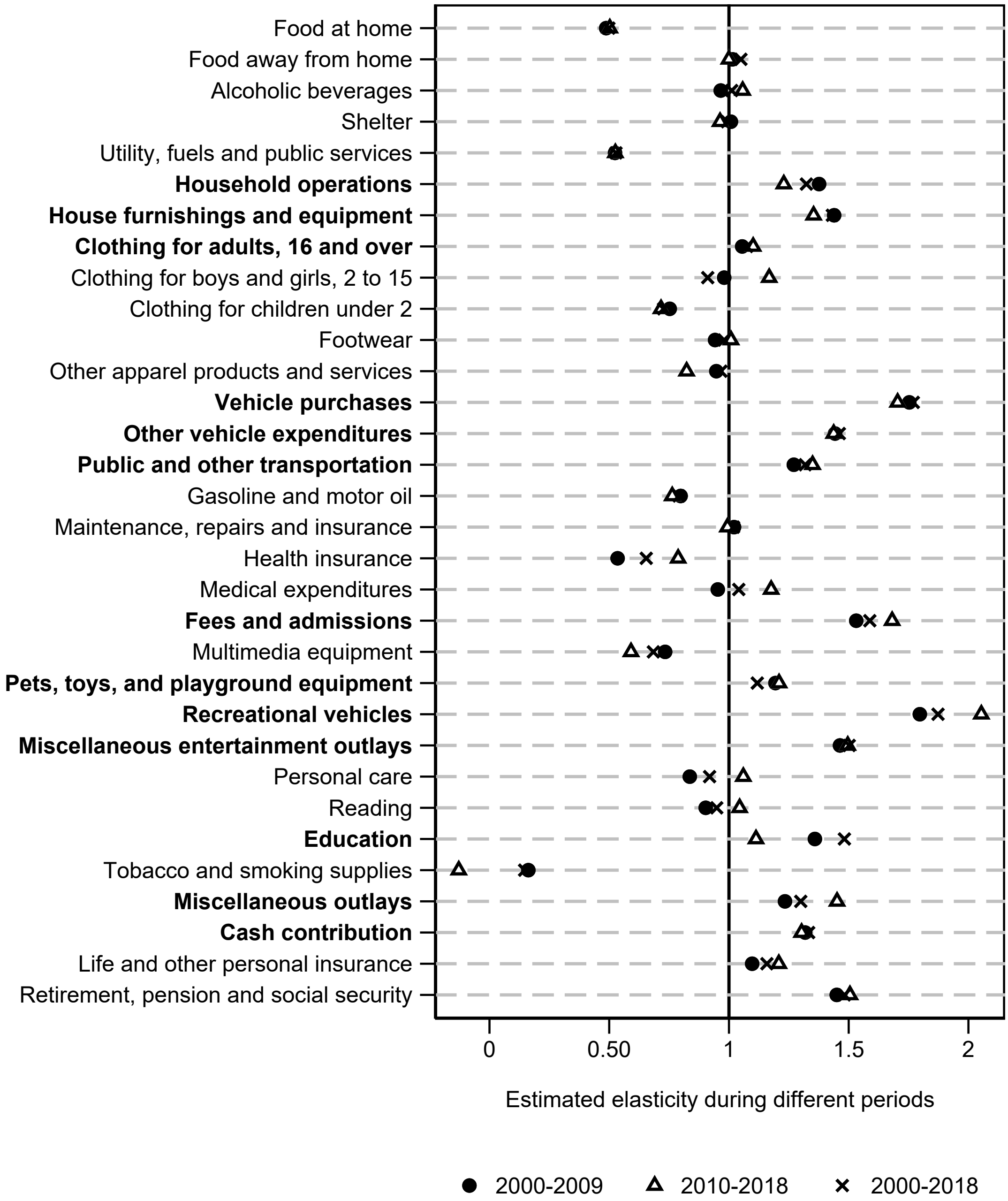
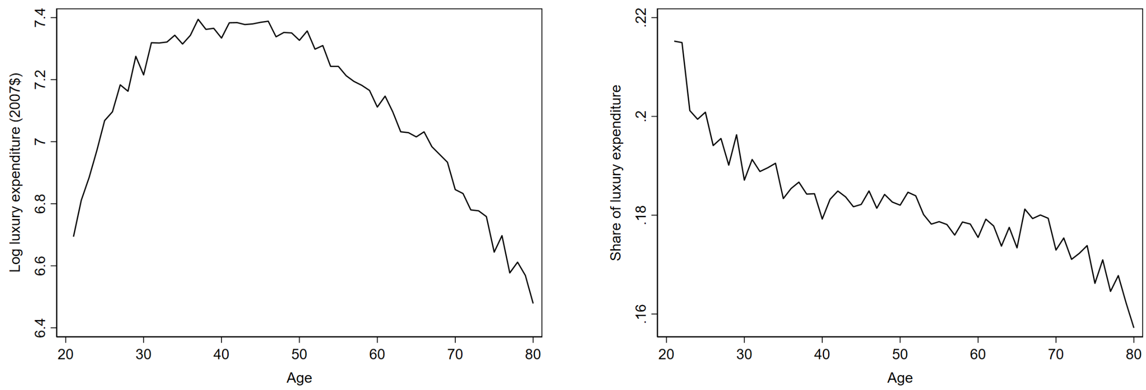


Figure 2: *Total Expenditure Elasticity*

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.

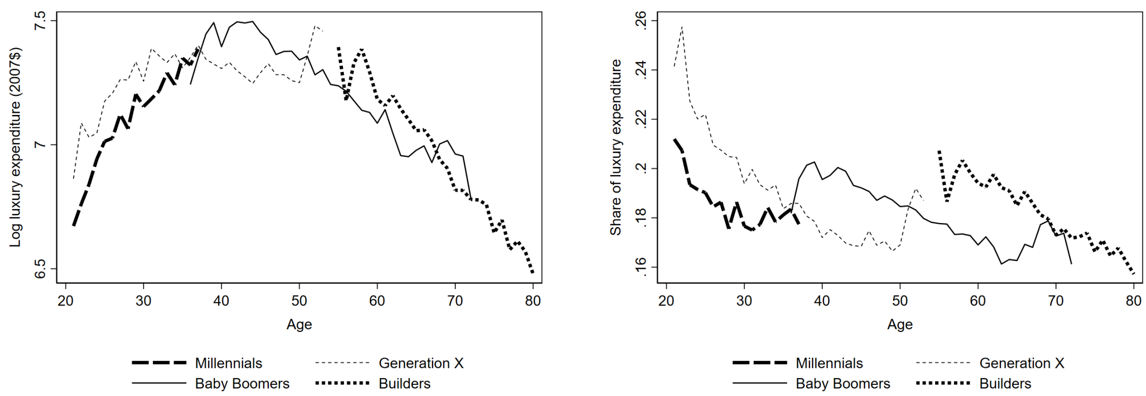


(a) Log Level **(b)** Share

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

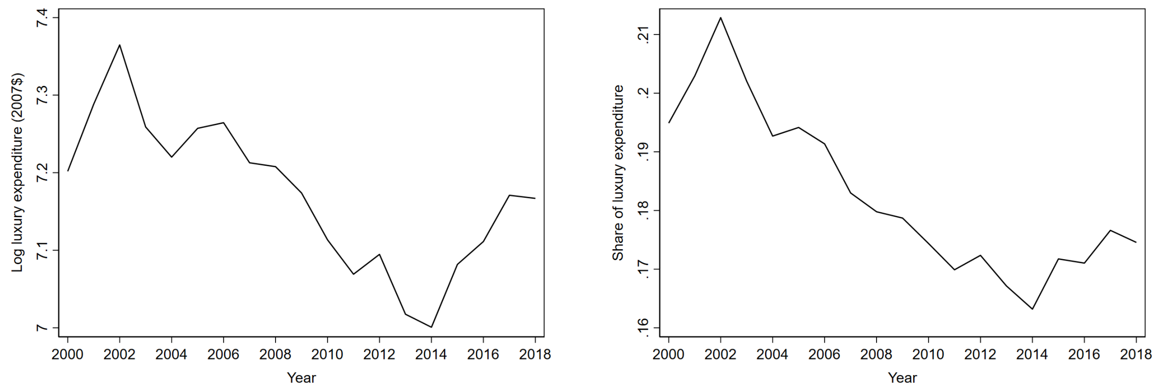


(a) Log Level **(b)** Share

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



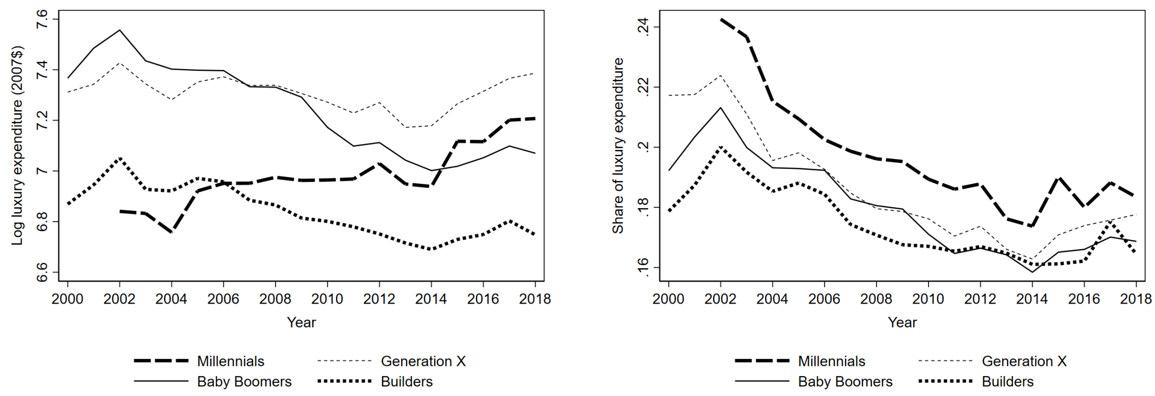
(a) Log Level

(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



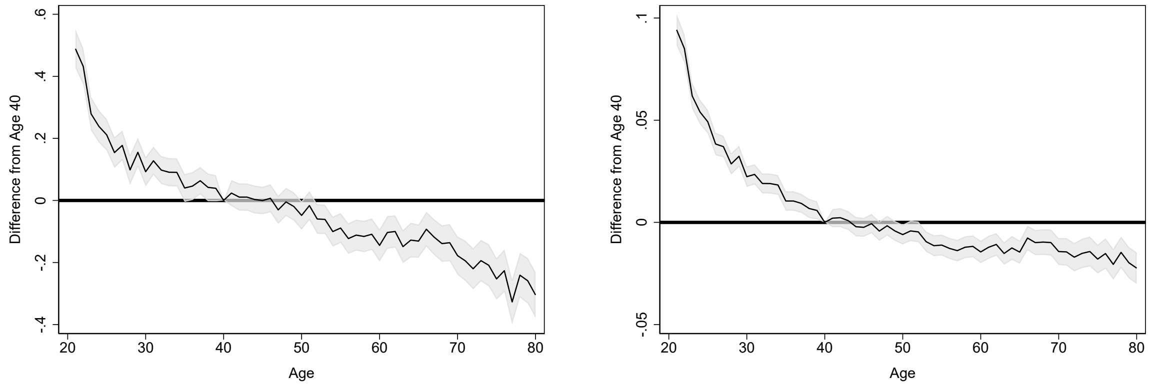
(a) Log Level

(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.

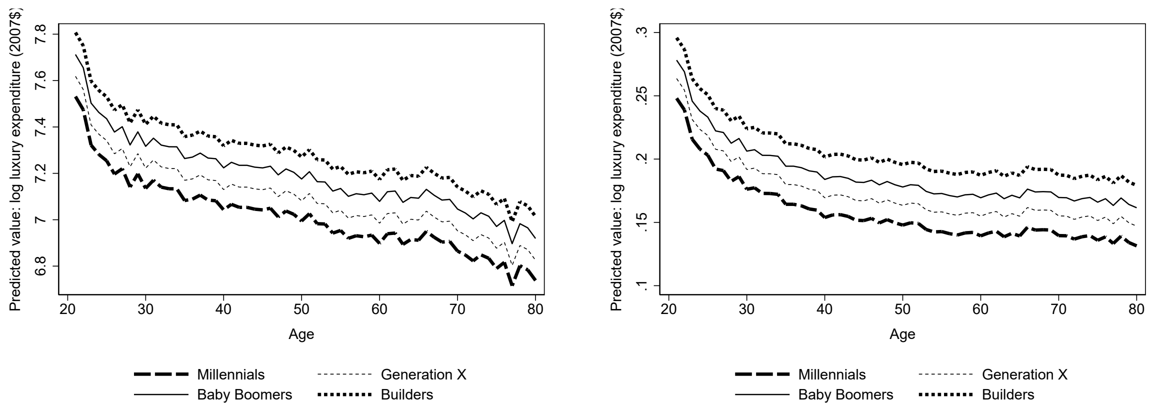
Sources: Own calculations based on Consumer Expenditure Survey (CE) 2000–2018



(a) Log Level **(b)** Share

Figure 7: *Main Results: Age Effect on Luxury Expenditure*

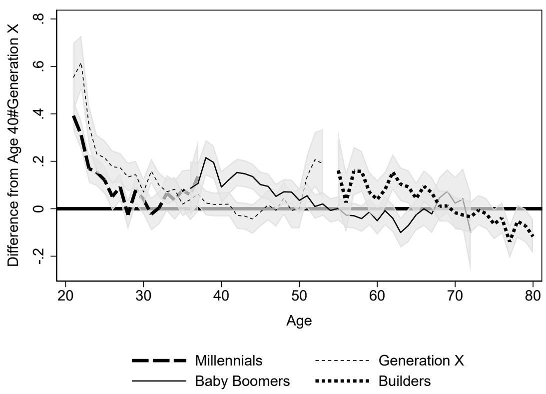
Notes: Both figures show the estimated coefficients on age dummies from Column (3) and Column (7) in Table 3, including 95% confidence intervals, with Figure 7(a) showing the effect on log level of luxury expenditure and Figure 7(b) showing the effect on share of luxury expenditure. Coefficients are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



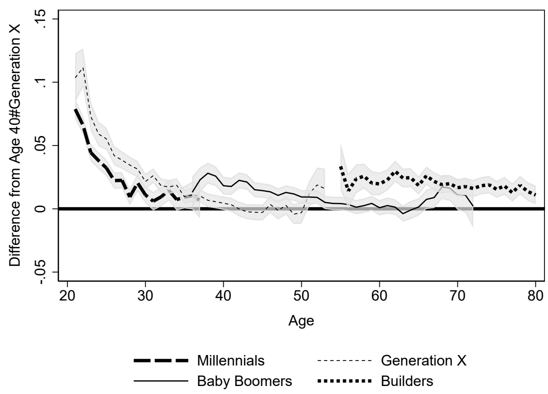
(a) Log Level **(b)** Share

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.



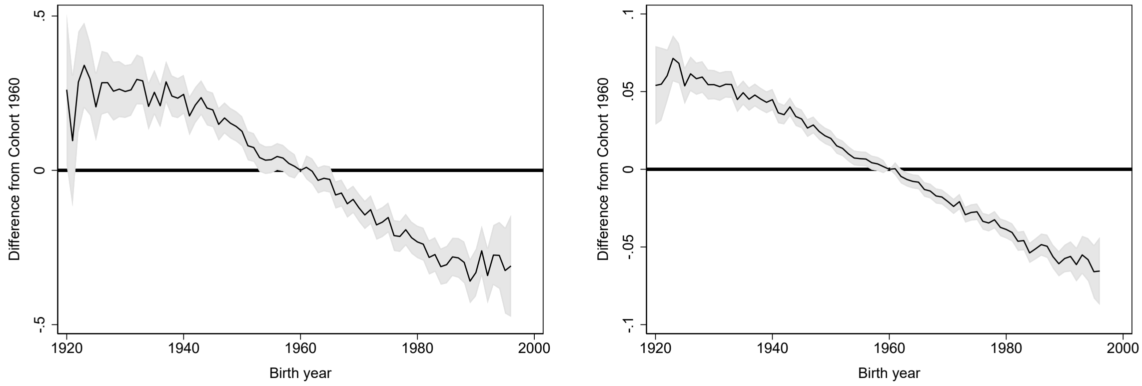
(a) Log Level



(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.

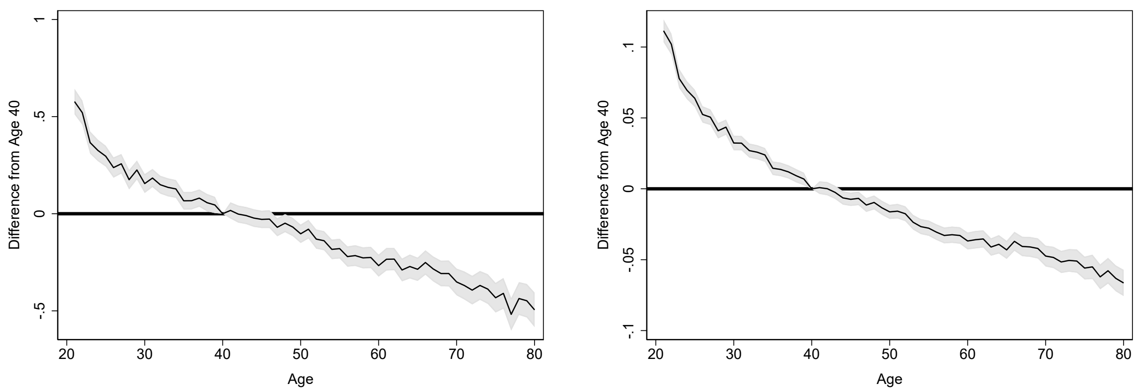


(a) Log Level

(b) Share

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.

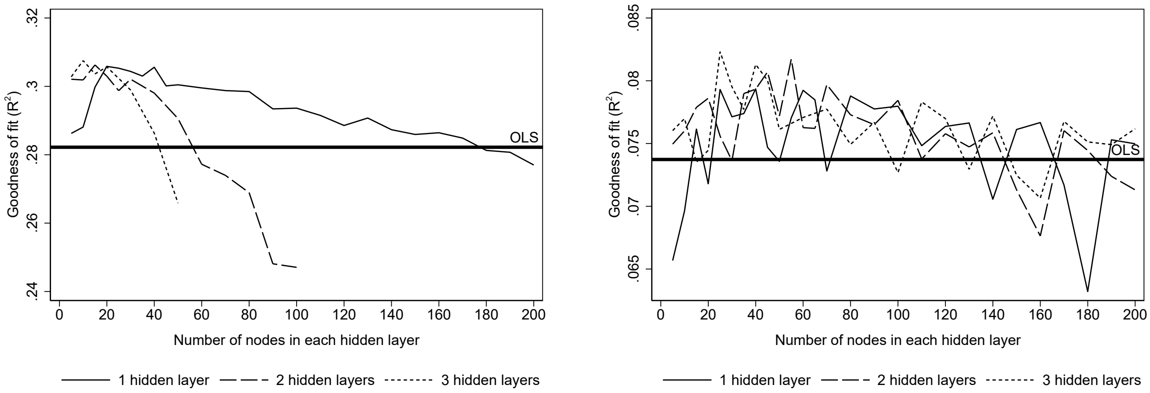


(a) Log Level

(b) Share

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

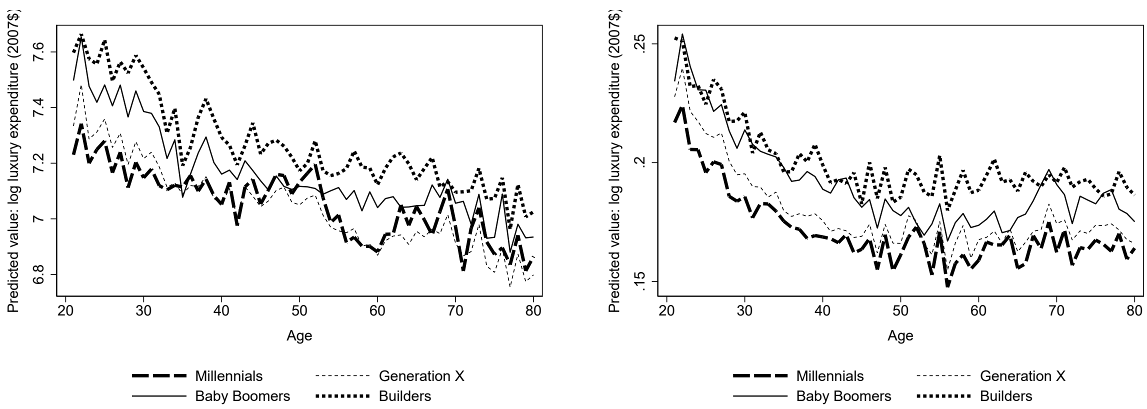
Notes: Both figures show the estimated coefficients on age dummies, including 95% confidence intervals, with Figure 11(a) showing the effect on log level of luxury expenditure and Figure 11(b) showing the effect on share of luxury expenditure. Coefficients are relative to reference age 40, which is marked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



(a) Log Level **(b)** Share

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

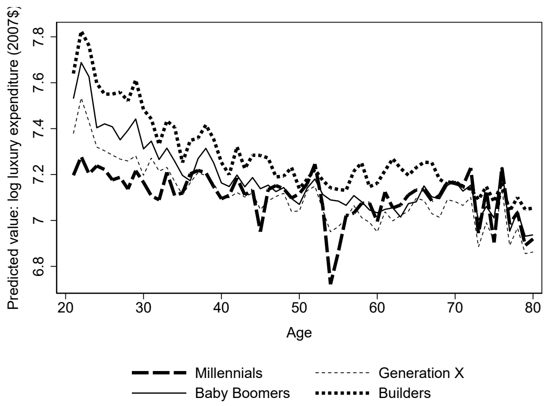
Notes: Both figures plot the goodness of fit of predictions (R^2) in the testing set, with Figure 12(a) showing the results in log level of luxury expenditure and Figure 12(b) showing the results in the share of luxury expenditure. Models of different structures—different numbers of layers and nodes—are 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.



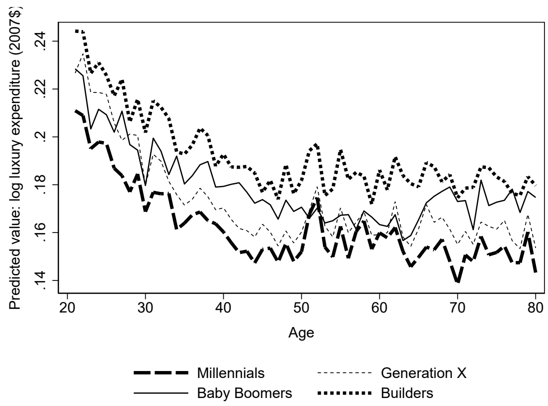
(a) Log Level **(b)** Share

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.



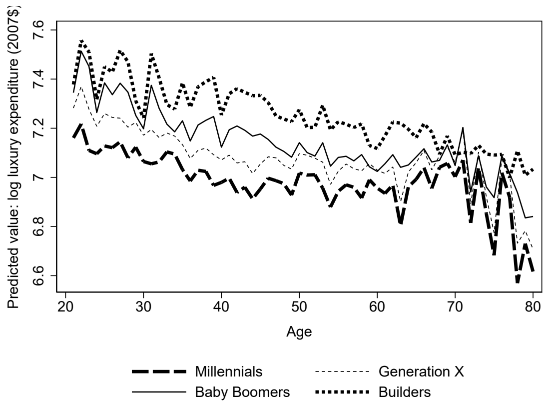
(a) Log Level



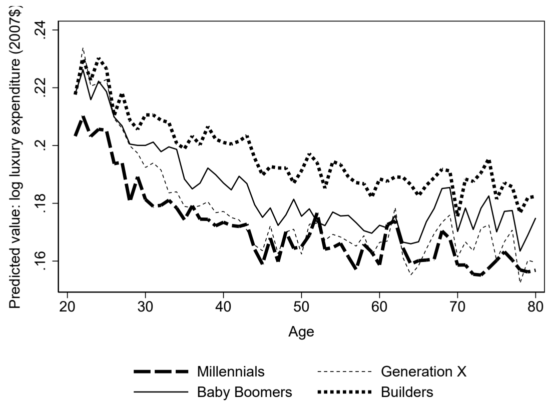
(b) Share

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.



(a) Log Level



(b) Share

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***	-0.0735***	-0.0872***	-0.0823***	0.0180***	-0.0139***	-0.0156***	-0.0148***
	(0.0087)	(0.0110)	(0.0109)	(0.0114)	(0.0010)	(0.0013)	(0.0012)	(0.0013)
Baby Boomers	-0.0533***	0.0780***	0.0939***	0.0955***	-0.0054***	0.0136***	0.0145***	0.0150***
	(0.0062)	(0.0099)	(0.0098)	(0.0102)	(0.0007)	(0.0011)	(0.0011)	(0.0011)
Builders	-0.1019***	0.1350***	0.1887***	0.2044***	0.0044***	0.0286***	0.0322***	0.0353***
	(0.0083)	(0.0167)	(0.0164)	(0.0173)	(0.0009)	(0.0018)	(0.0018)	(0.0019)
Period	0.0292***	0.0177***	0.0198***	0.0181***	0.0050***	0.0033***	0.0033***	0.0032***
	(0.0015)	(0.0016)	(0.0016)	(0.0017)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ln(income)	0.8016***	0.8066***	0.6409***	0.6453***	0.0331***	0.0352***	0.0273***	0.0280***
	(0.0035)	(0.0037)	(0.0042)	(0.0045)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Household scale (equivalence)			0.0568***	0.0513***			-0.0031***	-0.0038***
			(0.0058)	(0.0062)			(0.0006)	(0.0006)
Number of adults			-0.0177***	-0.0098*			-0.0025***	-0.0015**
			(0.0055)	(0.0058)			(0.0006)	(0.0006)
Male			-0.0182***	-0.0262***			-0.0014**	-0.0025***
			(0.0054)	(0.0057)			(0.0006)	(0.0006)
Married			0.2594***	0.2488***			0.0149***	0.0134***
			(0.0067)	(0.0071)			(0.0007)	(0.0007)
Below 9th grade			-0.4844***	-0.4914***			-0.0318***	-0.0316***
			(0.0148)	(0.0162)			(0.0014)	(0.0015)
High school, diploma			-0.3767***	-0.3738***			-0.0281***	-0.0274***
			(0.0114)	(0.0122)			(0.0010)	(0.0011)
College graduate			0.2415***	0.2363***			0.0162***	0.0157***
			(0.0062)	(0.0065)			(0.0007)	(0.0007)
Masters degree and above			0.4004***	0.3948***			0.0286***	0.0283***
			(0.0085)	(0.0089)			(0.0010)	(0.0010)
Black			-0.1588***	-0.1418***			-0.0118***	-0.0088***
			(0.0090)	(0.0094)			(0.0009)	(0.0009)
Native American			-0.0980***	-0.1250***			0.0013	-0.0053
			(0.0360)	(0.0395)			(0.0036)	(0.0039)
Asian or Pacific Islander			-0.2095***	-0.1683***			-0.0145***	-0.0086***
			(0.0128)	(0.0134)			(0.0014)	(0.0015)
Other races			0.0280	0.0386			0.0035	0.0060**
			(0.0232)	(0.0243)			(0.0026)	(0.0027)
Urban			-0.0256*	0.0400			-0.0031*	-0.0005
			(0.0145)	(0.0443)			(0.0016)	(0.0048)
Metropolitan statistical area			0.0517***	0.0233			-0.0104***	-0.0099***
			(0.0114)	(0.0353)			(0.0012)	(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: *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***	-0.0319**	-0.2867***	-0.1900***	-0.1384***	-0.0389***	0.1190***	-0.0190	-0.0529***
	(0.0142)	(0.0147)	(0.0114)	(0.0193)	(0.0217)	(0.0122)	(0.0325)	(0.0241)	(0.0190)
Baby Boomers	-0.2051***	0.0600***	0.2742***	0.0994***	0.0105	0.0248**	-0.0331	0.0195	0.0027
	(0.0111)	(0.0131)	(0.0104)	(0.0179)	(0.0197)	(0.0114)	(0.0269)	(0.0185)	(0.0169)
Builders	-0.4324***	0.1370***	0.6169***	0.1603***	0.0799**	0.0689***	-0.2285***	0.0435	0.0491*
	(0.0172)	(0.0212)	(0.0170)	(0.0300)	(0.0326)	(0.0196)	(0.0591)	(0.0274)	(0.0275)
Period	-0.0284***	0.0042**	0.0526***	0.0341***	-0.0080**	0.0006	-0.0063	-0.0115***	0.0020
	(0.0016)	(0.0021)	(0.0016)	(0.0029)	(0.0031)	(0.0018)	(0.0047)	(0.0026)	(0.0027)
ln(income)	0.3593***	0.3984***	0.3583***	0.4225***	0.3810***	0.4745***	0.3603***	0.4286***	0.2930***
	(0.0043)	(0.0053)	(0.0043)	(0.0072)	(0.0073)	(0.0049)	(0.0119)	(0.0069)	(0.0070)
	(0.0535)	(0.0625)	(0.0501)	(0.0876)	(0.0910)	(0.0552)	(0.1295)	(0.0928)	(0.0819)
Age	✓	✓	✓	✓	✓	✓	✓	✓	✓
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 5: *Robustness: Generation Specific Definition of Luxury*

	Log luxury expenditure			
	Millennials	Generation X	Baby Boomers	Builders
	(1)	(2)	(3)	(4)
Millennials	-0.0537***	-0.0098	-0.0200**	-0.0176**
	(0.0109)	(0.0089)	(0.0086)	(0.0080)
Baby Boomers	0.0731***	0.0425***	0.0514***	0.0507***
	(0.0098)	(0.0083)	(0.0080)	(0.0075)
Builders	0.1648***	0.1238***	0.1381***	0.1188***
	(0.0161)	(0.0139)	(0.0136)	(0.0127)
Period	0.0183***	0.0101***	0.0100***	0.0114***
	(0.0015)	(0.0013)	(0.0013)	(0.0012)
ln(income)	0.6272***	0.6015***	0.5961***	0.5697***
	(0.0041)	(0.0037)	(0.0036)	(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***	-0.0054***	-0.0073***	-0.0073***
	(0.0012)	(0.0013)	(0.0013)	(0.0014)
Baby Boomers	0.0105***	0.0099***	0.0121***	0.0121***
	(0.0010)	(0.0011)	(0.0012)	(0.0012)
Builders	0.0290***	0.0311***	0.0348***	0.0326***
	(0.0018)	(0.0019)	(0.0020)	(0.0020)
Period	0.0031***	0.0029***	0.0032***	0.0038***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ln(income)	0.0261***	0.0293***	0.0304***	0.0286***
	(0.0004)	(0.0005)	(0.0005)	(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 6: *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***	0.0199***	0.0177***
	(0.0028)	(0.0025)	(0.0031)
ln(income)	0.5882***	0.7302***	0.6100***
	(0.0076)	(0.0072)	(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***	0.0032***	0.0031***
	(0.0003)	(0.0003)	(0.0003)
ln(income)	0.0184***	0.0333***	0.0284***
	(0.0008)	(0.0007)	(0.0007)
Age	✓	✓	✓
Household characteristics	✓	✓	✓
Observations	123806	162682	124983
R^2	0.0563	0.0828	0.0750

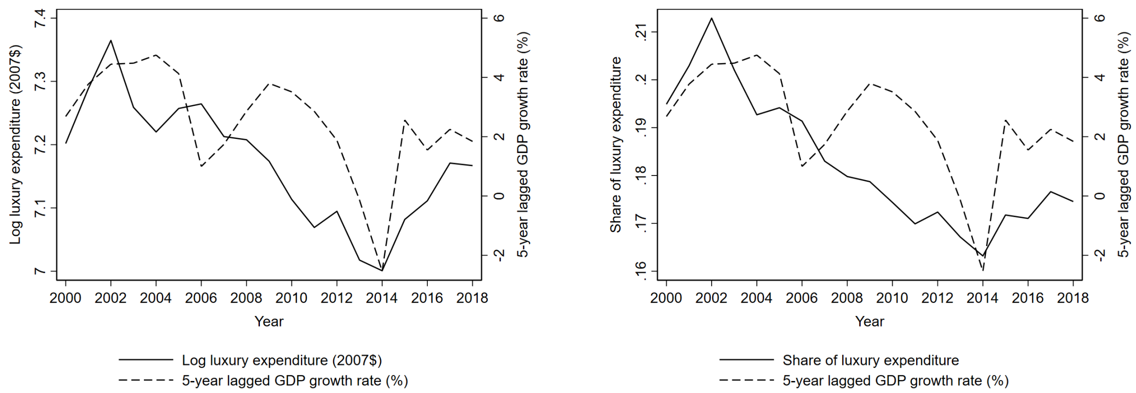
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for 5-year lagged GDP growth rate as proxy for period effect. Luxury expenditure is quarterly based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

Table 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	*Food away from home*	*Clothing/jewelry*
Clothing for adults, 16 and over	*Entertainment*	*Personal care*
Vehicle purchases	*Reading*	*Vehicles*
Other vehicle expenditures	*Lodging except for shelter*	
Public and other transportation	*Vehicles*	Heffetz (2011)
Fees and admissions	*Transportation*	(Top lists based on visibility index)
Pets, toys, and playground equipment		*Cigarettes*
Recreational vehicles		*Cars*
Miscellaneous entertainment outlays		*Clothes, jewelry*
Education		*Furniture, appliances*
Miscellaneous outlays		*Recreational equipment*
Cash contribution		
		Friehe and Mechtel (2014)
		Motor vehicles
		Shoes, apparel (adults, children, babies)
		Jewelry, watches, headpieces
		Skin and body care
		Dental treatments, protheses
		Furniture, Household appliances
		Phones, TVs, Radio sets, Cameras

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



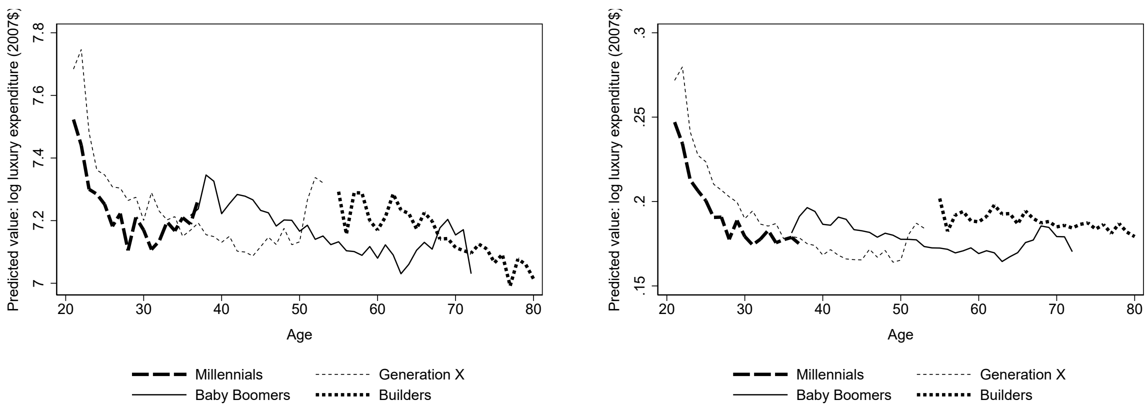
(a) Log Level

(b) Share

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.

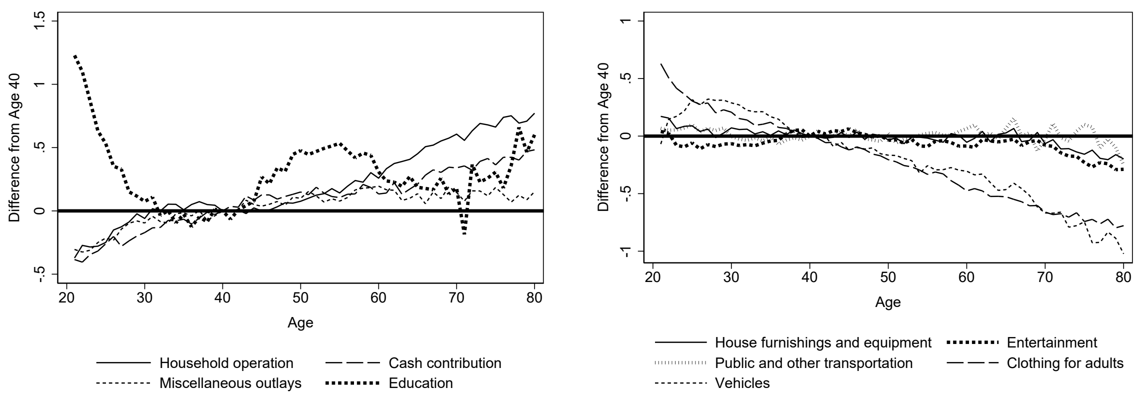
Sources: The World Bank; Consumer Expenditure Survey (CE) 2000–2018



(a) Log Level **(b)** Share

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.



(a) Specific Categories I **(b)** Specific Categories II

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.

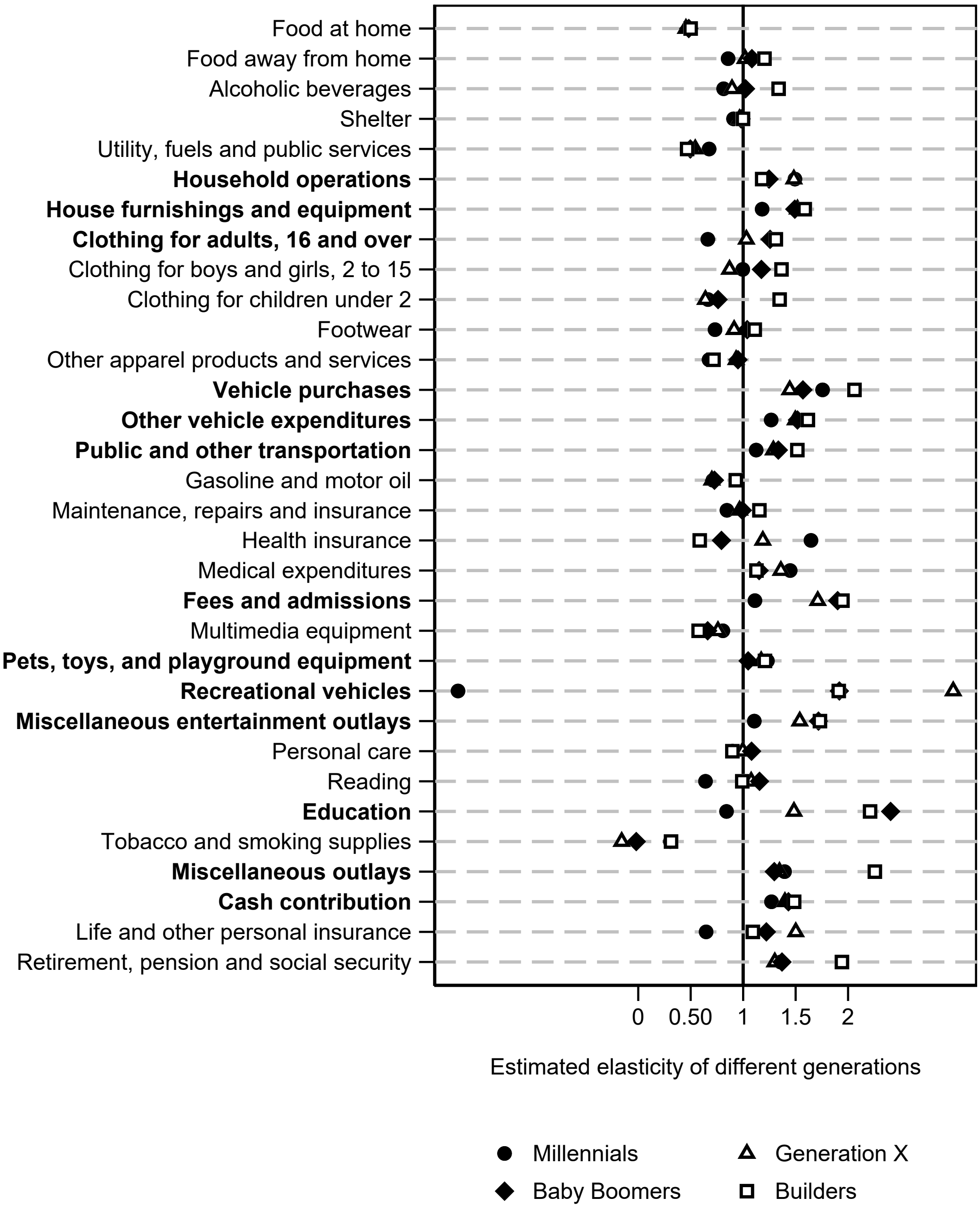
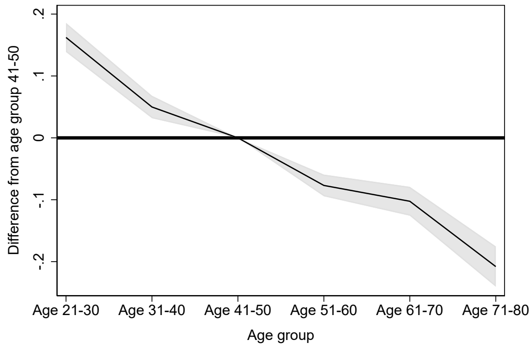
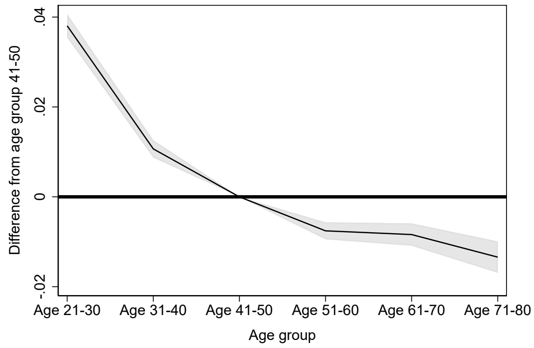


Figure A.4: *Generation Specific Total Expenditure Elasticity*

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.



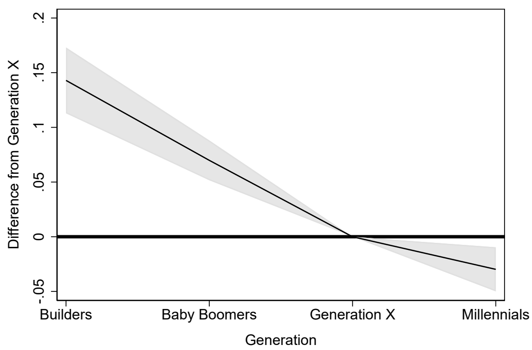
(a) Log Level



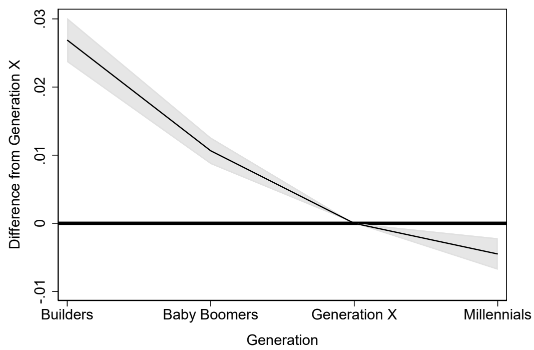
(b) Share

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%
Iraq/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%
Iraq/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%
Iraq/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%
Iraq/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	*Food at home*
Food away from home	*Food excluding meals as pay; Meals as pay*
Alcoholic beverages	*Alcoholic beverages*
Shelter	*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*
Utilities, fuels and public services	*Natural gas, electricity, fuel oil and other fuels; Telephone services; Water and other public services*
Household operations	*Domestic services; Other household expenses*
House furnishings and equipment	*Household textiles; Furniture; Floor coverings; Major appliances; Small appliances, miscellaneous housewares; Miscellaneous household equipment*
Clothing for adults, 16 and over	*Clothing for men, 16 and over; Clothing for women, 16 and over*
Clothing for children, 2 to 15	*Clothing for boys, 2 to 15; Clothing for girls, 2 to 15*
Clothing for children under 2	*Clothing for children under 2*
Footwear	*Footwear*
Other apparel products and services	*Other apparel products and services*
Vehicle purchases	*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*
Other vehicle expenditures	*Vehicle rental, leases, licenses, and other charges*
Public and other transportation	*Public and other transportation on trips; Public and other transportation, excluding trips*
Gasoline and motor oil	*Gasoline and motor oil*
Maintenance, repairs and insurance	*Maintenance, repairs and insurance on transportation*
Health insurance	*Health insurance*
Medical expenditures	*Medical services, prescription drugs and medical supplies*
Fees and admissions	*Fees and admissions for entertainment events*
Multimedia equipment	*Televisions, radios, and sound equipment*
Pets, toys, and playground equipment	*Pets, toys, and playground equipment*
Recreational vehicles	*Motored and non-motored recreational vehicles*
Miscellaneous entertainment outlays	*Photographic and sports equipment and boat and RV rentals*
Personal care	*Personal care products and services*
Reading	*Reading*
Education	*Education*
Tobacco and smoking supplies	*Tobacco and smoking supplies*
Miscellaneous outlays	*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*
Cash contribution	*Cash contribution*
Life and other personal insurance	*Life and other personal insurance*
Retirement, pensions society security	*Retirement, pensions society security*

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		
	Correlation Coefficient	P-value	Correlation Coefficient	P-value	N
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: *Summary Statistics of Expenditure on Specific Categories*

	N	Mean	SD	Min	Max
Household operations	443497	232.730	579.208	0	39293.450
Millennials	51797	243.292	567.149	0	10180.170
Generation X	132364	305.477	712.837	0	39293.450
Baby Boomers	174083	201.315	469.271	0	20442.570
Builders	85253	177.512	545.756	0	37978.330
House furnishings and equipment	443497	310.795	851.507	0	29116.520
Millennials	51797	261.330	692.490	0	18711.300
Generation X	132364	328.2351	883.146	0	29116.520
Baby Boomers	174083	335.147	901.931	0	26335.610
Builders	85253	264.046	776.625	0	25726.840
Clothing for adults	443497	135.997	281.978	0	18798.150
Millennials	51797	103.302	222.007	0	6597.868
Generation X	132364	137,276	282.549	0	18798.150
Baby Boomers	174083	153,299	304.773	0	9576.674
Builders	85253	118.544	261.720	0	7847.080
Vehicles	443497	801.386	2012.877	0	40613.030
Millennials	51797	683.251	1646.734	0	33299.800
Generation X	132364	883.104	1819.598	0	39352.650
Baby Boomers	174083	858.482	2086.306	0	39000.000
Builders	85253	629.699	2312.225	0	40613.030
Public and other transportation	443497	124.316	496.074	0	29514.800
Millennials	51797	105.702	361.046	0	13787.200
Generation X	132364	122.499	453.959	0	13628.000
Baby Boomers	174083	133.021	516.782	0	29514.800
Builders	85253	120.671	579.070	0	21970.340
Entertainment	443497	319.139	771.349	0	34256.470
Millennials	51797	239.289	573.521	0	24470.130
Generation X	132364	355.461	769.068	0	27068.180
Baby Boomers	174083	349.007	808.568	0	34256.470
Builders	85253	250.270	793.433	0	31798.920
Education	443497	190.243	1068.495	0	41309.550
Millennials	51797	255.899	1378.327	0	39508.710
Generation X	132364	185.994	973.306	0	37156.300
Baby Boomers	174083	242.391	1206.447	0	38054.100
Builders	85253	50.462	560.629	0	41309.550
Cash contribution	443497	342.587	997.874	0	38335.280
Millennials	51797	172.100	621.418	0	30064.790
Generation X	132364	292.535	824.097	0	36304.790
Baby Boomers	174083	395.480	1063.700	0	37000.000
Builders	85253	415.876	1244.184	0	38335.280
Miscellaneous outlays	443497	134.369	669.217	0	38520.800
Millennials	51797	62.259	379.720	0	27092.930
Generation X	132364	116.949	579.663	0	34992.560
Baby Boomers	174083	157.081	728.841	0	38520.800
Builders	85253	158.852	794.046	0	28930.380

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

Table A.5: *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***	-0.0319**	-0.2867***	-0.1900***	-0.1384***
	(0.0142)	(0.0147)	(0.0114)	(0.0193)	(0.0217)
Baby Boomers	-0.2051***	0.0600***	0.2742***	0.0994***	0.0105
	(0.0111)	(0.0131)	(0.0104)	(0.0179)	(0.0197)
Builders	-0.4324***	0.1370***	0.6169***	0.1603***	0.0799**
	(0.0172)	(0.0212)	(0.0170)	(0.0300)	(0.0326)
Period	-0.0284***	0.0042**	0.0526***	0.0341***	-0.0080**
	(0.0016)	(0.0021)	(0.0016)	(0.0029)	(0.0031)
ln(income)	0.3593***	0.3984***	0.3583***	0.4225***	0.3810***
	(0.0043)	(0.0053)	(0.0043)	(0.0072)	(0.0073)
Household scale (equivalence)	0.3790***	0.0274***	-0.1928***	0.0342***	-0.0504***
	(0.0072)	(0.0076)	(0.0064)	(0.0105)	(0.0118)
Number of adults	-0.3300***	-0.0067	0.2334***	0.1197***	0.0356***
	(0.0063)	(0.0071)	(0.0059)	(0.0097)	(0.0108)
Male	-0.0861***	0.0321***	-0.0655***	0.0150	-0.0180*
	(0.0059)	(0.0068)	(0.0055)	(0.0096)	(0.0105)
Below 9th grade	-0.3155***	-0.1689***	-0.0963***	-0.1125***	-0.1513***
	(0.0180)	(0.0186)	(0.0149)	(0.0289)	(0.0257)
High school, no diploma	-0.1862***	-0.0981***	-0.1035***	-0.0324	-0.1946***
	(0.0129)	(0.0146)	(0.0116)	(0.0201)	(0.0228)
College graduate	0.1377***	0.1091***	0.1340***	-0.1378***	0.1338***
	(0.0067)	(0.0079)	(0.0064)	(0.0110)	(0.0128)
Masters degree and above	0.3040***	0.1540***	0.2368***	-0.3056***	0.2295***
	(0.0097)	(0.0111)	(0.0090)	(0.0160)	(0.0161)
Urban	0.0078	-0.0335*	0.1377***	-0.1579***	-0.1492***
	(0.0153)	(0.0182)	(0.0150)	(0.0251)	(0.0388)
Married	0.0935***	0.1739***	0.0507***	0.1656***	0.2796***
	(0.0069)	(0.0085)	(0.0069)	(0.0116)	(0.0131)
Metropolitan statistical area	0.1318***	0.0882***	0.0703***	-0.0358*	0.0237
	(0.0120)	(0.0141)	(0.0114)	(0.0198)	(0.0291)
Black	-0.0227**	-0.0381***	0.1007***	0.1593***	-0.0527***
	(0.0098)	(0.0121)	(0.0095)	(0.0160)	(0.0154)
Native American	-0.0870**	0.0216	-0.0283	0.1049*	-0.1676***
	(0.0381)	(0.0437)	(0.0334)	(0.0605)	(0.0625)
Asian or Pacific Islander	-0.1455***	-0.1366***	-0.0559***	-0.2373***	0.2045***
	(0.0136)	(0.0163)	(0.0126)	(0.0229)	(0.0201)
Other races	-0.0210	0.0014	-0.0588**	-0.0142	-0.1373***
	(0.0260)	(0.0310)	(0.0263)	(0.0438)	(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.6: *Results from Specific Categories (Full Table: Part 2)*

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

	Log luxury expenditure			Share of luxury expenditure		
	OLS	IV 1st stage	IV 2nd stage	OLS	IV 1st stage	IV 2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)
Millennials	-0.0691***	-0.0083**	-0.0741***	-0.0137***	-0.0087**	-0.0150***
	(0.0082)	(0.0037)	(0.0083)	(0.0011)	(0.0037)	(0.0012)
Baby Boomers	0.0791***	0.0073**	0.0825***	0.0131***	0.0077**	0.0140***
	(0.0073)	(0.0035)	(0.0074)	(0.0010)	(0.0036)	(0.0010)
Builders	0.1787***	0.0038	0.1828***	0.0306***	0.0051	0.0319***
	(0.0121)	(0.0061)	(0.0122)	(0.0016)	(0.0061)	(0.0016)
Period	0.0213***	-0.0014**	0.0221***	0.0032***	-0.0017***	0.0034***
	(0.0012)	(0.0006)	(0.0012)	(0.0002)	(0.0006)	(0.0002)
ln(total expenditure)	1.7814***		1.5673***	0.1218***		0.0657***
	(0.0039)		(0.0070)	(0.0006)		(0.0009)
ln(income)		0.4090***			0.4153***	
		(0.0018)			(0.0018)	
Age	✓	✓	✓	✓	✓	✓
Household characteristics ✓	✓	✓	✓	✓	✓	✓
Observations	422382	422145	422145	438897	438658	438658
R^2	0.5904	0.5809	0.5846	0.2471	0.5903	0.2062
F		2764.19			2992.13	

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. In the first stages, the dependent variable is ln(total expenditure).

Table A.8: *Robustness: Different Household Scales*

	Log luxury expenditure		Share of luxury expenditure	
	Modified	Square root	Modified	Square root
	(1)	(2)	(3)	(4)
Millennials	-0.0872***	-0.0866***	-0.0156***	-0.0156***
	(0.0109)	(0.0108)	(0.0012)	(0.0012)
Baby Boomers	0.0939***	0.0944***	0.0145***	0.0145***
	(0.0098)	(0.0098)	(0.0011)	(0.0011)
Builders	0.1887***	0.1894***	0.0322***	0.0322***
	(0.0164)	(0.0164)	(0.0018)	(0.0018)
Period	0.0198***	0.0198***	0.0033***	0.0033***
	(0.0016)	(0.0016)	(0.0002)	(0.0002)
ln(income)	0.6409***	0.6395***	0.0273***	0.0274***
	(0.0042)	(0.0042)	(0.0004)	(0.0004)
Household scale (modified)	0.0947***		-0.0052***	
	(0.0097)		(0.0010)	
Household scale (square root)		0.1354***		-0.0060***
		(0.0105)		(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 22 for details.

Table A.9: *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***		-0.0205***	
	(0.0209)		(0.0026)	
Millennials II	-0.0878***		-0.0152***	
	(0.0110)		(0.0013)	
Baby Boomers	0.0939***		0.0147***	
	(0.0098)		(0.0011)	
The Silent Generation	0.1887***		0.0326***	
	(0.0164)		(0.0018)	
The Greatest Generation	0.1926***		0.0409***	
	(0.0313)		(0.0033)	
Millennials		-0.0254**		-0.0029**
		(0.0122)		(0.0014)
Baby Boomers		0.0266**		0.0013
		(0.0112)		(0.0012)
Builders		0.0621***		0.0065***
		(0.0197)		(0.0021)
Period	0.0198***		0.0032***	
	(0.0016)		(0.0002)	
ln(income)	0.6409***	0.6426***	0.0273***	0.0274***
	(0.0042)	(0.0042)	(0.0004)	(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.

B Heterogeneous Effects Details

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

Model 1.

$$L_{it} = \alpha_0 + \boldsymbol{\beta_a D^a_{it}} + \boldsymbol{\beta_g D^g_i} + \boldsymbol{\beta_{gp} D^g_i} \cdot \text{Period}_t + \alpha_1 \text{Period}_t + \alpha_2 \ln(\text{income})_{it} + \boldsymbol{\beta_h X_{it}} + \varepsilon_{it}$$

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

Model 2.

$$L_{it} = \alpha_0 + \boldsymbol{\beta_a D^a_{it}} + \boldsymbol{\beta_g D^g_i} + \boldsymbol{\beta_{ga} D^g_i} \cdot \boldsymbol{D^a_{it}} + \alpha_1 \text{Period}_t + \alpha_2 \ln(\text{income})_{it} + \boldsymbol{\beta_h X_{it}} + \varepsilon_{it}$$

includes the interaction terms between generation and age dummies $\boldsymbol{\beta_{ga} D^g_i} \cdot \boldsymbol{D^a_{it}}$. 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***	-0.0150***	-0.1612**	-0.0247**
	(0.0155)	(0.0017)	(0.0756)	(0.0102)
Baby Boomers	0.0863***	0.0137***	-0.1697**	-0.0108
	(0.0136)	(0.0014)	(0.0731)	(0.0080)
Builders	0.1990***	0.0306***	-0.1041	0.0032
	(0.0217)	(0.0023)	(0.1129)	(0.0119)
Period	0.0201***	0.0032***	0.0189***	0.0033***
	(0.0027)	(0.0003)	(0.0016)	(0.0002)
Period × Millennials	-0.0020	-0.0005		
	(0.0049)	(0.0006)		
Period × Baby Boomers	0.0021	0.0003		
	(0.0037)	(0.0004)		
Period × Builders	-0.0045	0.0005		
	(0.0049)	(0.0005)		
ln(income)	0.6409***	0.0273***	0.6413***	0.0273***
	(0.0042)	(0.0004)	(0.0042)	(0.0004)
Age	✓	✓	✓	✓
Age × 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:* $\boldsymbol{\beta_{gp} = 0}$;

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

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 $\boldsymbol{\beta_{ga} D_i^g \cdot D_{it}^a}$ 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. *Null:* $\boldsymbol{\beta_{gp} = 0}$	0.5419	0.3892
Model 2: Test 2. *Null:* $\boldsymbol{\beta_{ga} = 0}$	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 $\boldsymbol{\beta_{gp}}$ 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

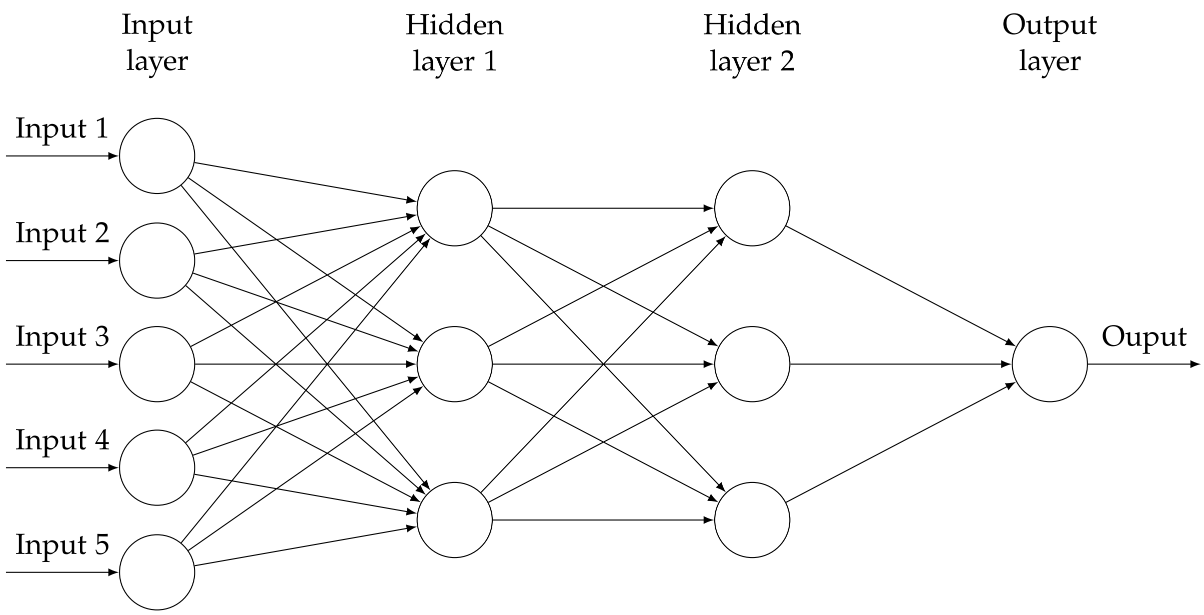


Figure C.1: *Illustration of A Full Connected Neural Network*

layer, made up of independent variables $\boldsymbol{X}$, 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 $\boldsymbol{Z}$. 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 non-linear transformation through an activation function $f(.)$. 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 non-linearly 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 $\boldsymbol{w}$ and biases $\boldsymbol{b}$ 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 non-linear 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 (RuLU),

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

introduced by Nair and Hinton (2010), is taken as the activation function $f(\cdot)$ for non-linear transformation in the neural network. ReLU shows more stable performance in convergence that 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÷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.