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

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Abstract

Millennials 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, Millennials 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 Millennials observed in the cross section can be fully attributed to their young age. These results challenge the conventional view of Millennials as a spoiled generation indulging in luxury.

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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 Millennials 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 collinear 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 evidence on each category shows 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 evidence 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), the 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: 1) the Quarterly Interview Survey contains data on large and recurring expenditures during the three months prior to the interview, and 2) the Diary Survey is designed for small and frequent purchases for a consecutive period of two weeks. 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 during each calendar quarter. Each household is interviewed every three months over four consecutive quarters, and is supposed to recall expenditures during the past three months.[12] All households that complete the fourth interview or preliminarily leave the survey, are dropped from the sample and replaced. Although each household can provide data for a maximum of one year, I treat records of each interview independently. I do not report the sum of expenditures across all interviews of one household because the following reasons distort these results: less than 50% of all households complete four surveys; and fully participating households tend to be older, richer, and more likely to own their homes.

The data set consists of various files that report expenditure information in different levels of detail since the end of 1979, and data from the FMLI files from 2000 to 2018 are used. These FMLI files from the Quarterly Interview Survey provide summary level expenditures and other household characteristics. Since 2000, the questionnaire design and expenditure categorization

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

[12] 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). Data from these interviews are not used in this paper.

have been consistent, thus the consumption bundle always stays identical and Millennials are included in the samples of each year. I aggregate specific expenditure categories in the FMLI files into 32 categories, and Table A.2 reports the details.[13] Besides expenditure, I also take data on the household characteristics and the total amount of household income after taxes in the last 12 months from the FMLI files.[14] All expenditure and income data are deflated to 2007 dollars using the Consumer Price Index (CPI). Household characteristics of each record include demographic information of household head (e.g., age, gender, race, marital status and education), household structure (e.g., household size and number of adults), urban residence, information on metropolitan statistical area, region, and interview quarter. Note that redundant variables from the survey are excluded. For instance, the number of children in a household is excluded, as it can be directly inferred from household size and the number of adults. The pooled sample contains 526828 observations.

3 Defining Luxury Expenditure

First, I 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 rises by more than one percent with an increase in total expenditure of one percent. 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 elasticity to one. Concerning measurement errors and extreme values in the data, I drop households with negative expenditures in any category from the full sample. Furthermore, households in the top or bottom one percent of the total expenditure distribution within each year are removed. I do not consider specific generations or age ranges for the elasticity estimation, since the definition of luxury should represent the perception of luxury within the whole population.

Following the approach of Heffetz (2004, 2011, 2018), I conduct a non-parametric estimation using the prepared sample. To be specific, I start with estimating the expenditure of each category as a function of total expenditure at 101 total expenditure points, using the weighted local linear regression with a quartic kernel developed by Fan (1992). Next, gradients between pairs of neighboring points are computed, and 100 local expenditure elasticities are derived from these gradients. Finally, the average elasticity of all households is obtained from the local elasticites weighted by the number of households located in each of the 100 intervals. This is repeated for all 32 expenditure categories.

For a stable and reliable measure of luxury, the estimation is executed using data of different time periods: 2000–2009, 2010–2018, and 2000–2018. Because the perception of luxury depends on subjective preferences that typically do not change too frequently, I consider the

[13] The FMLI files also report aggregated expenditure categories, but they are too broadly defined and the heterogeneity among individual categories might already average out. For example, *shelter*, *utilities, fuels & public services*, *household operations*, and *house furnishings & equipment* are all included in a single category called *total housing outlays*.

[14] Complete income reports after taxes were the only source of published income data before 2004, afterwards the CE program started to impute missing values. Estimation of personal taxes was introduced in the second quarter of 2013, which has been collected instead of reported tax values. As a result, missing incomes are used before 2004, imputed or collected income values are used for the years 2004–2013, and imputed or collected income data are combined with estimated taxes after 2013.

total expenditure elasticities as relatively stable across time. However, averages across the entire 19-year sample period might cover some important deviations (i.e., when estimated over different periods, the elasticities can fluctuate around one for some categories), and hence the finial classification could be imprecise. Therefore, I also separately estimate elasticities during the 2000s and the 2010s, besides the whole sample period. Only categories with elasticities consistently larger than one in any period are defined as luxury.

The estimation results are shown in Figure 2, where one is indicated by a vertical line as the elasticity threshold. The elasticity-based luxury definition above leads to 15 categories of luxury goods:

- *household operations*
- *house furnishings and equipment*
- *clothing for adults*
- *vehicle purchases*
- *other vehicle expenditures*[15]
- *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*
- *miscellaneous outlays*[16]

After this, the two categories, *retirement, pensions, social security* and *life and other insurance* are excluded because they belong to consumption transferred into the future. As a result, the remaining 13 are defined as luxury and boldfaced in Figure 2. Thus, luxury expenditure is the sum of expenditures over these categories in the following analysis.

Arguments whether some categories really belong to luxury might arise here, since the estimation results are not necessarily in line with every personal opinion. For instance, it is debatable whether education should be treated as investment or expenditure. The methods of financing education involve complex financial issues that are not homogeneous across households or generations. For simplicity and objectivity, here I mainly rely on the economic definition of luxury instead of arguing in detail about the rationale behind it. I also show the results from individual categories in Section 5.5. For categories that are agreeably considered as "classic" luxury, results are consistent with the main findings, as discussed in Section 8.1.

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

[16] *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.

4 Descriptives

In this section, I summarize some descriptive statistics after refining the pooled sample with 526828 observations. Then, I graph overall and generation-specific sample means over the life cycle and across time to show patterns of luxury expenditure.

4.1 Sample Selection and Summary Statistics

Several steps are taken to refine the pooled sample for the following analysis.[17] First, I exclude Generation Z from the sample since there are only few observations and members from this generation have not completed their education yet, which might distort their expenditure structure. Next, I only keep households whose heads are younger than 81 as only few old households were surveyed. Furthermore, households whose heads are younger than 21 are excluded since in the US they do not have access to some expenditure categories like alcoholic beverages, tobacco, or smoking supplies.[18] On top of that, I drop households with negative expenditure in any category and negative income (before or after taxes) from the sample to account for measurement errors. For the data before 2004, I drop incomplete income reports.[19] Finally, to mitigate the impacts of extreme values, I drop households in the top or bottom one percent of the total expenditure and income (before and after taxes) distribution within each year. The resulting sample contains 443497 observations after the selection process.

Generation is created as a categorical variable based on the birth year of household heads. I combine the two oldest generations, the Greatest Generation and the Silent Generation, together into one single generation in the main specification, since Millennials are the focus of this paper and less data of old generations are included in the survey. McCrindle (2007) calls this combined generation "Builders" because they have transformed an agrarian into an industrialized economy by building the infrastructure and organizations of the new post-war society. Figure 1 displays the size of each generation in the sample across time: overall there are 51797 observations from Millennials, 132364 from Generation X, 174083 from Baby Boomers, and 85253 from Builders.

Table 2 lists summary statistics for the refined sample, where both the level and share of luxury expenditure are the main dependent variables for the analysis in the following. On average, households spend \$2591.56 per quarter (in 2007 dollars) on luxury, accounting for around 18.3% of their total expenditure. Millennials exhibit the lowest expenditures on luxury in terms of absolute level probably because Millennials are just at the beginning of their career path and receive relatively low income. Builders have the second lowest level of luxury expenditures, and they have the lowest total expenditure level, followed by Millennials. However, Millennials on average have the largest share of luxury expenditure among all generations, which matches the established social impression of Millennials as influential

[17] Instead of the trimmed sample from the elasticity estimation in Section 3, I start with the full sample of 526828 observations again here.

[18] There are consistently more than 3000 observations for each age lower than 81, but for households older than 80, the number of observations fluctuates between 4972 and 0. The lower age bound also rules out most members of Generation Z.

[19] See Footnote 14 for detailed information on this.

luxury consumers. Nevertheless, the average picture is not yet enough for this conclusion, as it is also related to age.

Regarding demographics, the average age in the sample is 48.5, which is driven by the fact that Baby Boomers and Generation X are overrepresented in the survey.[20] Slightly more than half of household heads are women, and households with married heads make up 54.5%. The largest group of household heads (46.1%) are high school graduates, and 81.5% of the household heads are Whites. The spatial distribution of households is uneven as most of them are located in urban and metropolitan statistical areas, and the largest number of surveys happened in the South region of the US. The surveys are distributed almost uniformly across the four calendar quarters.

Due to the economies of scale in consumption, household sizes should be adjusted. Different choices of scales are discussed in the literature, all of which have advantages and drawbacks (see, e.g., Fernández-Villaverde and Krueger, 2007; Aguiar and Hurst, 2013). In the main specification, I use the "OECD equivalence scale", also called "Oxford scale", which assigns a value of 1 to the first household member, a value of 0.7 to each additional adult, and 0.5 to each child. This scale reduces the average household size from 2.59 to 1.99. Alternatively, the "OECD-modified scale" and the "square root scale" are mainly employed in robustness checks, but deliver almost identical results compared to main specification.[21]

4.2 Age Profiles

To present the average share and log level 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 luxury expenditure level over the life cycle is characterized by a "hump" peaking around age 40 in Figure 3(a), corresponding to the dynamics of earning years. Nonetheless, Figure 3(b) reveals a monotonic decline of the share of luxury expenditure over the life cycle. After falling drastically from about 21.5% at age 21 to 18% at age 40, it stays on a stable decrease until another sharp drop at age 70. The key insight from Figure 3 is that age is an active factor which affects luxury expenditure in terms of both level and share, and that young people exhibit a large amount of luxury consumption. Although Millennials are the youngest generation in the sample, only the mean consumption by age is displayed. So the specific behaviors of Millennials are not immediately clear from these averages, as the expenditure of Generation X at the same age is also included.

As the generation heterogeneity behind Figure 3 is still hidden, I provide further information on the evolution of average luxury expenditure for each generation in Figure 4. Each line represents the expenditure behavior of a specific generation over the 19-year sample period. Different generations are observed through different life stages, with overlaps among age brackets which can be used for comparing neighboring generations. The vertical distance

[20] See Figure 1 for the size of each generation in the sample. The average ages are: Millennials 27.0, Generation X 36.7, Baby Boomers 53.2, and Builders 70.0.

[21] The "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. The "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 an overview of all scales.

between lines implies the existence of the generation effect, although it is still contaminated by other effects here. The overall "hump-shaped" expenditure levels and declining expenditure shares 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. Figure 4(b) shows that the differences are especially substantial in expenditure share. Even though the data might contain some amount of noise, Millennials have been consistently consuming less luxury than Generation X at any given age from 21 to 37. This is the entire available age range of Millennials in the data.

However, these average expenditure patterns cannot tell to what extent the results are driven by differences in the demographic composition between generations, such as education levels or household size. To isolate the generation effect from such compositional effects, I will turn to a regression analysis in Section 5.

4.3 Time Trends

Next, I examine luxury expenditure across time to have an overall perception of the period effect. Figure 5 presents the results. Clearly, the level and share of luxury expenditure follow the same time trend, declining from the early 2000s until 2014 and then starting to recover. The lowest expenditure in 2014 reflects the long-term influences of the Great Recession.

Subsequently, the generation-specific time trends are analyzed and Figure 6 shows the resulting expenditure level and share. Generation X and Baby Boomers have the highest absolute luxury expenditure level. These generations are still closer to their peak earning ages and thus have the highest income and total expenditure (see Table 2), which is closely linked to high luxury expenditures. Around 2010, when most Baby Boomers gradually approach retirement, Generation X naturally replaces them as the leading luxury purchaser. In Figure 6(a), Millennials diverge from other generations as their expenditure level continuously increases across time, consistent with the perception that Millennials are major contributors in the luxury market. The generation differences in Figure 6(b) reflect the 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 luxury expenditure trends are synchronized among all generations to some degree, implying that every generation faces a similar period effect. This synchronization empirically supports the separability of the period effect from the generation effect. This is the base for my main specification, whereas additional identifications present heterogeneous effects.

5 Regression Analysis

In the following, I present econometric models that identify the age effect and the generation effect, and I quantitatively measure 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

$$L_{it} = \alpha_0 + \boldsymbol{\beta_a D^a_{it}} + \boldsymbol{\beta_g D^g_i} + \alpha_1 \text{Period}_t + \alpha_2 \ln(\text{Income})_{it} + \boldsymbol{\beta_h X_{it}} + \varepsilon_{it}, \tag{1}$$

where L_{it} is either the log level of luxury expenditure or the share of luxury expenditure of household i during the last 3 months in year t. I take an age dummy vector $\boldsymbol{D^a_{it}}$ for every age from 21 to 80, with age 40 as the base group. Likewise, $\boldsymbol{D^g_i}$ is a vector of generation dummies for Millennials, Baby Boomers, and Builders, where Generation X is the base group.

Period_t stands for the 5-year lagged GDP growth rate as a proxy for the period effect. With age and generation dummies, an additional time control will induce a collinearity problem because age can be computed from calendar time and birth year which is inferred from the generation. To avoid this, I use a proxy variable approach suggested by Dohmen et al. (2017), which substitutes the period effect with GDP growth rate that captures the cyclical pattern of expenditure variations across time.[22] To account for the enduring influences of the economy on luxury expenditure (like the long-lasting consequences of the Great Recession shown in Figure 5) the lag of the GDP growth rate should be considered. In Table A.3, multiple lag period lengths, from one to six years of lag, are scrutinized to find the most suitable proxy variable.[23] It turns out that 5-year lagged GDP growth rate results in the highest correlation with luxury expenditure level and share. To further corroborate this approach, Figure A.1 plots both 5-year lagged GDP growth rate and average luxury expenditure across time. It can be seen that the cyclical patterns of luxury expenditure can be epitomized by the GDP growth to some degree.

Finally, $\ln(\text{Income})$ is the log of the total amount of household income after taxes in the last 12 months. $\boldsymbol{X_{it}}$ is a control variable vector of the household characteristics specified in Table 2, including household demographics, size, location, and information on the interview quarter. This choice 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 from Section 4.3 empirically support that the period effect is separable from the generation effect. Thus it is assumed, that there are no interaction terms between age and generation dummies in Eq. (1). This way the age and generation effect are explored separately here, but more general specifications are discussed in the following.

5.2 Main Results

Estimation results are presented in Table 3. To start with, I create a naïve regression model to investigate generational variations of luxury expenditure without accounting for age, using

[22] The standard approach developed by Deaton (1997) in consumption literature assumes that the time effect captures the cyclical fluctuations (Aguiar and Hurst, 2013). See Section 6.2 for robustness checks that this method delivers similar results to the main findings.

[23] Data on GDP growth rates 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).

generation dummies, 5-year lagged GDP growth rate as a proxy for period effect, and income. Next, I additionally include age dummies as 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 $\boldsymbol{X_{it}}$.

Column (1) and (4) display the results of the naïve model, for both log and share of luxury expenditure as dependent variables, respectively. Without controlling for age, the estimated coefficients on generation dummies are decreasing (except for the expenditure share of Builders), which coincides with the established impression that Millennials have a high spending power in the luxury market. However, in the baseline model including age dummies, the generation effect immediately switches direction as shown in Column (2) and (5). Earlier born generations tend to consume more luxury, conditional on age, time period, and income level. This finding is further confirmed by the preferred regressions in Column (3) and (6) which additionally control for household characteristics.[24] In all specifications with age controls, the generation effect is solid and significant, and the estimator magnitudes are relatively stable. The pure generation effect from the regression corresponds to the overview of generation specific age profiles in Figure 4: younger generations actually spend less on luxury.[25]

Millennials are consuming the least amount of luxury in terms of both level and share. Quantitatively, Column (2) shows that Millennials spend 7.35% less than Generation X on luxury, accounting for age, income, and time period. This number increases to 8.72% in Column (3) when household characteristics are additionally considered. Based on the average luxury expenditure of Generation X, i.e., \$2727.53 per quarter in Table 2, the estimation leads to generational differences from \$200 to \$238 per quarter. At the same time, the share of luxury expenditure of Millennials is around 1.50% less with respect to Generation X as displayed in Column (5) and (6). 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. Considering the monotonic increase of luxury expenditure across generations, Millennials behave even more conservatively when compared with Baby Boomers or 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, as parents are more likely to purchase luxury for their children. Referring to education, 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 the age effect on luxury expenditure based on the preferred model in Column (3) and (6). The solid lines plot the coefficients on estimated age dummies where

[24] In the preferred specification, the region (Northeast/Midwest/South/West) rather than the specific state is controlled due to two reasons. First of all, the sample period is too long to rule out the considerable influences from large-scale migrations across states. Therefore, the state fixed effect is obscured in the sample as expenditure preferences geographically move along with the people. However, the region fixed effect is comparatively stable because of larger areas and fewer transitions. Secondly, there is a significant amount of missing state information in the data. For the same reasons, I cluster standard errors at household level, while related work that uses short-term data usually reports standard errors at state level. Nevertheless, I also investigate the inclusion of both region and state fixed effects in Table A.5. The resulting coefficients barely change as displayed in Column (2) and (4).

[25] All results in this paper are unweighted. Nevertheless, Table A.5 reports results considering frequency weights, according to the size of each generation in the sample, as shown in Figure 1 and Section 4.1.

shaded areas indicated 95% confidence intervals. The horizontal zero lines mark the reference age 40. Conditional on other variables, luxury expenditure monotonically decreases over the life cycle, with respect to both level and share, meaning that the interest in luxury decrease with age. The received idea of Millennials' high luxury expenditure seems to arise from their young age, which is unrelated to the effect of their generation identity.

5.3 Counterfactual Predictions

Next, I construct counterfactual age profiles of luxury expenditure for all generations based on the regression results. The estimators from the preferred model in Column (3) and (6) in Table 3 are used to predict the dependent variables. Instead of using samples from a specific generation g, I calculate the means over the entire data set.[26] Specifically, for generation g at age a, the predicted values represent the average luxury expenditure of all households, assuming they were treated as generation g at age a. The life-cycle luxury expenditure is predicted after repeating this process for every generation at every age from 21 to 80. In this way, each control variable value in entire data set is used, so the obtained counterfactual patterns exactly delineate pure age and generation effects conditional on all other controls.

Figure 8 plots the resulting 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. When comparing these predictions to real values in Figure 4, the expenditure shares in Figure 8(b) match well with Figure 4(b). However, the predicted expenditure level in Figure 8(a) completely diverges from the "hump" shaped age profile in Figure 4(a) which is caused by aggregate effects. Figure 8 works as a visual representation of the main findings: Firstly, the decreasing life-cycle luxury expenditure for every generation is predicted from the model. Secondly, younger generations spend less on luxury than older generations, so Millennials have been consuming the least at all ages between 21 and 80.

Additionally, Figure 8 graphically explains how the stereotype might have emerged: Currently Millennials are still in their early life stages. When comparing Millennials to other generations who are older now, without considering potential future expenditures of Millennials, it is easy to mistakenly accredit a high luxury consumption to them. Similarly, it is often overlooked how seniors behaved when they were young. This analysis fills the gap by predicting that Millennials will follow their own age profiles which shows a generally lower luxury expenditure down to their 70s and 80s. In a nutshell, it is important to focus on the same life stages when examining the generation effect, in order to isolate it from the age effect.

5.4 Heterogeneous Effects

The main regression model is based on the separability assumption, which does not contain any interaction terms. However, age and time period influence different generations heterogeneously, therefore questioning the uniformity of life-cycle patterns and time trends across

[26]When only samples of individual generations are used to predict the life-cycle expenditure, two problems occur: First, values of other control variables vary across generations, which contaminates the predictions by introducing other effects not caused by age or generation differences. Second, values of other control variables of each generation remain in a limited range over the life cycle, which is not very realistic.

generations. Following Fitzenberger et al. (2021), I develop more general models that feature multiple interaction terms between generation dummies and age or period controls.

In Appendix B, I find that the period effect is separable, while the generation effect cannot be disentangled from the age effect. Details on the performed extensive procedures of regression and sensitivity tests are elucidated there as well. I adjust the main specification to allow for non-uniform trends due to the entanglements between the generation and age effect. This conduces to the ideal regression model

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

Instead of the individual age effect $\boldsymbol{\beta_a D_{it}^{a}}$ and generation effect $\boldsymbol{\beta_g D_{i}^{g}}$, it includes interaction terms $\boldsymbol{\beta_{ga} D_{it}^{g}} \boldsymbol{\cdot} \boldsymbol{D_{it}^{a}}$, while other controls remain unchanged.

Figure 9 shows the generation specific age effect on luxury expenditure by visualizing 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 the generation effect in Table 3. The coefficient estimation for the interaction terms is only possible at valid combinations of generation and age. As a result, Figure 9 only displays coefficients for observed age ranges in the data. Despite this incompleteness, similar patterns to the main results in Table 3 can be found here: the generation effect gives rise to less luxury expenditure of Millennials with respect to all preceding generations at the same age. Even though there are minor fluctuations, e.g., a slightly increasing trend for old Millennials, these deviations are not significant, so the main findings remain. For completeness, I visualize age and generation effects in Figure A.2 in Appendix A, by conducting the counterfactual analysis as explained in Section 5.3 with the interaction-based ideal model.

5.5 Evidence on Specific Categories

In this section, I analyze the individual categories of luxury goods to identify the heterogeneous patterns behind the main results. From the 13 different expenditure categories of luxury goods according to the classification in Section 3, I aggregate several closely related ones. Table A.4 reports the summary statistics of the resulting 9 categories.[27]

I run the regression based on the preferred model as described above for each of the 9 categories, and present the results in Table 4. The generation effects are mostly heterogeneous in terms of both magnitudes and significance levels, and monotonic and significant apart from certain outliers. Millennials tend to spend significantly less on the majority of the categories except for *household operations* and *education*. The expenditure gaps for *clothing for adults*, *vehicles*, and *public and other transportation* in Column (4) and (5) are also relatively large compared to the main results. Across all generations, I find the highest coefficient differences when estimating the effects on *clothing for adults* in Column (3), on which Builders spend 62% more than Generation X. For *household operations* and *education*, Column (1) and (7) are outliers, as they have an opposite generation effect that is mostly significant. So younger generations

[27]The combined 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*".

are obviously show more interest in these categories. In addition, for *cash contribution* and *miscellaneous outlays* in Column (8) and (9), the estimates are also monotonic across generations, but barely significant and economically weak.

The age effects presented in Figure A.3, are also non-uniform among categories. While older generations tend to spend less on *household operations* overall, there is an increasing trend over the life cycle. Furthermore, age profiles of expenditures on *cash contribution* and *miscellaneous outlays* diverge from the decreasing age effects in the main results in Figure 7. The declining age profile in the main results is mostly driven by the categories in Figure A.3(b), especially by the strong decreasing trends for *vehicles* and *clothing for adults*. The age effect of these two categories is even strong enough to hide the remaining divergent age profiles. The cyclical age effect on *education* might be caused by expenditures on personal education until about age 30, and education costs for offspring from age 45 to 65.

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 a generation-specific classification style. Afterwards the generation effect within the same age range is discussed, and the symmetric treatment of age and generation is analyzed. Finally, I investigate if the results are affected by changes to control variables other than the age and generation dummies.

6.1 Alternative Model Specifications

Generation specific definition of luxury expenditure categories As individual generations may perceive and define luxury differently, the elasticity estimation based on the overall sample might not fit all individual generations alike. Therefore, I estimate elasticities only using data of each generation following the same procedures in Section 3. An empirical problem is that there are not enough observations of expenditures of a single generation at the top and bottom of the distribution. This can lead to empty observation ranges between some of the 101 total expenditure points when estimating. To solve this, outlier households of each generation are trimmed in a similar way as the sample selection procedure in Section 3. That means, I exclude households in the top or bottom one percent of the total expenditure distribution for each generation. Besides, generation-specific elasticities are only estimated for the whole sample period from 2000 to 2018. Because generation-specific luxury definitions might vary heterogeneously across time, an average of the full period works best as it treats generations equally.[28]

The estimated elasticities using such generation-specific subsampling are shown in Figure A.4. Compared to the full estimation in Figure 2, the results are less stable due to larger standard errors. Based on the same luxury threshold, a generation defines a category as a luxury good if the estimated elasticity is higher than one. For comparison, the overall classifi-

[28] As an example, Millennials had been gradually coming of age from 2000 to 2018, so their perception of luxury was less stable compared to Baby Boomers during the same period. The estimation based on the whole sample period could average out the instabilities across time to some extent.

cation is also shown by the boldfaced category names in Figure A.4. The generation-specific classification indeed differs, but most of the luxury categories defined by the overall sample are consistent throughout every generation. Millennials have the most parsimonious selection of luxury. For example, they do not consider *education* and *clothing for adults* as luxury. Moreover, the estimated elasticity of *recreational vehicles* using the sample of Millennials is substantially negative. This is either caused by distorted results from a large amount of zero expenditures, or by lacking interest in recreational vehicle consumption from households higher total expenditure. In contrast, Builders and Baby Boomers view notably more categories as luxury.

I use the classification defined by each generation to construct the dependent variables and run the regression based on the preferred model in Eq. (1) including full controls. The results in Table 5 show that the generation effect is qualitatively stable and statistically significant. In comparison with the main results in Table 3 the effect is weakened, since individual definitions of luxury can not represent all households in the sample here. This finding also confirms that the main results are still qualitatively robust, even with some misclassifications due to measurement errors.

Common age range As each generation is only observed through certain life stages during the sample period from 2000 to 2018, the expenditure comparison is imprecise when households of different generations do not share common age ranges in the data.[29] Therefore, I run the same regression for groups of two neighboring generations at once, and just focus on households within their overlapping age range.

Table 6 shows the generation effect for the resulting three groups. Specifically, I compare Millennials and Generation X from age 21 to 37, Generation X and Baby Boomers from age 36 to 53, and Baby Boomers and Builders from age 55 to 72. Each column presents results from one group, where the older generation always acts as a reference. The negative and significant coefficients on all generation dummies imply the robustness of the main results: conditional on the same age, younger generations consume less luxury. Furthermore, the magnitudes of the coefficients are similar the magnitudes pf the main estimates as well: Millennials have about 8% less luxury expenditure than Generation X, and the difference in the share is about 1.5%. As a result, the lack of common age ranges among multiple generations in the data does not impact the generation effect.

Symmetric treatment of age and generation A generation is a collection of cohorts, but age is taken as individual dummies in the regression, so the results might be coincidental because of an asymmetric treatment of generation and age. To ensure that the generation effect is not only a broad age group effect, I use cohorts as a proxy for generation. With cohorts defined by their specific birth year and age dummies controlled individually, I can confirm whether the overall cohort trend follows the monotonic generation effect from the main results in Table 3.

Figure 10 plots the continuous cohort effect with 1960 as the reference birth year. Quantitatively, the results are comparable to the generation differences in Table 3. Qualitatively, they

[29] For example, Builders are tracked from the age 55, while Generation X is only featured until age 53. The youngest Builders were born in 1945 and 55 years old in 2000, while the oldest members of Generation X were born in 1965 and only 53 years old in 2018.

also match when using either the log level or share of luxury expenditure as the dependent variable. Conditional on age, younger cohorts spend monotonically less on luxury. The behavior of the oldest cohorts (born in the 1920s) and the youngest cohorts (born in the 1990s) is fluctuating, but are not significant enough to affect the overall results. The behavior of cohorts in between is more stable. Likewise, Figure 11 plots the age effect in the same way as Figure 7. Conditional on cohorts and other controls, the same age effect persists as a declining life-cycle luxury expenditure as well as similar estimator magnitudes are visible.

Furthermore, this strategy based on the cohort fixed effect also speaks to the concern about the size of each generation in the data. As shown in Figure 1, the two middle generations, Baby Boomers and Generation X are slightly overrepresented in the sample. In addition to the results from the weighted regression in Table A.5, this approach of controlling for cohorts provides further evidence. When generations are equally disaggregated into cohorts in Figure 10, the original generation effect is replicated by differences among cohorts, even within a generation. Thereby, the relative size of each generation does not influence the main findings.

To further confirm that the asymmetric treatment of age and generation does not change the results, an alternative approach is used. I keep the generation dummies from the main identification, but aggregate age into groups. Figure A.5 and Figure A.6 in Appendix A present consistent evidence of monotonic age group and generation effects in this setting.[30]

6.2 Adjustment of Controls

In the following, four concerns require adjustments of control variables: 1) the quality of the CE income data is low, 2) different household scales can be used, 3) the generational segmentation might be to broad, and 4) other solutions to the collinearity problem are possible. In this section, I show that changes to the control variables to account for these concerns do not lead to different results from the main findings.

Instrument variable 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 depends on the reporter. The permanent income hypothesis states that the 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 this proxy variable approach: endogeneity and measurement errors in the total expenditure data.[31] Luckily, a solution is provided there as well: controlling for total expenditure and using income as an instrument variable (IV). Following the same identification of the preferred model, I use both the IV approach and a simple OLS estimation while controlling for total expenditure. It can be seen from Table A.8 that generation effects are similar to the main results, while the coefficient magnitudes from the OLS estimation in Column (1) and (3) are slightly lower. Additionally,

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

[31] All expenditure categories are jointly determined in a consumption model, which makes total expenditure endogenous in the regression with any category as the dependent variable. Next, measurement errors in any of the categories could contaminate the total expenditure, which is the sum of expenditures on all individual categories in the original data of the CE program.

all values of R^2 in Table A.8 increase substantially compared to main results, since the total expenditure is explaining most of the variations and does trigger the endogeneity problem.

Different household scales Secondly, I check if the results stay identical when different household scales are applied. Aguiar and Hurst (2013) argue that results based on the consumer expenditure survey are usually sensitive to the choice of household scales, both across and within categories. For instance, teenagers and babies are both counted as children but might not deserve the same weights. Another example is that the economies of scale in *education* should be weaker than the economies of scale in *household operations*. Thus, I replace the "OECD equivalence scale" used in the main specification with the "OECD-modified scale" and the "squared root" scale respectively.[32] I find that the generation effect in Table A.9 is essentially replicating the main results.

Additional generational segmentation Thirdly, I rely on a additional disaggregated generational segments. In the main specification, I combine the Greatest Generation and the Silent Generation and name them "Builders" and exclude the youngest Generation Z in Section 4.1, therefore dividing households in the sample into four generations. Here, I separate the two oldest two generations like they are originally defined in Table 1.

Besides, I follow Kapferer and Michaut (2019) by dividing Millennials into two subgroups because of the concerns that they might be lacking homogeneity due to a too wide definition. As a result, 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.10 present the results, where Generation X is still taken as the base group. The estimated coefficients on the new generation dummies are consistent with the main results in Table 3: In addition to the direction of the generation effect, the estimators of the two Millenial subgroups are similar. The Greatest Generation does not behave too differently from the Silent Generation either, suggesting that aggregated setting in the main specification is actually reasonable.

An alternative solution to the collinearity problem Lastly, I use an different approach to solve the collinearity problem. I follow the standard normalization of Deaton (1997) who uses the period effect for cyclical fluctuations. Thus, the period effect is restricted to an average of zero over the sample period and is orthogonal to a linear time trend, such that all growth of luxury expenditure is only attributed to age and generation effects. Specifically, I use year dummies instead of the 5-year lagged GDP growth rate proxy, and drop the first two years in the regression.[33] Column (2) and (4) of Table A.10 show the estimated coefficients. The resulting generation effect, albeit quantitatively weaker, still corroborates the earlier findings.

[32]See Section 4.1 and Footnote 21 for details.

[33]The coefficients on the first two year dummies can be recovered from the period effect due to the restrictions on the zero average and orthogonality.

7 Model Flexibility using Machine Learning

In spite of the robust findings, the linear model might be too restrictive as demographic variables are usually highly non-linear and interactive. In this section, I use supervised neural networks as a flexible, non-linear machine learning technique to investigate the effects of age and generation.

7.1 The Benefits of Machine Learning

When interaction terms are added to the model in Eq. (2), the heterogeneous age effect across generations is revealed by the regression results in Figure 9. But are there other interactions? Clearly, a fixed linear model with certain manually defined interaction terms might be far from capturing the true variable relationships. Because demographic characteristics are typically strongly intertwined, such variable relationships could be fairly complicated. To this end, machine learning is liberated from the constraints imposed in the linear model, as non-linearity and interactions are integrated and optimized by design. Machine learning typically works better on big data, so the large sample size in this paper provides the ideal setting for machine learning algorithms to learn even intricate patterns.

However, estimating age and generation effects using machine learning is not straightforward. On one hand, there are no individual coefficients like $\hat{\beta}$ that exactly measure marginal effects, when the model gets complicated. On the other hand, even if coefficients are estimable, machine learning can not guarantee some necessary properties, e.g., unbiasedness and consistency.

Here, I provide a solution to estimate these effects based on the counterfactual predictions in Figure 8. They work as the visual representation of the age and generation effects. Specifically, I derive suitable machine learning models from a standard training process, and conduct predictions using the whole data set. By only manipulating age and generation information while keeping all other variables untouched, the averages of predicted output values pin down the differences between each combination of age and generation.

7.2 Neural Network Training

In this paper, I train standard *fully connected neural networks*, the basic idea of which is briefly introduced in Appendix C.1. The model training and results prediction process is implemented in the `scikit-learn` library in Python.

To start with, the activation function and hyperparameters are selected (see Appendix C.2 for details) to compare different network architectures in the following. The exact structure of the neural network, specifically the number of layers and number of nodes per layer, plays a particularly crucial role in the convergence process and the final prediction performance. Farrell et al. (2021) already summarizes how this issue is discussed in the literature, and find that there are no agreed optimal choices, as the models are data-driven. Therefore, following the normal machine learning procedure of grid search, I check different combinations of the number of layers and nodes to determine the most suitable models.

I randomly split the whole data set in two parts: 70% are used as the training set to optimize model, and the remaining 30% are used as a testing set to validate the model performance.[34] For that, I input data from the testing set into the trained models to get predicted output variables. The predicted results are compared to the real data, and a goodness of fit (R^2) determines the best models. As the model training only utilizes information in training set, the out-of-sample performances on the testing set show how well the trained models generalize and capture the real patterns.

I implement the following steps to search for the best neural network structure: To make the results from neural network comparable to the linear model, the input variables are identical to the independent variables in the preferred model from the OLS regression. The log level and share of luxury expenditure are separately used as outputs. Besides transforming all categorical variables into 0-1 dummies, I use a min-max normalization for the continuous input variables in the training set as

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

As a result, all inputs range from 0 to 1 to even out contributions from variables with different scales in the training process. Likewise, I also normalize the variables in testing set with the scale statistics from the training set, to prevent an information leak from the testing set. I train models with one, two, or three hidden layers, while trying different numbers of nodes from 5 to 200 in steps of 10 to find a rough optimum. Afterwards, this optimum is refined in a second round with smaller steps of 5 around it. For models with more than one layer, the number of nodes per hidden layer is kept identical for simplicity.

Figure 12 shows the performance of all trained models on the testing set during the grid search, by plotting the goodness of fit (R^2) of these predictions from different models. The horizontal lines represent the goodness of fit of the OLS out-of-sample predictions. For that the same procedures including data set splitting, model training, and testing are adopted for comparable results. Intuitively, a very simple neural network with few nodes does not learn complex relationships in the data very well. Using a more complex structure with more weights, the network fits the training data better. However, at some point the trained model moves towards overfitting by learning too complex structures from the training data (essentially corresponding to noise instead of meaningful patterns). This leads to incrementally worse prediction performances on the testing set, when the model fits the training data well but fails to generalize. Figure 12 clearly shows this process: In the beginning, the goodness of fit on the testing set increases with the number of nodes per hidden layer, and then starts to decrease with additional nodes after reaching an optimum. With too many nodes, the neural network even works worse than the simple OLS. The results regarding expenditure share are less stable, but the general trend is still clear. Figure 12(a) also compares the different numbers of hidden layers in the models. As each additional layer accelerates the complexity, models with more hidden layers exhibit this overfitting problem earlier and more strongly.

Overall, the relatively low R^2 for all neural networks means that the fit is far from perfect.

[34] The training process basically estimates weights $\boldsymbol{w}$ and biases $\boldsymbol{b}$ of the model based on a mean squared error loss function as explained in more detail in Appendix C.2).

One reason might be that expenditure as a subjective human behavior can not be predicted accurately by simple demographic and economic variables. Nonetheless, the focus of this paper is not a precise reproduction of the output variables, but the luxury expenditure differences among different generations, even just qualitatively. In this sense, neural networks are able to deliver the desired results with more realistic, flexible interactions between variables.

7.3 Age and Generation Effects from Neural Networks

I consider the goodness of fit shown in Figure 12 to determine the best models with the optimal number of nodes. Note that using the CE data set, neural networks with multiple hidden layers are not substantially better than the simple single-layer network, despite significant additional computation costs. This observation corresponds to the *universal approximation theorem* with bounded number of hidden layers, proved by Hornik et al. (1989), stating that even a neural network with a single hidden layer can be a universal approximator given a sufficient number of nodes. In my case, with a single hidden layer, the optimal number of nodes is 20 for the luxury expenditure level and 40 for the luxury expenditure share as the output variables.

The next step is to derive age and generation effects through prediction of these optimal models based on neural networks. For that, I use counterfactual predictions in similar way as described in Section 5.3. The log level and share of luxury expenditure of generation g at age a is predicted as follows: I use the whole data set and treat all households as generation g aged a, before processing it with the best trained models. Then, the average of the results are stored as counterfactual predictions of level and share of luxury expenditure for this generation g at age a. This procedure is repeated for every generation and age. As a consequence, values of other control variables in the data set equally influence every prediction, meaning only differences due to age and generation remain.

Figure 13 plots the final results predicted using the model with one hidden layer. There is a clear declining trend of luxury expenditure over the 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 start to fluctuate at age 30, but Millennials still consistently have a lower expenditure share. Therefore, the averages of predictions in Figure 13 are essentially not too different from the smoother counterfactual results based on simple linear models. The results from the best trained models with two and three hidden layers are presented in Figure 14 and Figure 15. The general findings also remain consistent here, although the specific predictions slightly vary depending on the different neural network structures. With additional hidden layers, it also becomes more prominent that Millennials have a lower luxury expenditure level than Generation X. For the expenditure share, the difference across generations is stable and consistently monotonic, for every network architecture.

Overall, the predictions from the main results with separable age and generation effects in Figure 8 are already disclosing the general trend, and might be preferable to more complex models due to Occam's razor. Instead of oversimplifying the relationships between variables, a linear regression model seems to be sufficiently intricate to arrive at the same conclusions from the main findings.

8 Discussion

Categories of luxury goods defined by elasticity might not necessarily coincide with the various subjective luxury definitions from individuals. In this section, I compare the luxury categories in this paper to these "classic" luxury definitions using evidence on specific categories from Section 5.5. In addition, I relate my results based on such evidence to the studies of conspicuous consumption in the literature. Finally, I discuss the intuition behind the main findings in this paper.

8.1 Comparison with "Classic" Luxury and Conspicuous Consumption

To start with, I examine how luxury goods defined by elasticity differ from the "classic" luxury goods that are categorized based on intuitive criteria from common sense. Table 7 compares the 13 categories defined in Section 3 to luxury as described by Paulin and Riordon (1998). Based on their personal point of view, they propose to divide the expenditure categories in the CE data into basic goods and services vs. luxury goods (which mainly feature recreation related expenditures). Overlaps do exist to some degree, as *entertainment*, *vehicles*, and *transportation* are considered to be luxury by both classification styles. However, others like *household related expenditures*, *clothing for adults*, *education*, *cash contribution*, and *miscellaneous outlays*, does not counts as luxury without economic measurements. In addition, *food away from home* actually does not pass the elasticity threshold although Paulin and Riordon (1998) count it towards "classic" luxury.

Afterwards, I investigate the effects on economically defined luxury categories that also belong to "classic" luxury. To be specific, I check the generation effect from those categories in Table 4. From every individual category, *entertainment*, *vehicles* and *transportation* are also considered as luxury by Paulin and Riordon (1998). On all three of them, the generation effect holds and indicates less expenditures for Millennials. Thus, my findings based on the luxury categories as classified in Section 3 are representative enough to apply to "classic" luxury. This provides clear evidence against the argument that Millennials are a growth engine of the luxury industry.

Another related concept is conspicuous consumption, first introduced by Veblen (1899). The Veblen effect refers to the observation that people buy visible goods to signal wealth, for example jewelry, cars, etc. Typically, this is achieved through expensiveness, suggesting an upward-sloping demand curve (see, e.g., Leibenstein, 1950; Bagwell and Bernheim, 1996). Empirical research that focuses on conspicuous consumption has a very similar selection of visible goods, either by surveys or simple introspection. For example, the categories from Charles et al. (2009), Heffetz (2011), and Friehe and Mechtel (2014) are shown in the last column of Table 7. The former two also use the CE data, while categories from the latter are based on German income and expenditure samples. From these classifications, it is clear that conspicuous expenditure and luxury are different concepts only sharing few overlapping categories, and neither is a subset of the other.

Results from these overlapping categories (that are luxury and 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*, compared to Whites conditional other controls. As *clothing for adults* and *vehicles* are also luxury goods according to total expenditure elasticity, the race fixed effect in the full regression table Table A.6 confirms this finding.

The main results in Section 5.2 already discussed the positive correlation between luxury expenditure and the education level, which is further confirmed by the results from individual categories (except for *vehicles*) as shown in Table A.6 and Table A.7. This correlation to some extent contradicts the results from Friehe and Mechtel (2014), who find that households with higher education level tend to spend less on visible goods. Based on results from overlapping categories, this contradiction can be explained by the higher education level of new generations.[35] This means, the negative education effect found by Friehe and Mechtel (2014) results from the omission of generation dummies.

8.2 What Do We Learn?

Several theories from both economic and sociological perspectives might explain the main findings. Firstly, Millennials have been facing many obstacles in the current economic environment as introduced in Section 2.2. Compared to preceding generations, Millennials have been benefiting the least and suffering the most in the macro business cycles (see, e.g., Smith, 2012; Gale et al., 2020). This situation is additionally deteriorating because of increasing peer competition (see, e.g., Emmons et al., 2019; Zeihan, 2016). Unsurprisingly, Millennials are struggling with crises like unemployment, financial difficulties, etc. (Halpert, 2012). As a consequence, they have been postponing marriage, housing, and fertility plans, let alone a luxury lifestyle (Danziger, 2015).

Secondly, few luxury purchases of Millennials correspond 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 and critical 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, my results also support some arguments in the literature on older generations. For example, Paulin and Riordon (1998) show that members of Generation X consume less luxury goods and more necessities compared to Baby Boomers. They are more disillusioned and skeptical due to both economic and societal uncertainty during their formative years, opposite to Baby Boomers who stress self-achievement and personal success (Eastman and Liu, 2012).

9 Conclusion

Having grown up in a time of prosperity and materialism, Millennials are stereotyped as a protected and indulged generation with an unprecedented appetite for luxury. However, cross-sectional observations of a high expenditure share on luxuries alone do not necessarily support this view, as they confounds age with generation effects. This paper separately identifies age

[35] *Household furnishings and equipment* and *clothing* are overlapping categories between the luxury definition in this paper and the definition of visible goods from Friehe and Mechtel (2014).

and generation effects on luxury expenditure from a panel of consumption expenditures in the US.

First, I classify 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. Next, a descriptive average expenditure on luxury over the life cycle and across time is shown. Following that, I extend the methodology of decomposing age, generation, and period effects to luxury expenditure, and also account for heterogeneous effects via interaction terms. To further strengthen the results, I use neural networks as a state-of-the-art machine learning technique, to derive more flexible, non-linear models. Finally, I compare the results with related topics of conspicuous consumption and "classic" luxury as subjectively defined in the literature, and discuss the general intuition behind the main findings.

The linear regression results show a decreasing trend of luxury expenditure over the life cycle for all generations, while the generation effect works oppositely: younger generations tend to consume less luxury than 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 remain robust to alternative model specifications and adjustment of controls. Moreover, the models trained from neural networks exhibit the same patterns across generations and over the life cycle. Therefore, Millennials are conveying attitudes of abstinence, consciousness, and rationality, instead of acting as an indulged generation. Their substantial expenditure power on luxury is actually the result of a strongly predominating age effect.

This distinct finding refreshes the conventional point of view, and provides novel challenges to luxury 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 a potential crisis in this industry, especially as they age. Therefore, comprehending more unbiased information from surface phenomena is essential for better strategies in the future, and more efforts are needed to conduct deeper market research on long-run demographics.

As for future research direction, it would be interesting to investigate data from other countries, to see if this is an international phenomenon. Furthermore, collecting panel data specifically in the luxury market might provide additional insights on the luxury expenditure of different generations.

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Figures and Tables

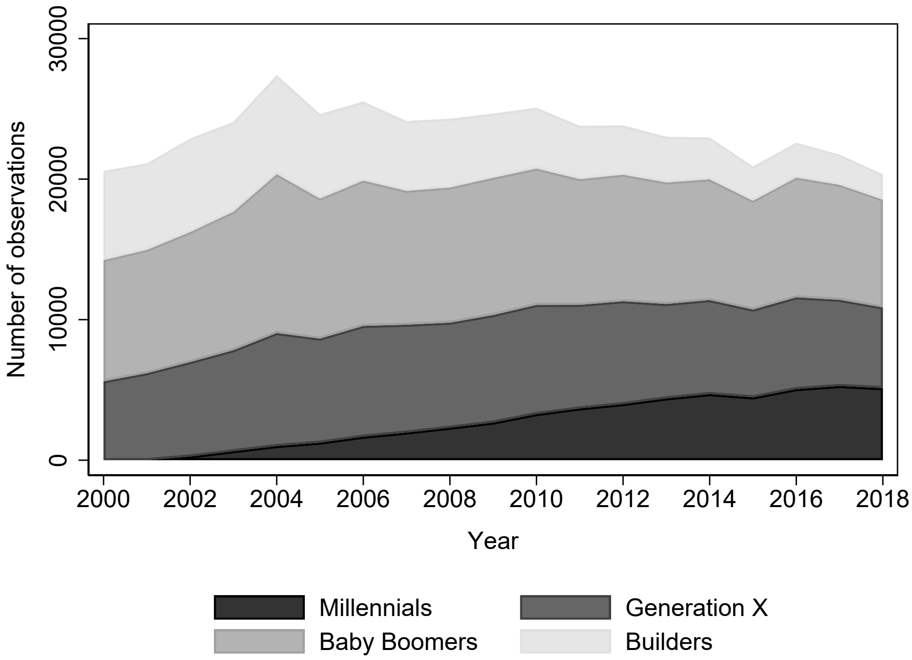


Figure 1: *The Size of Each Generation 2000–2018*

Notes: This figure reports the size of each generation across time in the refined sample (including 443497 observations) for the descriptives and regression analysis. 1906 is the earliest birth year of Builders in the refined sample, and this is different from the earliest birth year of the Greatest Generation 1902 defined in Table 1, The age range of each generation in the sample is: Millennials (21–37), Generation X (21–53), Baby Boomers (36–72), and Builders (55–80). The number of observations of each generation in the sample is: Millennials (51797), Generation X (132364), Baby Boomers (174083), and Builders (85253)

Sources: Consumer Expenditure Survey (CE) 2000–2018

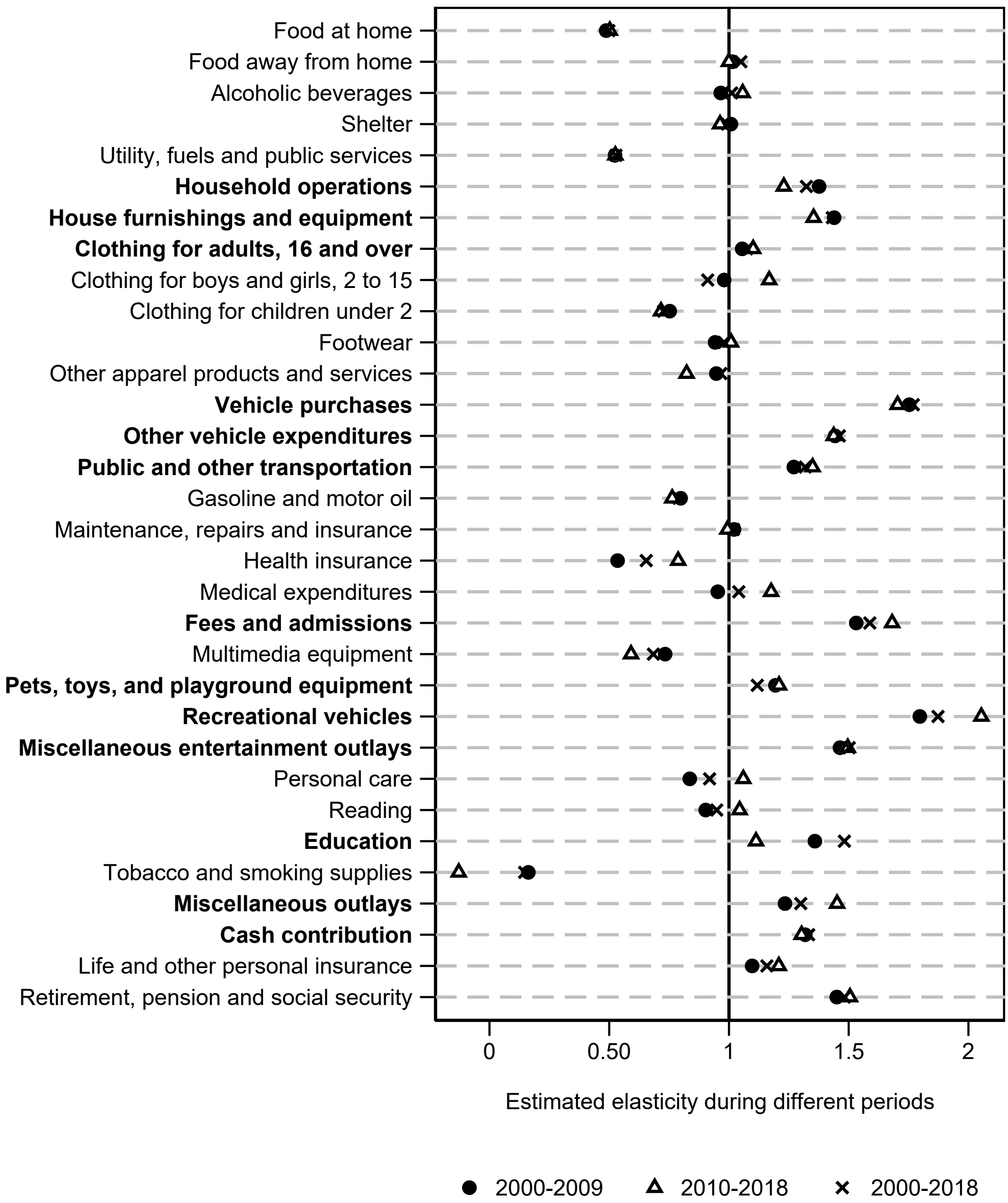
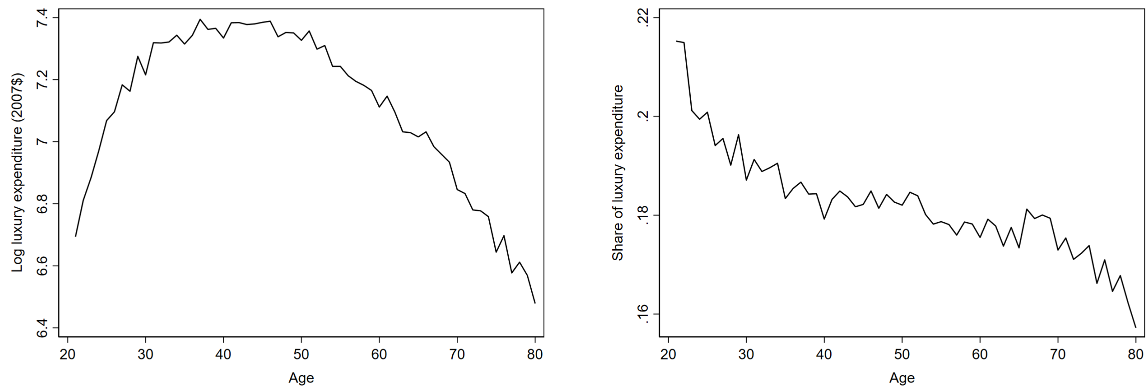


Figure 2: *Total Expenditure Elasticity*

Notes: This figure reports the estimated total expenditure elasticity of the 32 categories listed in the left column of Table A.2.The same estimation procedure is conducted using data from different time periods to keep the results consistent and stable. The 13 resulting luxury categories are the boldfaced.

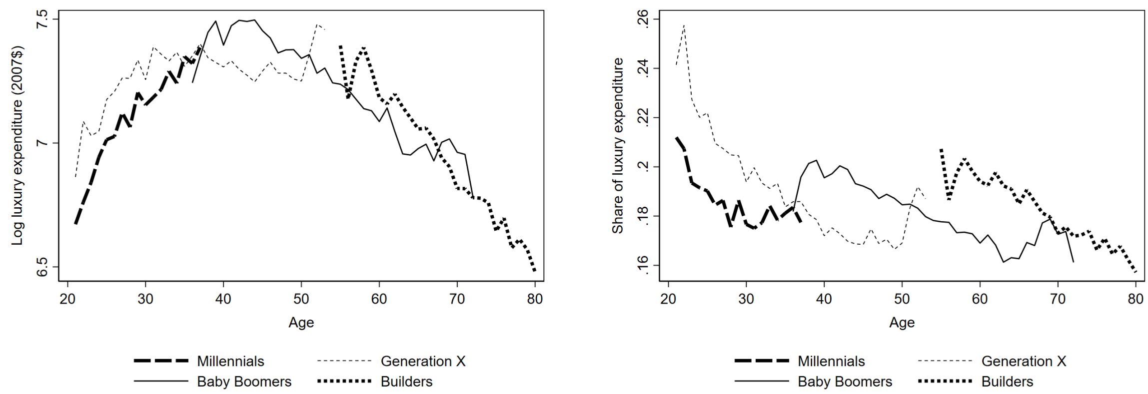


(a) Log Level **(b)** Share

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 the Consumer Expenditure Survey (CE) 2000–2018

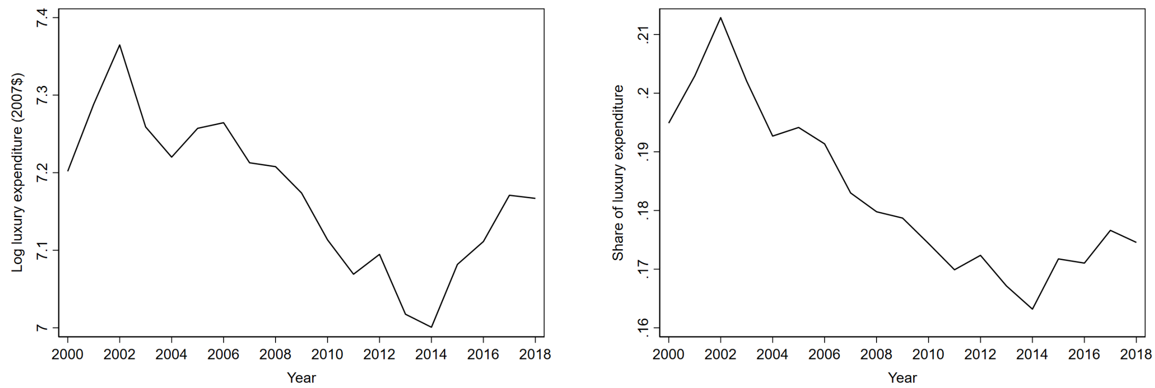


(a) Log Level **(b)** Share

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 the Consumer Expenditure Survey (CE) 2000–2018

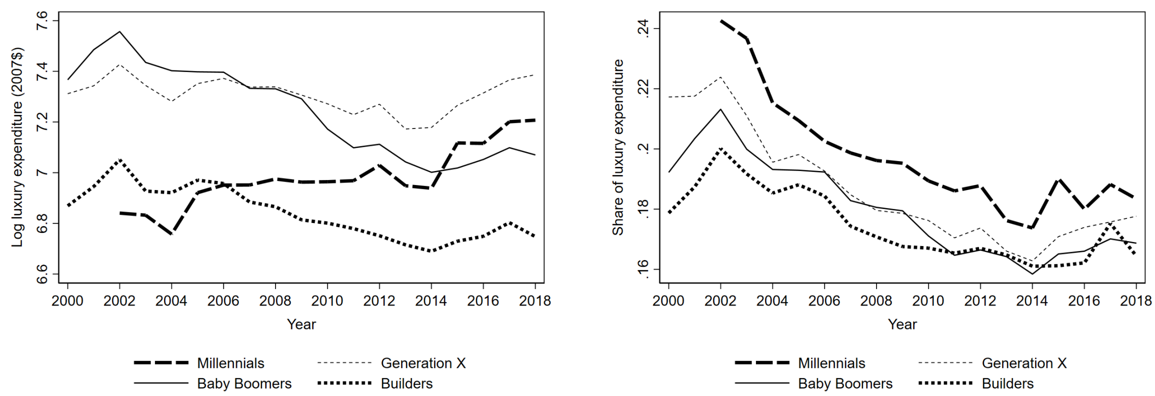


(a) Log Level **(b)** Share

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 the Consumer Expenditure Survey (CE) 2000–2018

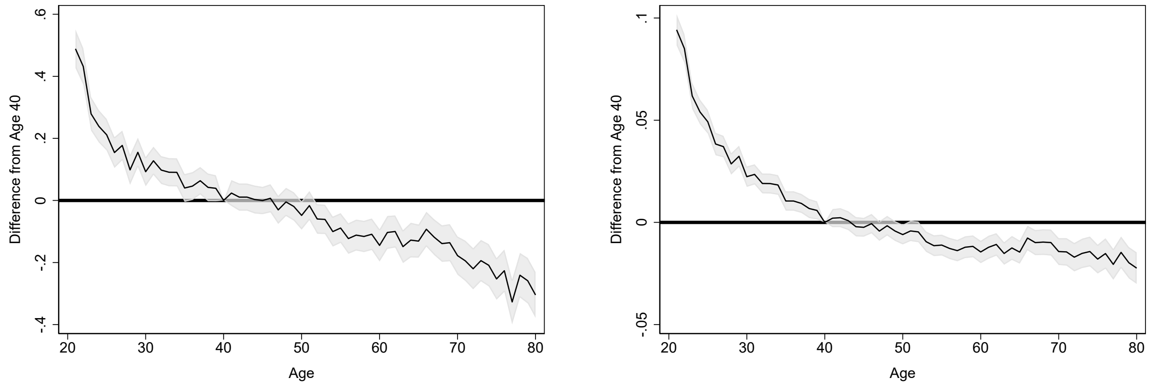


(a) Log Level **(b)** Share

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.

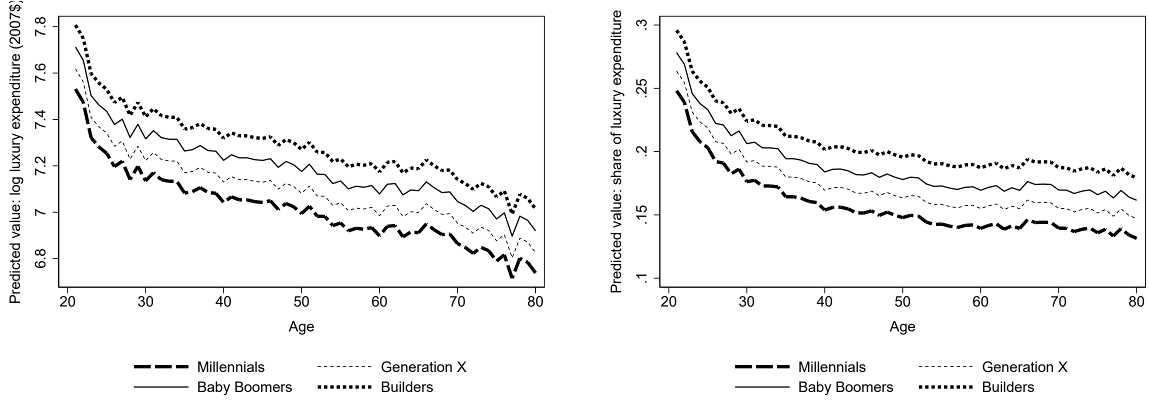
Sources: Own calculations based on the Consumer Expenditure Survey (CE) 2000–2018



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

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

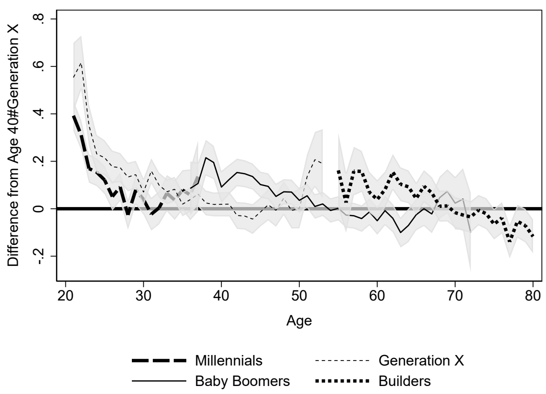
Notes: Both figures show the estimated coefficients on age dummies from Column (3) and (6) in Table 3, including 95% confidence intervals, with Figure 7(a) showing the effect on the log level of luxury expenditure, and Figure 7(b) showing the effect on the share of luxury expenditure. Coefficients are relative to the reference age 40, which is marked as horizontal zero lines.



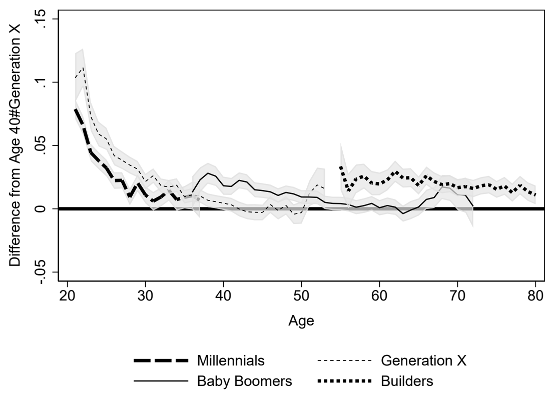
(a) Log Level **(b)** Share

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 (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.



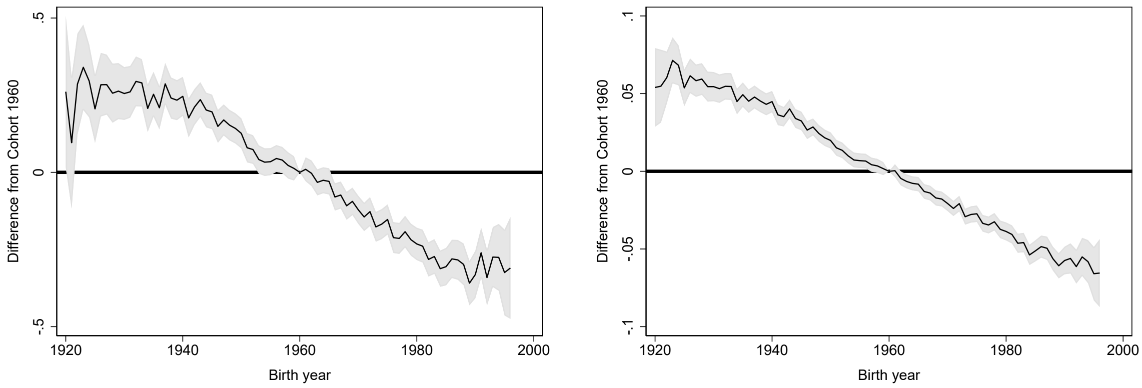
(a) Log Level



(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 Eq. (2), including 95% confidence intervals, with Figure 9(a) showing the effect on the log level of luxury expenditure, and Figure 9(b) showing the effect on the share of luxury expenditure. Coefficients are relative to 40-year-old Generation X, which is marked as the horizontal zero line.

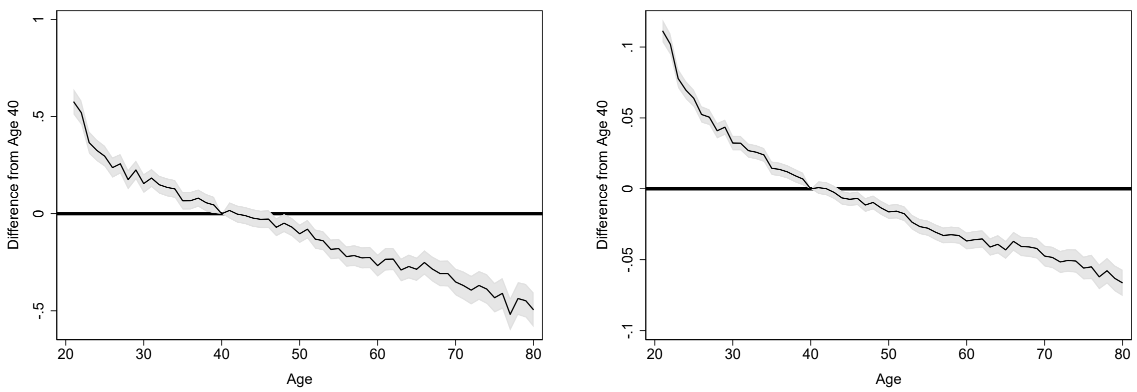


(a) Log Level

(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 the log level of luxury expenditure, and Figure 10(b) showing the effect on the share of luxury expenditure. Each cohort is defined by the specific birth year, and coefficients are relative to the reference cohort 1960, which is marked as the horizontal zero line.

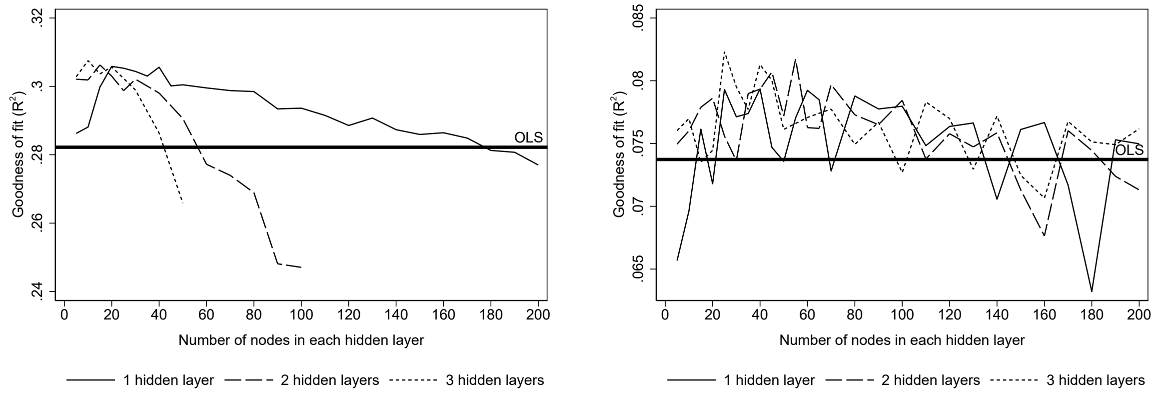


(a) Log Level

(b) Share

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

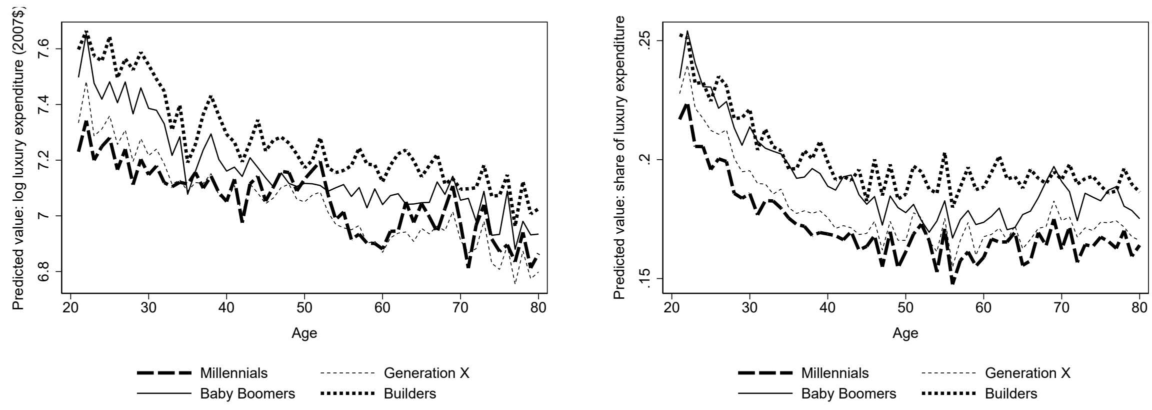
Notes: Both figures show the estimated coefficients on age dummies, including 95% confidence intervals, with Figure 11(a) showing the effect on the log level of luxury expenditure, and Figure 11(b) showing the effect on the share of luxury expenditure. Coefficients are relative to the reference age 40,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



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

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

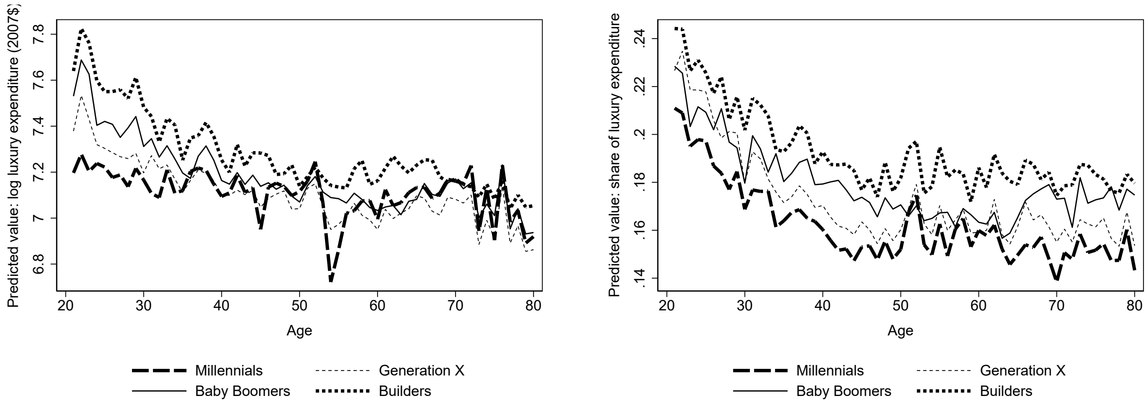
Notes: Both figures plot the goodness of fit of predictions (R^2) on the testing set, with Figure 12(a) showing the results of the log level of luxury expenditure, and Figure 12(b) showing the results of the share of luxury expenditure. Models of different structures (with a different numbers of layers and nodes) are trained using data from the training set. The goodness of fit of the OLS regression is calculated in the same way as the neural network predictions, and 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 number of nodes in the hidden layer are 20 for the log level of luxury expenditure and 40 for the share of luxury expenditure as the output variables.

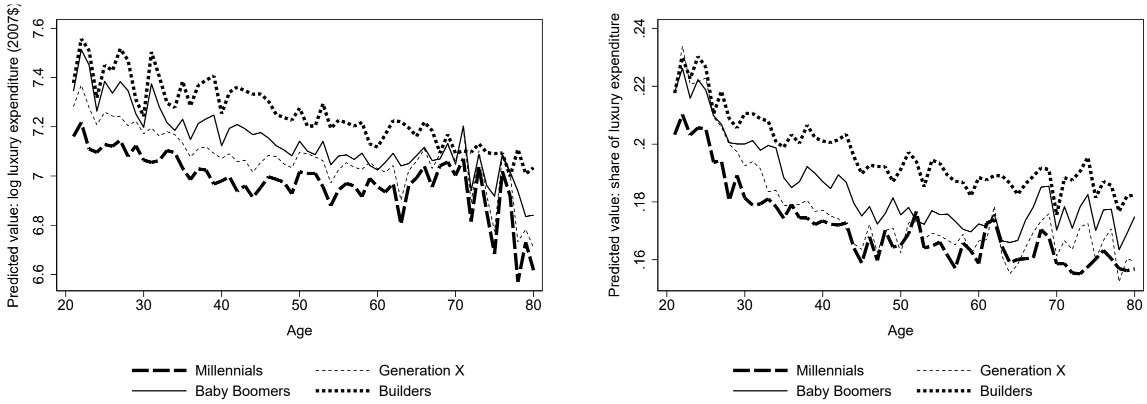


(a) Log Level

(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 number of nodes in all hidden layers are 15 for the log level of luxury expenditure and 55 for the share of luxury expenditure as the output variables.



(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 number of nodes in all hidden layers are 10 for the log level of luxury expenditure and 15 for the share of luxury expenditure as the output variables.

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	2591.56	3425.37	0	42948.56
Millennials	51797	2126.42	2812.12	0	39564.71
Generation X	132364	2727.53	3214.43	0	40640.74
Baby Boomers	174083	2825.22	3653.39	0	40824.00
Builders	85253	2185.93	3535.53	0	42948.56
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	56637.61	45088.50	831.48	310994.20
Total expenditure	443497	11615.09	7624.98	1501.62	51922.45
Millennials	51797	9564.92	5807.89	1507.52	51754.86
Generation X	132364	12426.74	7430.92	1511.90	51827.42
Baby Boomers	174083	12699.76	8205.20	1501.62	51922.45
Builders	85253	9385.70	6914.06	1517.80	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: This table reports summary statistics of the refined sample (including 443497 observations) for the descriptives 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 the 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)
Millennials	0.0545***	-0.0735***	-0.0872***	0.0180***	-0.0139***	-0.0156***
	(0.0087)	(0.0110)	(0.0109)	(0.0010)	(0.0013)	(0.0012)
Baby Boomers	-0.0533***	0.0780***	0.0939***	-0.0054***	0.0136***	0.0145***
	(0.0062)	(0.0099)	(0.0098)	(0.0007)	(0.0011)	(0.0011)
Builders	-0.1019***	0.1350***	0.1887***	0.0044***	0.0286***	0.0322***
	(0.0083)	(0.0167)	(0.0164)	(0.0009)	(0.0018)	(0.0018)
Period	0.0292***	0.0177***	0.0198***	0.0050***	0.0033***	0.0033***
	(0.0015)	(0.0016)	(0.0016)	(0.0002)	(0.0002)	(0.0002)
ln(Income)	0.8016***	0.8066***	0.6409***	0.0331***	0.0352***	0.0273***
	(0.0035)	(0.0037)	(0.0042)	(0.0003)	(0.0003)	(0.0004)
Household scale (equivalence)			0.0568***			-0.0031***
			(0.0058)			(0.0006)
Number of adults			-0.0177***			-0.0025***
			(0.0055)			(0.0006)
Male			-0.0182***			-0.0014**
			(0.0054)			(0.0006)
Married			0.2594***			0.0149***
			(0.0067)			(0.0007)
Below 9th grade			-0.4844***			-0.0318***
			(0.0148)			(0.0014)
High school, no diploma			-0.3767***			-0.0281***
			(0.0114)			(0.0010)
College graduate			0.2415***			0.0162***
			(0.0062)			(0.0007)
Masters degree and above			0.4004***			0.0286***
			(0.0085)			(0.0010)
Black			-0.1588***			-0.0118***
			(0.0090)			(0.0009)
Native American			-0.0980***			0.0013
			(0.0360)			(0.0036)
Asian or Pacific Islander			-0.2095***			-0.0145***
			(0.0128)			(0.0014)
Other races			0.0280			0.0035
			(0.0232)			(0.0026)
Urban			-0.0256*			-0.0031*
			(0.0145)			(0.0016)
Metropolitan statistical area			0.0517***			-0.0104***
			(0.0114)			(0.0012)
Age		✓	✓		✓	✓
Region			✓			✓
Quarter			✓			✓
Observations	426498	426498	422145	443249	443249	438658
R^2	0.2499	0.2521	0.2854	0.0456	0.0529	0.0721

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. While related work that uses short-term data usually reports standard errors at state level, for the reasons mentioned in Footnote 24, I cluster standard errors at household level. Generation X is taken as the base group among generation dummies. Period stands for the 5-year lagged GDP growth rate as the proxy for the 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 the 5-year lagged GDP growth rate as the proxy for the 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 the 5-year lagged GDP growth rate as the 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 the log or the share of luxury expenditure defined by each generation according to the estimated total expenditure elasticity using the 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

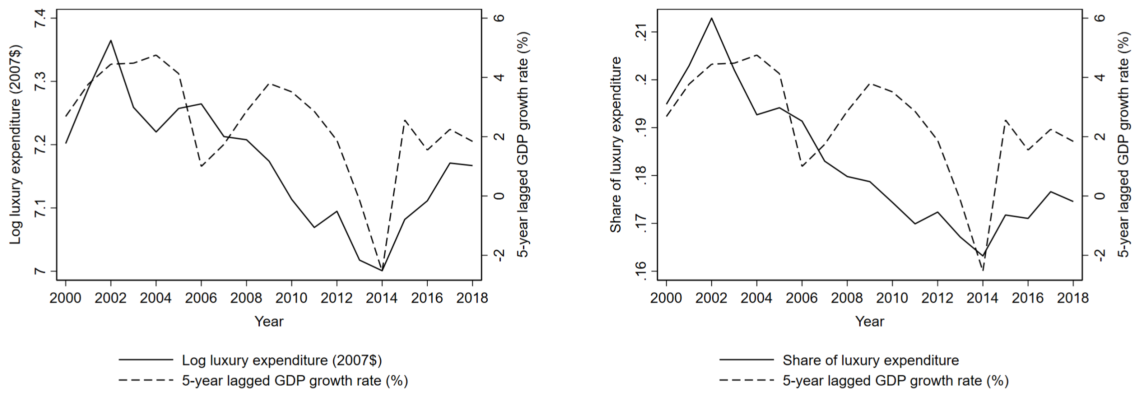
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. Generation X is taken as the base group among generation dummies. Period stands for the 5-year lagged GDP growth rate as the proxy for period effect. Luxury expenditure is quarterly-based, 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 elasticity measurement in this paper, categories that are arbitrarily considered as luxury based on common sense, or "classic" luxury, and visible goods defined in the literature based on Veblen (1899)'s conspicuous consumption theory. Heffetz (2011) develops the 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 social groups such as colleagues and friends.

A Additional Figures and Tables



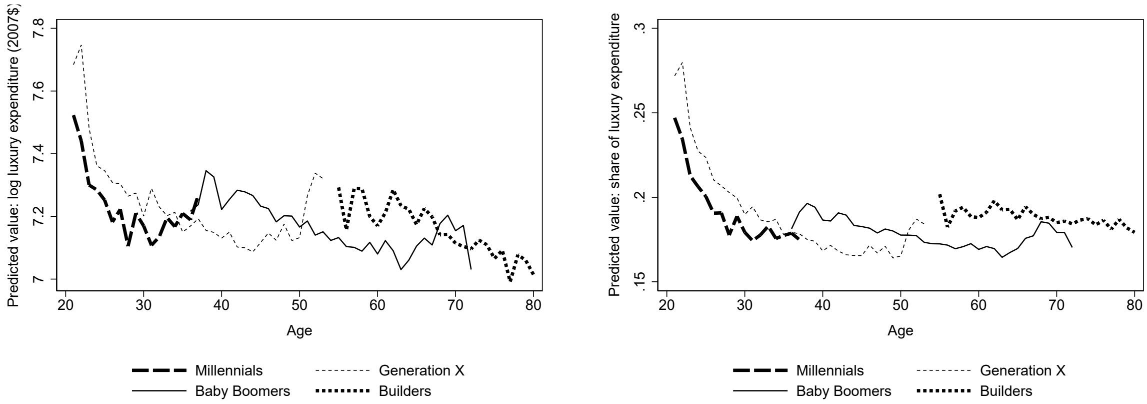
(a) Log Level

(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

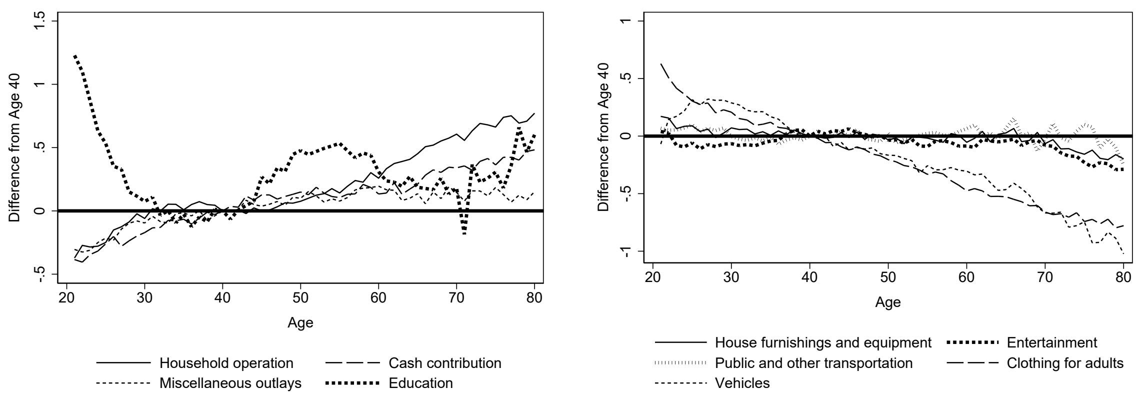


(a) Log Level

(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 Eq. (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 Eq. (1), with log level of expenditure of different luxury categories being dependent variables. Coefficients are relative to the reference age 40, which is marked as the horizontal zero line.

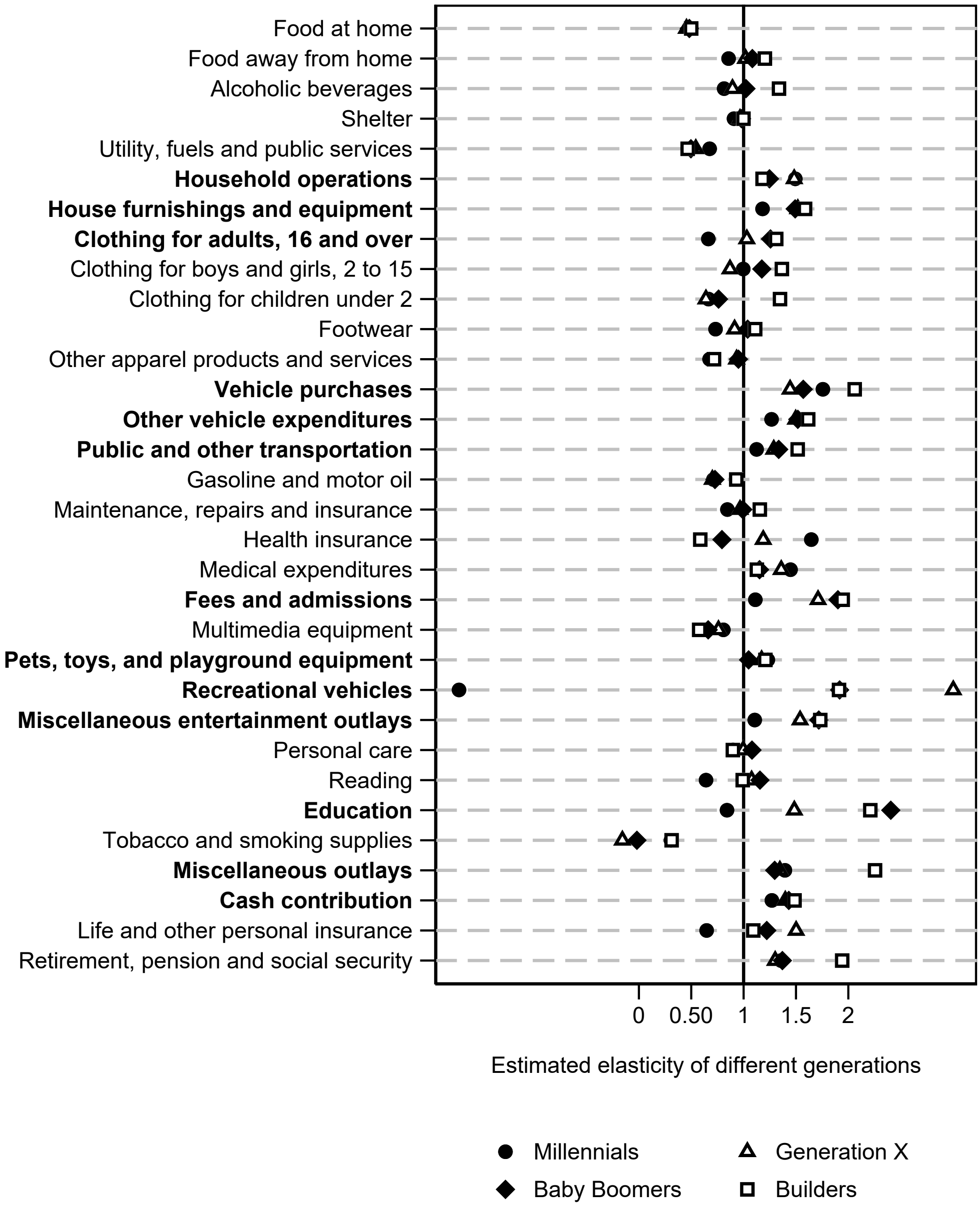
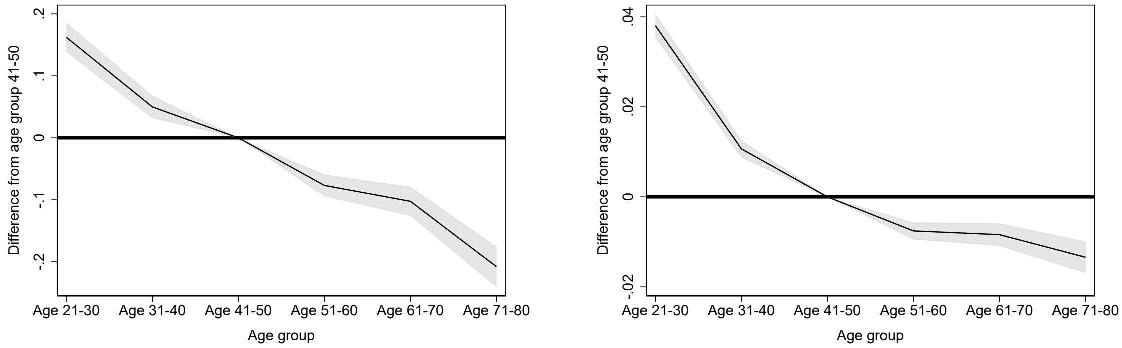


Figure A.4: *Generation Specific Total Expenditure Elasticity*

Notes: The figure reports how different generations classify the 32 expenditure categories into luxury and necessity, and the 13 categories that are classified as luxury by the overall sample households in the main specification are boldfaced. Estimations are only conduct for the whole sample period 2000–2018 using the 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.

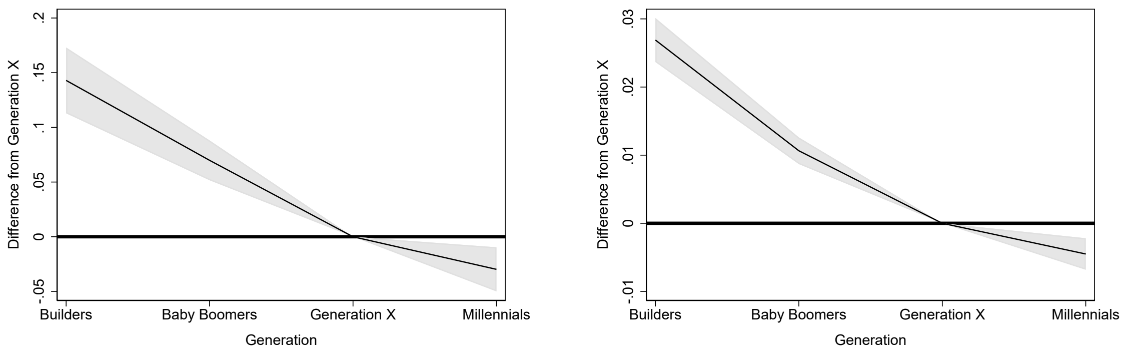


(a) Log Level

(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 the 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 the log level of luxury expenditure, and Figure A.6(b) showing the effect on the share of luxury expenditure. Coefficients are relative to the 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: This table shows the 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, fuels and public services*, *household operations* and *house furnishings and equipment* are all included in a single categories called *total housing outlays*, but this is too broadly defined and the heterogeneity among individual categories might already be averaged out.

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: This 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	232.73	579.21	0	39293.45
Millennials	51797	243.29	567.15	0	10180.17
Generation X	132364	305.48	712.84	0	39293.45
Baby Boomers	174083	201.32	469.27	0	20442.57
Builders	85253	177.51	545.76	0	37978.33
House furnishings and equipment	443497	310.80	851.51	0	29116.52
Millennials	51797	261.33	692.49	0	18711.30
Generation X	132364	328.24	883.15	0	29116.52
Baby Boomers	174083	335.15	901.93	0	26335.61
Builders	85253	264.05	776.63	0	25726.84
Clothing for adults	443497	136.00	281.98	0	18798.15
Millennials	51797	103.30	222.01	0	6597.87
Generation X	132364	137,28	282.55	0	18798.15
Baby Boomers	174083	153,30	304.77	0	9576.67
Builders	85253	118.54	261.72	0	7847.08
Vehicles	443497	801.39	2012.88	0	40613.03
Millennials	51797	683.25	1646.73	0	33299.80
Generation X	132364	883.10	1819.60	0	39352.65
Baby Boomers	174083	858.48	2086.31	0	39000.00
Builders	85253	629.70	2312.23	0	40613.03
Public and other transportation	443497	124.32	496.07	0	29514.80
Millennials	51797	105.70	361.05	0	13787.20
Generation X	132364	122.50	453.96	0	13628.00
Baby Boomers	174083	133.02	516.78	0	29514.80
Builders	85253	120.67	579.07	0	21970.34
Entertainment	443497	319.14	771.35	0	34256.47
Millennials	51797	239.29	573.52	0	24470.13
Generation X	132364	355.46	769.07	0	27068.18
Baby Boomers	174083	349.01	808.57	0	34256.47
Builders	85253	250.27	793.43	0	31798.92
Education	443497	190.24	1068.50	0	41309.55
Millennials	51797	255.90	1378.33	0	39508.71
Generation X	132364	185.99	973.31	0	37156.30
Baby Boomers	174083	242.39	1206.45	0	38054.10
Builders	85253	50.46	560.63	0	41309.55
Cash contribution	443497	342.59	997.87	0	38335.28
Millennials	51797	172.10	621.42	0	30064.79
Generation X	132364	292.54	824.10	0	36304.79
Baby Boomers	174083	395.48	1063.70	0	37000.00
Builders	85253	415.87	1244.18	0	38335.28
Miscellaneous outlays	443497	134.37	669.22	0	38520.80
Millennials	51797	62.26	379.72	0	27092.93
Generation X	132364	116.95	579.66	0	34992.56
Baby Boomers	174083	157.08	728.84	0	38520.80
Builders	85253	158.85	794.05	0	28930.38

Notes: This table reports summary statistics of the expenditure on the 9 individual luxury categories. See Section 5.5 for the detailed information on the disaggregation of 13 original luxury categories. All expenditure data are quarterly-based.

Table A.5: *Main Results: Frequency Weights and State Fixed Effect*

	Log luxury expenditure		Share of luxury expenditure	
	Frequency weights	State fixed effect	Frequency weights	State fixed effect
	(1)	(2)	(3)	(4)
Millennials	-0.0796***	-0.0823***	-0.0143***	-0.0148***
	(0.0110)	(0.0114)	(0.0012)	(0.0013)
Baby Boomers	0.0895***	0.0955***	0.0142***	0.0150***
	(0.0100)	(0.0102)	(0.0011)	(0.0011)
Builders	0.1926***	0.2044***	0.0327***	0.0353***
	(0.0167)	(0.0173)	(0.0018)	(0.0019)
Period	0.0197***	0.0181***	0.0033***	0.0032***
	(0.0017)	(0.0017)	(0.0002)	(0.0002)
ln(Income)	0.6108***	0.6453***	0.0245***	0.0280***
	(0.0046)	(0.0045)	(0.0005)	(0.0004)
Household scale (equivalence)	0.0544***	0.0513***	-0.0023***	-0.0038***
	(0.0064)	(0.0062)	(0.0007)	(0.0006)
Number of adults	-0.0236***	-0.0098*	-0.0050***	-0.0015**
	(0.0061)	(0.0058)	(0.0006)	(0.0006)
Male	-0.0133**	-0.0262***	-0.0015**	-0.0025***
	(0.0058)	(0.0057)	(0.0007)	(0.0006)
Married	0.2707***	0.2488***	0.0173***	0.0134***
	(0.0072)	(0.0071)	(0.0008)	(0.0007)
Below 9th grade	-0.5010***	-0.4914***	-0.0343***	-0.0316***
	(0.0159)	(0.0162)	(0.0015)	(0.0015)
High school, diploma	-0.3945***	-0.3738***	-0.0308***	-0.0274***
	(0.0122)	(0.0122)	(0.0011)	(0.0011)
College graduate	0.2470***	0.2363***	0.0170***	0.0157***
	(0.0068)	(0.0065)	(0.0008)	(0.0007)
Masters degree and above	0.4018***	0.3948***	0.0291***	0.0283***
	(0.0092)	(0.0089)	(0.0011)	(0.0010)
Black	-0.1571***	-0.1418***	-0.0124***	-0.0088***
	(0.0097)	(0.0094)	(0.0010)	(0.0009)
Native American	-0.0897**	-0.1250***	0.0009	-0.0053
	(0.0385)	(0.0395)	(0.0043)	(0.0039)
Asian or Pacific Islander	-0.1896***	-0.1683***	-0.0113***	-0.0086***
	(0.0141)	(0.0134)	(0.0016)	(0.0015)
Other races	0.0367	0.0386	0.0041	0.0060**
	(0.0263)	(0.0243)	(0.0030)	(0.0027)
Urban	-0.0115	0.0400	-0.0009	-0.0005
	(0.0156)	(0.0443)	(0.0018)	(0.0048)
Metropolitan statistical area	0.0410***	0.0233	-0.0122***	-0.0099***
	(0.0123)	(0.0353)	(0.0014)	(0.0038)
Age	✓	✓	✓	✓
Region	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
State		✓		✓
Observations	1376799	373198	1432292	387495
R^2	0.2692	0.2926	0.0653	0.0832

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (in parentheses) are clustered at household level. The frequency weight of each generation is calculated based on the size of each generation in the sample, which is shown in Figure 1: Millennials (51797), Generation X (132364), Baby Boomers (174083), and Builders (85253). So the frequency weight given to each generation is: Millennials (7), Generation X (3), Baby Boomers (2), and Builders (4). Generation X is taken as the base group among generation dummies. Period stands for the 5-year lagged GDP growth rate as the proxy for the 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 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 the 5-year lagged GDP growth rate as the proxy for the 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: *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 the 5-year lagged GDP growth rate as the proxy for the 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.8: *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 the 5-year lagged GDP growth rate as the proxy for the period effect. Expenditure data are 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. In the first stages, the dependent variable is ln(total expenditure).

Table A.9: *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 the 5-year lagged GDP growth rate as the proxy for the 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 household scale (modified) represents for "OECD-modified scale". The household scale (square root) represents for "square root scale". See Section 4.1 and Footnote 21 for details.

Table A.10: *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 the 5-year lagged GDP growth rate as the proxy for the 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.

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

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.

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

includes the interaction terms between generation and age dummies $\boldsymbol{\beta_{ga} D^g_i} \boldsymbol{\cdot} \boldsymbol{D^a_{it}}$. 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 the 5-year lagged GDP growth rate as the proxy for the 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

As one of the currently most popular machine learning methods, neural networks are employed in this paper to study information patters in the data. They are approximate mathematical models of biological processes in the brain and date back to the 1940s. Until recently, neural networks only had low impact because of limited computing power, lacking scalable optimization techniques, and small, unstructured data sets. Benefiting from theoretical and empirical breakthroughs in these areas in the 2000s and 2010s, neural network are now the state of the art technique in the machine learning community (Zhang et al., 2018; Farrell et al., 2021).

C.1 Fully Connected Neural Network

Figure C.1 below shows an example of a *fully connected neural network*. It starts with an input

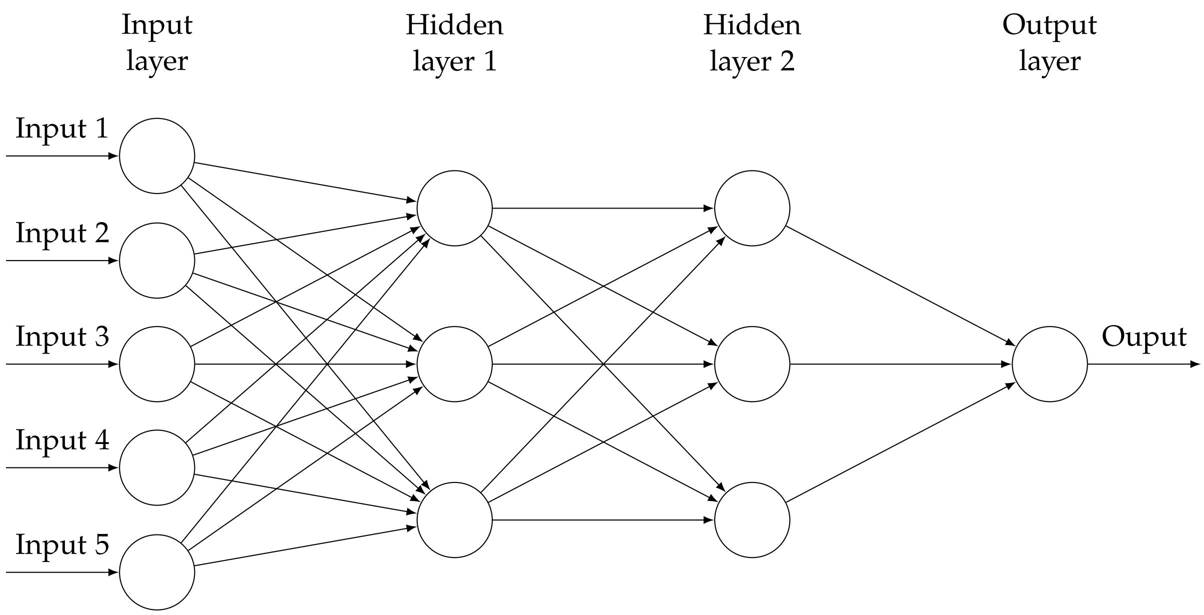


Figure C.1: *Illustration of a Full Connected Neural Network*

layer, that contains independent variables $\boldsymbol{X}$, and ends up with an output, the dependent variable Y. Input and output layers are connected through hidden layers, each of which consists of several hidden nodes or 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 respectively. Then, $Z_k^{(1)}$ experiences a transformation through a non-linear activation function $f(.)$. With only a 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 to the following layer, and this is iteratively repeated until the last layer of the network.

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 (ReLU),

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

introduced by Nair and Hinton (2010), is taken as the activation function $f(\cdot)$ for 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.