Experience Effects in Consumption*

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Abstract

This paper studies whether individual consumption patterns can be traced to prior lifetime experiences of macroeconomic conditions. Does the extended experience of economic downturn induce more cautious consumption, even when times have become better? Does the extended exposure to prosperous times have the opposite effect? Using detailed micro-data from the Nielsen Homescan Panel, Consumer Expenditure Survey (CEX), and Panel Study of Income Dynamics (PSID) on household purchases, we find that households who have witnessed times of higher unemployment rates spend significantly less, after controlling for income and demographics. They also are more likely to use coupons and allocate expenditure toward on-sale items, generic store brand items, and lower-end products. The effects are stronger for cohorts with shorter lifetime histories. That is, the young lower their consumption expenditure to significantly more than older cohorts during economic busts, and vice-versa during booms. Our results point to a novel link between consumption, life-cycle and the state of the economy — individuals' past experiences have a lasting effect on consumption behavior and give rise to heterogeneity in consumption behavior across cohorts, both in the cross section and over time. Furthermore, our findings suggest experience effects in consumption could constitute a novel source of micro-foundation underlying fluctuations in aggregate demand and long-run effects of macroeconomic shocks.

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1 Introduction

The crisis has left deep scars, which will affect both supply and demand for many years to come. — Blanchard (2012)

What are the long-run implications of financial crises and macroeconomic shocks? Textbook theory in macroeconomics contends that economic shocks give rise only to temporary deviations from the trend but do not affect potential output permanently. Some economists have called this theory into question. Cerra and Saxena (2008), Reinhart and Rogoff (2009), and Ball (2014), for example, provide evidence that crises have highly persistent effects on unemployment and aggregate output; Blanchard and Summers (1986) and Delong and Summers (2012) point to the loss of worker skills and reduction of capital stocks, due to reduced private investment during recessions, leaving long-term scars or what they term "hysteresis effects." Since the Great Recession in particular, economists are debating whether the U.S. and other developed economies may be suffering from "secular stagnation," a condition characterized by a prolonged period of slow economic growth.[1]

Research on the existence and extent of the long-term effects of economic shocks is still thin and starting to emerge only recently. Haltmaier (2012) and Reifschneider, Wascher, and Wilcox (2013) suggest that such effects occur because a recession damages an economy's labor force and productivity, thereby reducing its potential output. In this paper, we turn to micro-level evidence to examine the question of long-term effects of macro fluctuations and generate insights on potential granular sources of aggregate fluctuations. Specifically, we ask whether individual lifetime experiences of macroeconomic shocks have a lasting effect on consumption behavior. A growing literature in macro-finance has documented that personal exposure to macro risk variables, such as stock market performance, bond market returns, and inflation, has a lasting effect on individual expectations and willingness to take risk in

[1] The term "hysteresis effects" was first raised in Blanchard and Summers (1986) to characterize protracted period of high and rising unemployment in Europe, while "secular stagnation" was first raised in Hansen (1939) who conjectured a protracted period of low growth following the Great Depression. Both terms have been used in a number of recent works such as Delong and Summers (2012), Summers (2014a), and Summers (2014b) to describe potential scarring effects of the Great Recession.

these markets. Building on the psychological underpinnings of availability and recency bias (Kahneman and Tversky (1974) and Tversky and Kahneman (1974)), this evidence suggests that it is important to distinguish learning versus knowledge in the micro-modeling of human behavior, or consumption in the context of this paper. While standard models assume that individuals are endowed with stable preferences and incorporate all historical data when forming beliefs, evidence on learning from experience shows that data experienced during individuals' lifetimes exert excess influence in the formation of beliefs.

We conjecture that individuals who have lived through difficult economic times spend less and exhibit more expenditure switching in response to a downturn, entailing for example more usage of coupons and purchases of on-sale and lower quality items. The opposite holds for positive economic experiences during one's lifetime so far. Moreover, the idea of experience effects in consumption carries a key implication: consumption behavior is heterogeneous across cohorts, in general and in response to shocks in particular. Cohorts that have experienced substantial periods of bad economic environments exhibit lower consumption expenditure than those who have lived through mostly good times, controlling for income and other household characteristics. Moreover, younger cohorts would react more strongly to a given a macroeconomic shock than older cohorts since the shock makes up a larger fraction of their overall life histories so far.

Take the recent Great Recession as an example. Here, we conjecture that younger cohorts exhibited greater downward adjustments in their consumption spending. To illustrate this, Figure 1 plots the time-series of household consumption expenditure from the Nielsen Homescan Panel, our main data source, separately for young (below 40), mid-aged (between 40 and 60), and old individuals (above 60), and expressed as deviations from the cross-sectional mean expenditure. The plot shows that, in general, the consumption expenditure of the young is more volatile, consistent with exhibiting greater sensitivity to various shocks. Zooming in on the Great Recession period, their spending pattern was significantly more negatively affected than those of the other age groups.

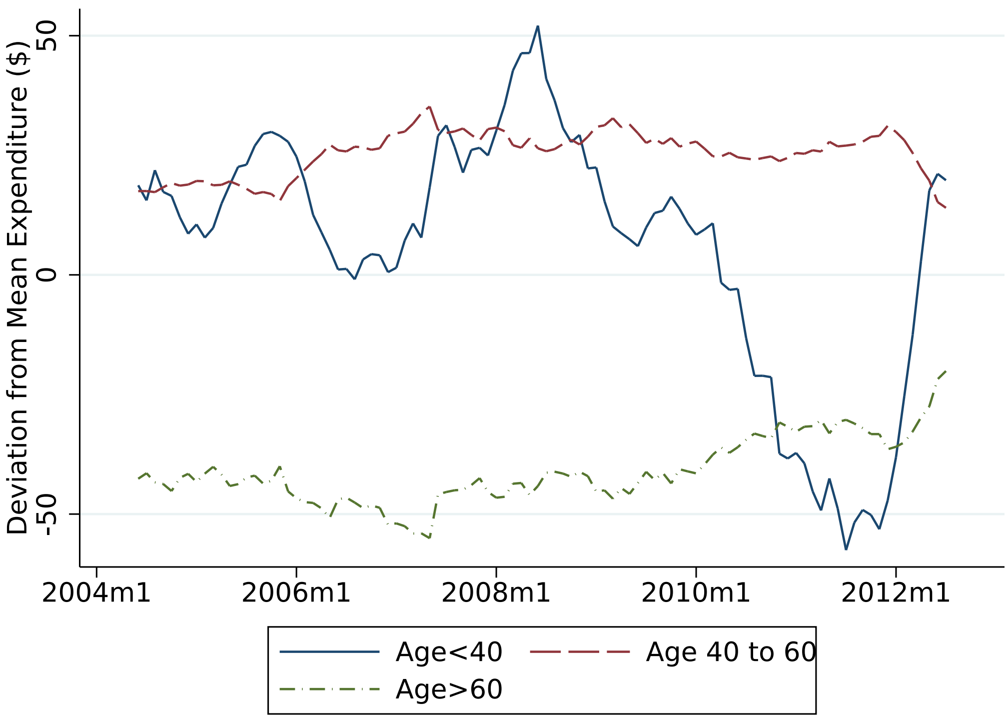

Figure 1: Six-month moving averages of monthly consumption expenditure of the young (below 40), mid-aged (between 40 and 60), and old individuals (above 60), expressed as deviations from the cross-sectional mean expenditure of all individuals. Expenditure deflated by personal consumption expenditure (PCE) price index from the U.S. Bureau of Economic Analysis (BEA). Observations are weighted with Nielsen sample weights. Source: Nielsen Homescan Panel.

To formally test the hypothesis that individuals who have lived through different macroeconomic conditions exhibit different consumption behavior, we use (and combine) several sources of data. Our main source of data is the Nielsen Homescan Data, a detailed panel dataset on purchases made by representative households in all U.S. markets over the period 2004-2012. We test whether households who have lived through worse economic times spend less on average and exhibit more expenditure switching to less expensive goods. To capture both the quantitative and qualitative margins of household purchases, we construct five monthly measures of household consumption: i) total consumption expenditure, ii) use of coupon, iii) purchase of generic store brand items, iv) a ranking of purchased products, where the ranking is constructed based on unit price of goods (in specific product modules, markets and month), where lower value represents lower-priced goods, and v) purchase of on-sale products.

We proxy for the exposure to rougher (or milder) economic times using the rate of unemployment that have occurred in an individual's lifetime so far. To construct a weighted measure of lifetime unemployment experience for each head of household, we apply the weighting scheme estimated in previous work (see Malmendier and Nagel (2011) and Malmendier and Nagel (2013)), which is roughly linearly declining. As such it simultaneously accounts for all experiences accumulated during an individual's lifetime, relative to earlier historical data, and allows for experience effects to decay over time, as memory may fade or as the individual becomes convinced that structural change renders early experiences less relevant.

All of our estimations control for age, income, labor market status, household demographics, and time fixed effects. The inclusion of age effects is important as it differentiates experience effects from the link between consumption and age through life-cycle effects, such as increasing precautionary motives and risk aversion with age, as analyzed in the existing consumption literature(e.g., Caballero (1990), Carroll (1994)) or declining income and liquidity constraints during retirement (e.g., Deaton (1991), Gourinchas and Parker (2002)). The controls for labor market status and demographics take into account the effect of these factors on intertemporal allocation of expenditure as argued, e.g., in Blundell, Browning, and Meghir (1994) and Attanasio and Browning (1995).

The panel structure of the data also allows for the inclusion household fixed effects to control for time-invariant unobserved heterogeneity at the household level. We present results from regressions both without and with household dummies. In the former case, our identification comes from time variation in cross-sectional differences in consumption and unemployment histories between cohorts whereas in the latter the identification further takes into account within-household time variation in consumption and unemployment histories.

We estimate a significant relationship, of sizable economic magnitude, between personal experiences of macroeconomic fluctuations and consumption behavior. Households that have lived through times of higher unemployment spend less overall, use more coupons, and purchase more on-sale items, store brand items, and lower-end products, after controlling for income and other household characteristics. Our estimates indicate that a one standard deviation increase in lifetime experience of unemployment is associated with a \$36 decline in monthly consumption of non-durable goods, which amounts to more than 5% of average monthly spending for the households in our sample. Furthermore, macroeconomic shocks have particularly strong effects on the young, who lower their consumption expenditure significantly more than older cohorts during economic busts, and vice-versa during booms.

While our main data source, the Nielsen Household Panel, contains unique features that are not available in the traditional data sources, including the household panel structure and rich, detailed information on purchases and products, it comes with a few limitations. First, the product categories covered by the Nielsen database encompass mainly food and non-food grocery and general merchandise items. as a result, we are not able to estimate the impact of macroeconomic experiences on household consumption of durable goods or all goods. Second, the Nielsen data is available only from 2004 on, while in the context of our study on experience effects, it would be ideal if we can track individuals over their entire lifespan and construct experience measures that introduce heterogeneity in macroeconomic experiences not only at the national level but also at the local level.

To address these limitations, we extend our analysis and check the robustness of our findings using alternative sources of consumption data, data that have been commonly used in the consumption literature, the Consumer Expenditure Survey (CEX) and the Panel Study of Income Dynamics (PSID). First, to alleviate the constraint due to limited coverage of product categories, we match the Nielsen data with CEX data, which contains household spending data across a comprehensive list of product categories. We match households in the Nielsen data to those in the CEX based on a set of observables that are common to both datasets, applying a nearest-neighbor matching estimator following Rosenbaum and Rubin

(1983) and Abadie and Imbens (2011). Second, on the issue of limited time series coverage, we apply our main estimation specification on the PSID data, which contains information on consumption of food at home and food away from home for a set of households that has been surveyed on a consistent basis since 1968. Results from both avenues of extensions confirm the findings from the Nielsen data, indicating experiences of macroeconomic fluctuations are strongly related to household consumption behavior.

Our findings on the persistent effects of macroeconomic fluctuation on household demand are in line with the outcomes conjectured by hysteresis effects and secular stagnation. Furthermore, the approach we take to arrive at such findings and the mechanisms implied by them point to experiences effects as a potential micro-foundation underlying these macro ideas. Our results suggest that changes in consumer behavior may reflect not only responses to labor markets adjustments but also changes in belief formation due to firsthand experiences of economic shocks. Hence, our results reveal a novel link between consumption, life-cycle and the state of the economy, showing that experience effects can be important for advancing understanding of individual consumption patterns and improving the micro-modeling of consumption. Moreover, they suggest experience effects could constitute a novel source of micro-foundation underlying fluctuations in aggregate demand and long-run effects of macroeconomic shocks. Finally, our results suggest the potential benefits of dampened macroeconomic fluctuations can be significant, thus calling for more discussion on optimal monetary and fiscal stabilization policy to eliminate unemployment and control inflation (Woodford (2003), Woodford (2010)).

2 Related Literature

Our work connects several strands of literature and entails notable policy implications. Foremost, the paper contributes to a long, rich volume of literature on consumption. Starting with the seminal works by Modigliani and Brumberg (1954) and Friedman (1957), this literature has formulated various incarnations of the life cycle–permanent income model. Within this general framework, consumption decisions are treated as part of an intertemporal allocation problem in which agents smooth marginal utility of wealth across predictable income changes over life-cycle. Subsequent variants build upon the original formulations with more rigorous treatments of the assumptions about uncertainty, curvature of the utility function, and time-separability (see Deaton (1992) and Attanasio (1999) for an overview). We view our paper to be complementary to this literature: Experience effects describe household consumption behavior, after taking into account most of the established features of the life-cycle framework. Our results indicate that two individuals may make significantly different consumption choices depending on the macroeconomic environments they lived through, even if they have identical income profile, demographics, and household composition.

Our finding may sound somewhat reminiscent of consumption models with intertemporal non-separability, such as habit formation models (Meghir and Weber (1996), Dynan (2000), Fuhrer (2000)) since, in both cases, current consumption predicts long-term effects. However, the channel through which experiences affect consumption is distinct. In habit formation models, households' utility is directly linked to their past consumption; in other words, there is utility loss associated with not obtaining its habitual consumption level. Under experience effects, instead, households adjust consumption patterns based on inferences they draw from their past (macroeconomic) experiences, without direct implications for utility gains or losses.

Another related strand of the consumption literature provides evidence on consumption expenditure switching. When faced with negative economic shocks, households reallocate total expenditure toward goods that are on-sale and of lower quality. For example, Nevo and Wong (2014) show that U.S. households lowered their expenditure during the Great Recession by increasing coupon usage, shopping at discount stores, and purchasing more items that are on sale, of larger sizes, and of generic brands. While they relate this behavior to a decrease in households' opportunity cost of time, we argue that experience effects are (also) at work, in particular in light of our results on inter-cohort differences in switching. Also relatedly, Coibion, Gorodnichenko, and Hong (2014) show that consumers also store-switch, as they reallocate expenditures toward lower-end retailers when economic condition worsen.

The key idea of our paper, experience effects from macroeconomic shocks builds on an emerging literature, which documents that individuals' lifetime exposure to macroeconomic, cultural, or political environments strongly affect their belief formations. This line of work is motivated by the psychology literature on the representativeness heuristic and the availability heuristic (Kahneman and Tversky (1974) and Tversky and Kahneman (1974)). The representativeness heuristic refers to peoples' tendency to assess the likelihood of an event by assessing the extent to which the data at hand are representative of that event. The availability heuristic refers to peoples' tendency to estimate events likelihoods by the ease with which certain past occurrences come to mind.

Prior economic applications include Malmendier and Nagel (2011), who find that investors' lifetime stock market and bond market experiences predict future risk taking. Malmendier and Nagel (2013) show life-time inflation experiences strongly predict subjective inflation expectations. Evidence in line with experience effects is also found in college graduates who graduate into recessions (Kahn (2010), Oreopoulos, von Wachter, and Heisz (2012)), retail investors and mutual fund managers who experienced the stock market boom of the 1990s (Vissing-Jorgensen (2003), Greenwood and Nagel (2009)), and CEOs who grew up in the Great Depression (Malmendier and Tate (2005), Malmendier, Tate, and Yan (2011)). Our findings on experience effects in consumption point to the relevance of such effects in a novel context.

A novelty of our empirical analysis, compared to the existing literature, is that the detailed panel data allow us to identify such effects using time variation in within-household evolvement in consumption and unemployment experiences, whereas earlier works such as Malmendier and Nagel (2011) and Malmendier and Nagel (2013) rely solely on time variation in cross-sectional differences between cohorts to identify experience effects.

By providing robust evidence on experience effects in consumption using detailed micro-level data, our paper brings a new perspective and a micro-foundation in understanding the long-term effects of economic shocks, a topic that has garnered much attention recently given the Great Recession of 2008-2009.

3 Methodology and Data

In this section, we outline the main empirical analysis of the paper, describing the data sources, construction of the key variables as well as the regression specifications.

3.1 Data

To estimate and establish the relationship between household consumption and experiences of macroeconomic conditions, two key sets of variables are required: measures of consumption from household panel data as the dependent variables and a measure of lifetime macroeconomic experience as the main explanatory variable.

3.1.1 Consumption

We use the household panel data from Nielsen Homescan Dataset to construct measures of consumption. The dataset contains information on product purchases made by a panel of approximately 40,000-60,000 U.S. households from 54 geographically dispersed markets (each roughly corresponding to a Metropolitan Statistical Area (MSA)) over the period 2004-2012. The households provide detailed information about the products they purchase: for each product at the Universal Product Code (UPC) level, data on price, quantity, date of purchase, identifier on the store from which the purchase was made, as well as product characteristics, including brand, size and packaging, are reported. Furthermore, the households also record whether the purchase involves coupon use or retailer deal. In cases when coupons were used, the households record the dollar values of the coupons. The products encompass categories of food and non-food grocery, health and beauty aids, and general merchandise items, summing up to approximately 3.2 million unique UPCs covering 125 general product categories.[2]

Households also report information on their demographics, including age, sex, race, education, occupation, employment status, family composition, household income, and location of residency up to the zip code level. The information is updated annually, and the demographics of the households are representative of the population demographics at the national level. For our analysis, we drop households with heads below the age of 25 or above 75.

To fully capture consumption behavior, we aim to construct measures of consumption that reflect both the quantitative and qualitative margins of household purchases. Below are the five monthly measures that we use as the main dependent variables of the analysis:

i.) Total expenditure ($): total expenditure reported, net of coupon use;

ii.) Coupon use ($);

iii.) Purchase of generic store brand ($): An item is identified as a "store brand product" based on the brand code associated with the UPC;

iv.) Ranking of purchased products: The ranking is constructed based on the unit price of goods within each given product module, market and month. Note among product modules, the level of detail is such that we can distinguish among, as an example, regular milk, flavored milk, and buttermilk. The ranking is normalized between 0 and 1, where lower value represents lower-priced goods.

v.) Purchase of on-sale products (quantity): An item is defined as being on sale if the household recorded that the item purchased involved a deal.

3.1.2 Macroeconomic Conditions

As for a measure of macroeconomic experience, we specifically focus on unemployment rate as an indicator of macroeconomic condition, following Coibion, Gorodnichenko, and Hong (2014), and thereby use unemployment series are used as the underlying data in constructing

[2]Several studies have examined the quality of the data. For example, Einav, Leibtag, and Nevo (2010) compare the self-reported data in Homescan with data from cash registers and conclude that the reporting error is of similar magnitude to that found in commonly used economic data sets.

the experience measure. In our case, historical unemployment data that go all the way back to the 1920s are required to construct a measure of lifetime unemployment experience for all individuals in the household panel. Due to the fact that the modern-day series on unemployment rate from the BLS only go back to the 1940s, we have to combine those with several historical unemployment series to construct the experience measure: a) data from Romer (1986) for unemployment for the period 1890-1930; b) data from Coen (1973) for unemployment for the period 1930-1939; c) BLS series that count persons aged 14 and over in the civilian labor force for the period 1940-1946; and d) BLS series that counts persons aged 16 and over in the civilian labor force for the period 1947-present.[3]

3.2 Summary Statistics

To link measures of consumption to the macroeconomic conditions experienced by each household in the Nielsen data, we merge the Nielsen data with monthly unemployment data since birth for all households. Our data sample consists of 98,547 households, making up approximately 3.5 million household purchase transactions. The top panel of Table 1 provides summary statistics on the age, income profile, and characteristics of the households. The average income of the sample, \$50k-\$59k, is in line with the average income at the national level. The middle panel of Table 1 provides summary statistics on the consumption measures. Note the average consumption expenditure from Nielsen is approximately one-third of the average total consumption expenditure from the CEX in dollar value, since Nielsen data cover mostly non-durable products.

[3] While estimates on unemployment rates by Lebergott (1957) and Lebergott (1964) from 1890 to 1940 are among the most widely cited data on pre-BLS unemployment estimates, many researchers have found issues with his work and sought to modify the estimates to better match the modern BLS series. Romer (1986) is often regarded as a decisive revision of Lebergott's estimates for the period 1890-1930. She argues that main errors in the Lebergott's data stem from his estimation assumption that employment in some sectors is moves one for one with output in those sectors and that the labor force does not to vary with the business cycle. Given both assumptions are not valid, an unemployment series derived using these assumptions is excessively volatile. Coen (1973)'s unemployment estimates from 1922-1940 also have garnered validity. He finds that both armed forces and cyclical variations in average hours per worker have been ignored in previous studies, and these variables appear to have significant effects on measures of labor participation. He thereby derive estimates of pre-war unemployment rates from adjusted labor force predictions.

Figure 2, a plot of consumption expenditure over life-cycle constructed based on coefficients from a regression of consumption expenditure on age dummies and time dummies, shows that the life-cycle pattern derived from our data sample resembles the usual hump-shaped profile from standard life-cycle models.

Table 1: **Summary Statistics on Nielsen Data**

variable	**mean**	**sd**	**p10**	**p50**	**p90**	**N**
Age of male head of HH	50	12	33	49	67	3,913,933
Income	\$50k-\$59k		\$20k-\$25k	\$50k-\$60k	\$100k+	3,913,933
Household size	2.8	1.5	1	2	5	3,913,933
Consumption expenditure	713	534	206	586	1361	3,913,933
Coupon use	.029	.052	0	0	.083	3,903,053
Store brand purchase	.054	.14	0	.23	.52	3,889,055
Product ranking	.47	.11	.34	.47	.61	3,889,168
Sale item purchase	.24	.24	0	.17	.61	3,913,933
Unemployment experience	5.9	0.17	5.8	5.9	6.2	3,913,933

Coupon use is value of coupon use/total expenditure. Store brand purchase is value of store brand items bought/value of all items bought. Product ranking is a ranking of goods that continuously ranges from 0 to 1 based on unit price of goods in specific product modules and markets, where lower value represents lower-priced goods. Sale item purchase is quantity of sale items bought/total number of items bought. The sample period runs monthly from 2004 to 2012.

3.3 Empirical Methodology

Our objective is to explore the relationship between the individual consumption and lifetime experiences of macroeconomic conditions. In this context, an appropriate measure of lifetime experience should not only underscore all macroeconomic experiences accumulated during an individual's lifetime relative earlier historical data but also allow for flexibility to differentiate recent experiences from ones in the distant past in one's lifetime. As an example, for a 30-year-old in the mid-1980s, a period during which unemployment rate reached over 10%, the experience of living through high unemployment around the 1970s (unemployment reached around 9% then) as a 20-year-old may still have some influence on his behavior but may also has become less relevant relative to the more recent macro condition. Consequently,

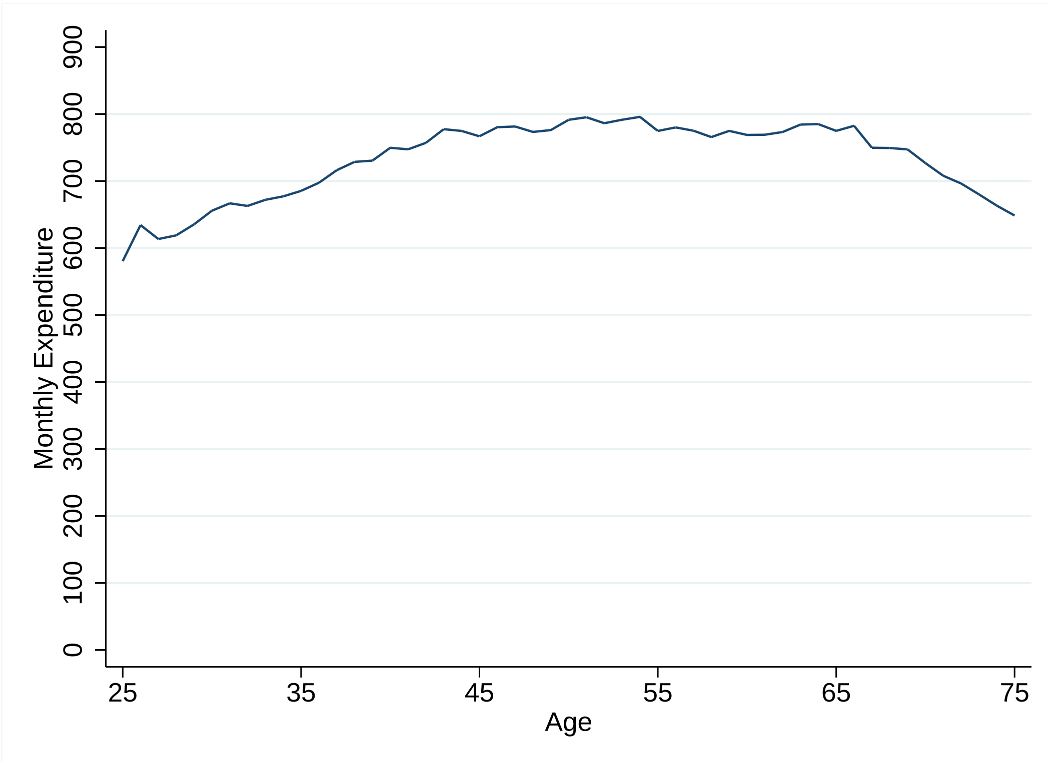

Figure 2: Monthly consumption expenditure by age cohorts, derived from a regression of consumption expenditure on age dummies and time dummies. Regressions are weighted by household sampling weights from Nielsen.

we construct a weighted average of past unemployment rates for each household i in year t, using a parsimonious specification of weights that introduces only one additional parameter to capture past experiences, as in Malmendier and Nagel (2011):

$$UE_{it}(\lambda) = \sum_{k=1}^{age_{it}-1} w_{it}(k,\lambda) U_{t-k}, \tag{1}$$

where

$$w_{it}(k,\lambda) = \frac{(age_{it}-k)^{\lambda}}{\sum_{k=1}^{age_{it}-1} (age_{it}-k)^{\lambda}} \tag{2}$$

where U_{t-k} is the unemployment rate in year $t-k$, and the weights w_{it} are a function of k, denoting how many months ago the unemployment was experienced relative to consumer's age at time t, and λ, a shape parameter for the weighting function. If $\lambda > 0$, the weights are decreasing in the time lag k; in other words, unemployment experience closer to current age at time t receives higher weight.[4].

In the analysis, we specifically apply a linearly-declining weight (i.e., $\lambda = 1$) for the experience measure, based on the estimates in Malmendier and Nagel (2011). Such weighting scheme emphasizes individuals' recent experiences, letting them carry higher weights, while still allows for some impact from early life histories. The bottom panel of Table 1 shows summary statistics on the weighted unemployment experience measure. Figure 3 plots the weighted lifetime unemployment experience of the young (below 40), mid-aged (between 40 and 60), and old individuals (above 60), constructed based on the linearly-declining weighting scheme using national unemployment rate. The plot highlights heterogeneity across generations both in their unemployment experience in the cross section and in their relative unemployment experience over time. These two margins of variation are central to our identification strategy: not only do the young and old differ in their experience at a given point in time, where their experiences stand relative to each other also change over time.

Using the weighted experience measures and data on consumption, we estimate the following regression to test consumers' sensitivity to experienced unemployment condition:

$$C_{imt} = \alpha + \beta UE_{it}(\lambda) + \delta U_t + \kappa(U_{mt} - U_t) + \gamma' x_{it} + \eta_t + \varsigma_m + \upsilon_i + \varepsilon_{it} \tag{3}$$

where C_{it} represents measures of consumption, $UE_{it}(\lambda)$ denotes experienced macroeconomic unemployment conditions, U_t denotes contemporaneous macro unemployment rate, $U_{mt} - U_t$ is the difference between contemporaneous local (county-level) and national unemployment rate, x_{it} is a vector of control variables including age controls, income controls, and household characteristics (unemployment status, household size, education, and race), η_t are time dummies, ς_m are local market dummies, and υ_i are household dummies. The standard errors are clustered at the household level.

[4]Please see Malmendier and Nagel (2011) for more information on the weighting specification.

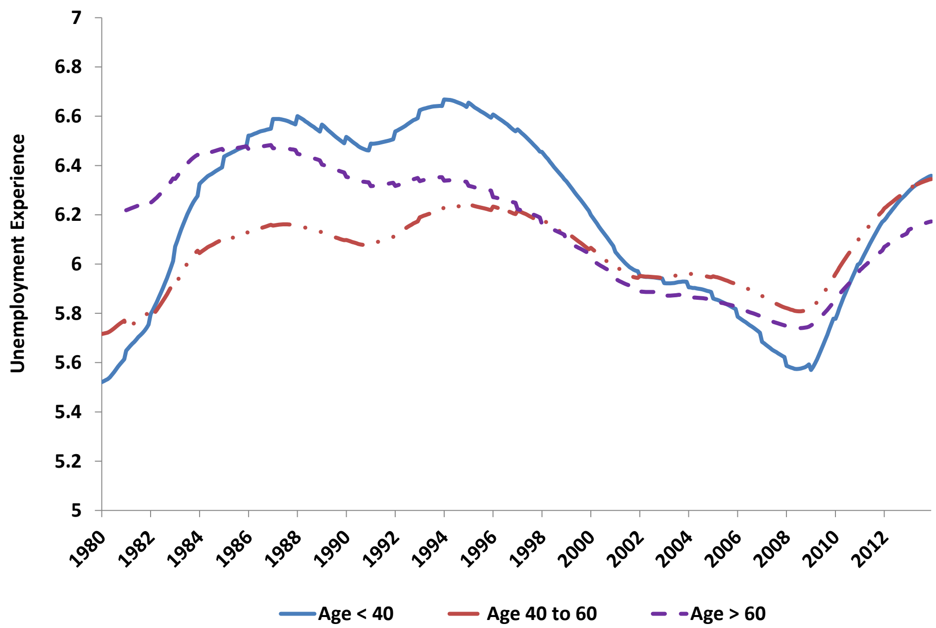

Figure 3: Weighted lifetime unemployment experience of the young (below 40), mid-aged (between 40 and 60), and old individuals (above 60), constructed based on the linearly-declining weighting function.

Our main coefficient of interest is β. Based on our hypothesis that the consumers who have experienced higher unemployment spend less on average, we predict a negative β. We also control for current macroeconomic condition using the contemporaneous national unemployment rate as well as a variable on the difference between the contemporaneous local and national unemployment rate. The latter variable further adds another level of heterogeneity in terms of identification, especially if there exists some persistence in the correlation between the national and local unemployment condition for each local market over time.[5]

In the subsequent section, we present results from equation 3 estimated both without and with the inclusion of household dummies. In the former case, our identification comes

[5]We are not able to directly use local unemployment rate for our experience measure because we do not have information on where the households in our sample have lived prior to the sample period.

from time variation in cross-sectional differences in consumption and unemployment histories between cohorts. In the latter case, we fully exploit the panel structure of the dataset and identify experience effects in consumption from time variation in within-household evolvement in consumption and unemployment histories.

In addition, to address concerns that our findings on the relationship between consumption and lifetime experience may be correlated with some habit persistence in consumption, we estimate an alternative version of specification 3 that includes a lagged consumption measure on the right hand side:

$$C_{imt} = \alpha + \zeta C_{imt-1} + \beta UE_{it}(\lambda) + \delta U_t + \kappa(U_{mt} - U_t) + \gamma' x_{it} + \eta_t + \varsigma_m + \upsilon_i + \varepsilon_{it} \qquad (4)$$

where C_{imt-1} aims to capture habits in consumption.

The dynamic specification in Equation 4 requires a correction for the correlation between the lagged dependent variable and the fixed effects in the error term, which gives rise to "dynamic panel bias" (Nickell (1981)). To obtain unbiased and consistent coefficients, we estimate equation 4 using a dynamic GMM panel estimator, following Holtz-Eakin, Newey, and Rosen (1988), Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). Accordingly, both level and differenced equations are used, and the lagged dependent variable is instrumented using lagged differences for the level equation and lagged levels for the differenced equation. The goodness of fit statistics for the system GMM estimators are calculated as the square of the correlation coefficients between the actual and the fitted values of the dependent variable.

4 Empirical Results

4.1 Baseline

Table 2 present results from regression specifications 3 and 4. Column (1) and (2) show estimates from pooled OLS regressions. As shown, households who have experienced higher unemployment conditions during their lifetime spend significantly less, controlling for contemporaneous macro conditions, local market conditions, and a range of household controls including income, age, and employment status. The economic magnitude is significant: a change from the 10th to 90th percentile of unemployment experience implies a $45 decline in monthly consumption of non-durable goods, which amounts to more than 6% of average monthly spending for the households in our sample. Column (3) and (4) report estimates from regressions with household fixed effects, thus controlling for time-invariant unobserved heterogeneity at the household level. Results also point to a significantly negative relationship between lifetime unemployment experience and total spending.

Column (5) and (6) show results based on system GMM regressions which take into account consumption habits. Our estimates indicate that a one standard deviation increase in lifetime experience of unemployment is associated with a $36 decline in monthly consumption of non-durable goods. Note we test for first- and second-order autocorrelation in the first-differenced errors and find that they are first-order serially correlated, but not second-order serially correlated. This supports the validity of the moment conditions used by the system GMM estimators.

Table 2: **Total Expenditure and Lifetime Unemployment Experienced**

	Pooled		FE		GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced unemployment	-108.2***	-108.7***	-73.44***	-74.81***	-211.734***	-212.389***
	(13.93)	(13.94)	(10.29)	(10.32)	(23.644)	(23.376)
National unemployment	-10.51***	-10.55***	-10.55***	-10.60***	-21.583***	-21.583***
	(0.495)	(0.497)	(0.472)	(0.474)	(1.193)	(1.191)
Local - National unemployment		-0.850		-1.249***		-1.157***
		(0.638)		(0.387)		(0.324)
Age controls	Yes	Yes	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market area dummies	Yes	Yes	Yes	Yes	Yes	Yes
Household dummies	No	No	Yes	Yes	No	No
N	3771876	3771284	3771876	3771284	3634444	3634219
R-sq	0.119	0.119	0.011	0.011	0.323	0.325

Pooled OLS, fixed effects, and system GMM regression with total consumption expenditure in dollars as the dependent variable. Experienced unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Age controls are age and age squared of the male household heads. Household characteristics include unemployment status, household size, education, and race. Regressions are weighted by household sampling weights from Nielsen. The sample period runs from 2004 to 2012. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.001, 0.01 and 0.05 levels, respectively.

The overall economic magnitude of the experience effects in consumption is large, particularly considering our estimates reflect behavioral change due to fluctuation in the macroeconomy, not direct income shocks. To put the estimates into a specific economic context, let us use them to explore the implication of adverse unemployment conditions during the Great Recession on household consumption. The average monthly unemployment rate from 2008-2012 was 8.07%, with the maximum during the period being 10%. Comparing these numbers with historical averages, the average unemployment rate during the 60 years prior to 2008, from 1947-2007, was 5.56%. If we consider two individuals, a "22-year-old" and a "60-year-old" as of December 2007, their lifetime unemployment experience, based on our experience weighting scheme, was 5.2% and 5.825%, respectively, when they entered the crisis in 2008. By the end of 2012, their lifetime unemployment experience was 6.3% vs. 6.101%, respectively. In other words, the unemployment experience for the "22-year-old" increased by 1.1%, whereas that for the "60-year-old" increased by 0.276%. Relating these experiences to consumption behavior, our model estimates imply that the monthly consumption expenditure of the "22-year-old" lowered by approximately 48% while that of the "60-year-old" lowered by approximately 6%, as illustrated in Figure 4.

4.2 Heterogeneity Across Cohorts

The results from Table 2 suggest people overweight their experience of more recent macroeconomic conditions, which naturally gives rise to heterogeneity in consumption behavior across cohorts. Specifically, one implication of our findings is that unemployment shocks have a particularly strong effect on cohorts with shorter lifetime histories, in other words, the young people: we predict the young lower their consumption expenditure to a significantly greater degree than older cohorts during economic busts, and vice-versa during booms.

We directly test the implication by regressing the log change in consumption on the log change in unemployment condition from month t to $t-1$, with the information separated into two variables depending on whether the change is positive or negative. We also include

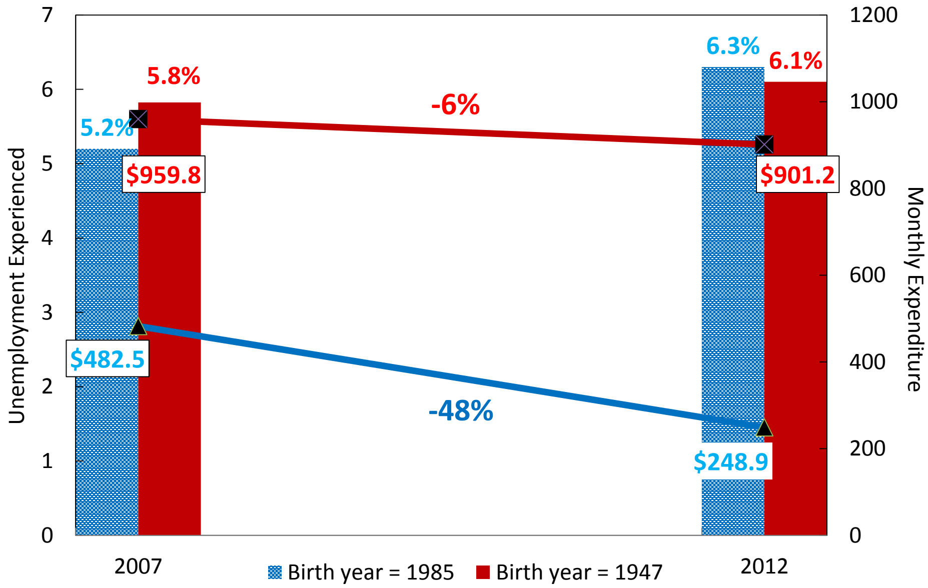

Figure 4: Example of the impact of the Great Recession on weighted lifetime unemployment rate and monthly consumption expenditure of a 22-year-old vs. 60-year-old (as of 2007) from December 2007 to December 2012. The bars show the weighted lifetime unemployment rate based on a linearly-declining weighting scheme. The lines show the monthly expenditure: the values for 2007 are from actual data, and the values for 2012 are calculated based on model estimates.

interactions of these two variables on positive and negative unemployment changes with the age of the heads of household in the regressions.[6] The results support our conjecture. As shown in Table 3, unemployment shocks, whether positive or negative, have a significantly stronger effect on the young. This finding distinguishes experience effects from alternative theories from the consumption literature such as liquidity constraints of the young (e.g. Gourinchas and Parker (2002)). Those explanations predict that the young react more strongly

[6]Note given the purpose of this regression is to estimate the elasticity of consumption to changes in macroeconomic conditions, we construct both the dependent variable and independent variables as log changes from time t to $t-1$. Estimation that instead construct dependent variable as log change from t to $t+1$ and independent variable as log changes from time t to $t-1$ would contain effects from consumption reaction to news from both t to $t-1$ and t to $t+1$.

to negative unemployment shocks but not to positive shocks, which are not supported by our regression results. Thus, our findings highlight experience effects as a distinct force in affecting people's consumption behavior.

4.3 Measures of Consumption Expenditure Switching

Next, we go beyond total expenditure as a measure of household consumption and explore the effect of lifetime unemployment experience on margins of consumption that reflect quality, including use of coupons and purchase of generic store brand items, on-sale items, and lower-end products within a product category. As shown in Table 4, households that have lived through higher unemployment conditions are more likely to use coupons and allocate expenditure toward on-sale items, generic store brand items, and lower-end products.[7] This set of results show that people who have lived through large fluctuations in unemployment adjust the quality of their consumption accordingly. This suggests a thorough study on the long-term impact of macroeconomics shocks on consumption calls for analysis beyond simple aggregate spending figures but also evidence of product substitution and consumption reallocation, margins that entail important welfare implications.

5 Extensions

Our findings in the previous section are based on estimates using the Nielsen data, which contains many unique features, such as the panel structure and rich micro-level information on purchases and products, that are not obtainable from traditional sources of consumption data. However, it comes with some limitations. First, there is a limit to the scope of products covered by the Nielsen database, as only data on food and non-food grocery and general merchandise items are available. Therefore, we are not able to estimate the impact of macroeconomic experiences on consumption across all goods. Second, the Nielsen data is

[7]See Appendix Tables A.1-A.4 for more detailed estimation results from regression on measures of consumption expenditure switching.

Table 3: **Age-Heterogeneity in Reaction to Unemployment Fluctuation**

	(1) Expenditure	(2) Expenditure	(3) Expenditure
National unemployment positive change	0.615***	0.659***	
	(0.135)	(0.135)	
Age * National unemployment positive change	-0.0067**	-0.0067**	
	(0.0023)	(0.0023)	
National unemployment negative change	-1.238***	-1.197***	
	(0.270)	(0.271)	
Age * National unemployment negative change	0.0251***	0.0252***	
	(0.0049)	(0.0049)	
Local unemployment change		-0.0424***	
		(0.0116)	
Local unemployment positive change			0.471***
			(0.0587)
Age * Local unemployment positive change			-0.0083***
			(0.0011)
Local unemployment negative change			-0.187**
			(0.0689)
Age *Local unemployment negative change			0.0019
			(0.0012)
Age controls	Yes	Yes	Yes
Income control	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Market area dummies	Yes	Yes	Yes
N	3614340	3613719	3613719
R-sq	0.005	0.005	0.005

OLS regression with dependent variable being the log change in monthly total expenditure and the main regressors being the log change in national or local unemployment rate separated into two variables depending on whether the change is positive or negative, both from time t to $t-1$. Household characteristics include household size, education, and race. The sample period runs monthly from 2004 to 2012. Regressions are weighted by Nielsen household weights. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 4: **Expenditure Switching and Lifetime Unemployment Experienced**

	(1)	(2)	(3)	(4)
A: Coupon Use				
Experienced unemployment	0.0216***	0.0217***	0.00465***	0.00462***
	(0.00332)	(0.00339)	(0.00139)	(0.00139)
National unemployment	0.00103***	0.00103***	0.00105***	0.00105***
	(0.0000810)	(0.0000811)	(0.0000478)	(0.0000478)
B: Store Brand Items Purchase				
Experienced unemployment	0.0171***	0.0171***	0.00905***	0.00902***
	(0.00461)	(0.00481)	(0.00282)	(0.00282)
National unemployment	0.000405	0.000392	0.000348	0.000347
	(0.000274)	(0.000275)	(0.000172)	(0.000172)
C: Product Ranking				
Experienced unemployment	-0.0551**	-0.0642**	-0.04133***	-0.0425***
	(0.0258)	(0.0263)	(0.01449)	(0.0145)
National unemployment	-0.0028***	-0.0026***	-0.00300***	-0.00296***
	(0.0009)	(0.00130)	(0.0007)	(0.0007)
D: On-sale Items Purchase				
Experienced unemployment	0.119***	0.115***	0.00978***	0.0107***
	(0.0165)	(0.0156)	(0.00466)	(0.00468)
National unemployment	0.00275***	0.00294***	0.00276***	0.00279***
	(0.000306)	(0.000310)	(0.00016)	(0.000161)
Age controls	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Market area dummies	Yes	Yes	No	No
Household dummies	No	No	Yes	Yes
N	3596853	3596289	3453445	3452920

Panel A presents estimates from OLS regression with the dependent variable being the ratio of value of coupon usage/total expenditure. Panel B presents estimates from OLS regression dependent variable being the ratio of value of generic store brand items/value of all items bought. Panel C is based on OLS regression with the dependent variable being a transformed ranking of goods constructed based on the unit prices of goods in specific product modules, markets and month, where lower value represents lower-priced goods. The original dependent variable continuously ranges from 0 to 1, and the transformation ln(y/(1-y)) maps the original variable to the real line. Panel D presents estimates from OLS regression with the dependent variable being the ratio of quantity of on-sale items purchased/total number of items purchased. Experienced unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Column 2 and 4 include the regressor (local-national unemployment). Other controls follow from definition in 2. Regressions are weighted by household sampling weights from Nielsen. The sample period runs monthly from 2004 to 2012. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.001, 0.01 and 0.05 levels, respectively.

limited on the time series dimension, available only for the period 2004-2012. In the context of our study, it would be ideal if we can track individuals over their entire lifespan and construct experience measures that reflect heterogeneity in macroeconomic experience not only at the national level but also at the local level. To get around these limitations, we extend our analysis and check the robustness of our findings using alternative sources of consumption data, the CEX and PSID.

5.1 Matching on CEX

To shed light on the impact of unemployment experience on durable consumption as well as total consumption, we extract those information from the CEX, a repeated cross-sectional survey that contains household spending data across a comprehensive list of product categories at the quarterly frequency, and match them onto the Nielsen data. Specifically, we construct a nearest-neighbor matching estimator, following Rosenbaum and Rubin (1983) and Abadie and Imbens (2011). We match households on their observable characteristics including age, income, marital status, household size, education, race, region of residency, employment status, as well as their consumption of non-durable items, or, more specifically, items that fall under the product categories covered by both Nielsen and the CEX. Table 5 provides summary statistics on the matched sample. Note the averages on total consumption spending and durable consumption spending for the matched dataset are comparable to the regular CEX data.

Table 5: **Summary Statistics on Matched Nielsen-CEX Data, quarterly**

variable	**mean**	**sd**	**p10**	**p50**	**p90**	**N**
Total consumption expenditure	4369	4681	1712	3246	7020	1,160,028
Durable consumption	1080	4350	0	111	1480	1,160,028
Non-durable consumption	2515	1196	1359	2276	3966	1,160,028
Non-durable consumption (Nielsen)	2139	1602	618	1757	4083	3,913,933

The sample period runs monthly from 2004 to 2012.

Table 6 shows results from estimating specification 3 using the matched sample. They support our earlier findings and show that households who have experienced higher unemployment conditions during their lifetime spend significantly less on all goods, durable and non-durable. The economic magnitudes are large and significant: a one standard deviation increase in lifetime unemployment experience is associated with a $70 decline in monthly total consumption and $38 decline in durable consumption. Comparing this set of results to ones from Table 2, the estimates seem sensible, as the earlier set of results shows that a one standard deviation increase in lifetime experience is associated with a $36 decline in monthly consumption of all goods covered by the Nielsen data, which are mostly non-durable goods.

Table 6: **Expenditure and Lifetime Unemployment Experienced, Nielsen+CEX Matched Sample**

	Pooled			FE		
	Total	Durables	Non-durable	Total	Durables	Non-durable
Experienced unemployment	-1505.6***	-938.6***	-501.9***	-500.8**	-252.6	-233.1***
	(155.3)	(140.5)	(45.99)	(228.3)	(214.5)	(47.96)
National unemployment	-40.50**	17.56	-50.77***	-59.01***	3.042	-54.57***
	(14.38)	(13.07)	(3.343)	(13.14)	(12.08)	(2.790)
Age controls	Yes	Yes	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market area dummies	Yes	Yes	Yes	Yes	Yes	Yes
Household dummies	No	No	No	Yes	Yes	Yes
N	1320903	1320903	1320903	1320903	1320903	1320903
R-sq	0.063	0.015	0.178	0.007	0.003	0.042

Pooled OLS and FE regressions with total consumption expenditure in dollars as the dependent variable. Experienced unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Age controls are age and age squared of the male household heads. Household characteristics include unemployment status, household size, education, and race. Regressions are weighted by household sampling weights from Nielsen. The sample period runs from 2004 to 2012. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.01, 0.05, and 0.1 levels, respectively.

5.2 PSID

To address the second issue of limited time series coverage, we study the effect of individual experiences of macroeconomic conditions on consumption using the PSID data, which contains information on consumption of food at home and food away from home for a set of households that has been surveyed on a consistent basis since 1968. The original 1968 PSID data surveys 4,802 core family units[8]. Those family units along with all split-off family units (which consists of, e.g., children who start their own family units) are surveyed every subsequent year until 1997. After 1997, the survey becomes biennial. In the dataset, information on each family member in each family unit is recorded at the individual level, with additional information on household characteristics and consumption recorded at the family unit level. For the purpose of our exercise, we focus on observations at the family unit level. Table 7 provides summary statistics on family units in the PSID data for the sample period 1968-2011 at the annual level. Comparing those to variables from Nielsen while taking into account differences in reporting frequency and observation units, the average expenditures for a family unit in the PSID data are an order of magnitude smaller those for a household unit from Nielsen. This is likely due to the fact that the Nielsen sample covers more than just food products.

To analyze the effect of macroeconomic experiences on consumption, we exploit the panel structure as well as the long time coverage of the dataset to introduce additional layers of heterogeneity in the experience measure. Specifically, given that we can precisely track state-to-state migrations of each family over time, we construct unemployment experience measures at the state-level for each head of family unit, which add additional cross-sectional variation within each cohort. However, we run into a data limitation at the same time: official state-level unemployment rates from the BLS are available only from 1976 onwards. If we simply restrict the sample to whenever the data is available, experience measures constructed for

[8]A family unit is defined as a group of people living together as a family. It is distinct from a household unit, which is the physical dwelling of family units. While there can be multiple family units in a household unit, members of a family unit are related either biologically or by law.

Table 7: **Summary Statistics on PSID, annual**

Variable	Mean	SD	Min	Max	N
Age of Family Head	43.5	16.3	16	102	214,358
Total Family Income ($)	34,667	54,810	-122355	6,317,099	214,336
Total People in Family	2.89	1.69	1	19	214,366
Head Years of Education	12.7	3.16	0	17	210,172
Home-Food Expenditures ($)	3,042	2,324.5	0	67,600	211,614
Restaurant Expenditures ($)	1,002	1,449	0	52,000	206,811
State unemployment rate	6.50	1.73	2.58	14.33	214,366

Note: Total Family Income is defined as the sum of (1) Taxable Income of Head and Wife, (2) Total Transfer Income of Head and Wife, (3) Taxable Income of Others in FU, and (4) Total Transfer Income of Others in FU. Because Taxable Income is defined to include income from such things as assets, the values can be negative due to losses. Sample period runs from 1968-2011.

families from later periods would be systematically more precise than those constructed for families from earlier periods, which would lead to biased regression estimates. To get around this limitation, we construct three experience measures for each family: i) a linearly-declining weighted state unemployment rate experienced by households from year $t-5$ to $t-1$, with weights dependent on the age of individual; ii) measure (i) on state unemployment experience as well as a lifetime linearly-declining weighted national unemployment rate experienced by households as two separate variables; iii) a lifetime linearly-declining unemployment experienced by households based on state rates from year $t-5$ to $t-1$ and national rates from birth to year $t-6$.

Table 8 reports estimation results from fixed effects regressions based on equation 3 using information on consumption expenditures on food at home and food away from home and the three constructed experience measures, along with a standard set of control variables as in the previous regressions. Columns (1)-(3), (4)-(6), and (7)-(9) show estimates on food expenditures using experience measure (i), (ii), and (iii), respectively. The results strongly echo the negative relationship between unemployment experience and consumption from the previous sets of estimates based on the Nielsen and CEX data. Moreover, they show that families who have lived in *states* of higher unemployment conditions during their lifetime spend significantly less. As shown in the columns (4)-(6), once state-level unemployment experiences are taken into account, national unemployment rates no long have significant explanatory power for consumption. The economic magnitude of the estimates is large and significant: a family at the 90th percentile of lifetime state-level unemployment experience lowers their annual food expenditure by more than \$600 relative to a family at the 10th percentile of unemployment experience at the state level, which is more than 15% of average annual spending for the families in our sample.

6 Conclusion

As the global economy recovers from the largest economic downturn since the Great Depression while a number of countries continues to be embroiled in large-scale economic crises, a better understanding of the long-term effects of economic shocks has proven to be of utmost importance for both academics and policy-makers. In this paper, we put forward the idea that experiences of macroeconomic shocks play a significant role in affecting household consumption and thereby serve as an importance force in determining the long-term consequences of macroeconomic shocks. We use detailed household panel data to test the impact of lifetime experiences of macroeconomic fluctuations on consumption. Results show that households who have experienced more difficult unemployment conditions during their lifetime spend significantly less, use more coupons, and allocate expenditure toward more on-sale items, generic store brand items, and lower-end products.

Our findings point to experience effects as a novel force underlying household consumption and as a novel perspective in understanding the long-term effects of economic shocks. This *experience effects in consumption* contains important policy implications: the potential benefit of dampened macroeconomic fluctuations may be significant, which calls for more considerations from policy-makers on optimal stabilization policy, monetary or fiscal. For future research, our empirical methodology could be applied to a larger cross-section of countries, particularly countries that have experienced more volatile macroeconomic events such as the emerging market countries and some European countries. Such exercises would help to determine the extent to which personal experiences affect household consumption—the key ingredient in all macro and macro-finance frameworks.

Table 8: **Expenditure and Lifetime Unemployment Experienced, PSID**

	Measure 1			Measure 2			Measure 3		
	All	Home	Rest	All	Home	Rest	All	Home	Rest
Exp state unemp	-52.30***	-38.93***	-13.37	-52.43***	-38.99***	-13.44			
	(15.46)	(10.89)	(9.783)	(15.45)	(10.89)	(9.783)			
Exp national unemp				-288.5	-126.3	-162.3			
				(182.2)	(132.1)	(109.0)			
Exp combined unemp							-179.2**	-129.9**	-49.35
							(59.27)	(42.50)	(36.87)
National-state unemp	-1.226	-11.09	9.863	-1.280	-11.11	9.833	1.655	-8.463	10.12
	(12.23)	(9.468)	(7.028)	(12.23)	(9.468)	(7.025)	(12.48)	(9.622)	(7.277)
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	108150	108150	108150	108150	108150	108150	108150	108150	108150
R-sq	0.296	0.276	0.135	0.296	0.276	0.135	0.296	0.276	0.135

Fixed effects regressions with expenditure on food at home (“home”), food away from home (“Rest”), and all food (“All”) in dollars as the dependent variable. “Exp state unemp” is a linearly-declining weighted state unemployment rate experienced by households from year $t-5$ to $t-1$, with weights dependent on the age of individual. “Exp national unemp” is a lifetime linearly-declining weighted national unemployment rate experienced by households. “Exp combined unemp” is a lifetime linearly-declining unemployment experienced by households based on state rates from year $t-5$ to $t-1$ and national rates from birth to $t-6$. Age controls are age and age squared of the male household heads. Household characteristics include unemployment status, household size, education, and race. Regressions are weighted by household sampling weights from the PSID. The sample period runs from 1976 to 2011. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.001, 0.01 and 0.05 levels, respectively.

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Appendix

Table A.1: **Coupon Use and Lifetime Unemployment Experienced**

	(1)	(2)	(3)	(4)
Experienced unemployment	0.0216***	0.0217***	0.00465***	0.00462***
	(0.00332)	(0.00339)	(0.00139)	(0.00139)
National unemployment	0.00103***	0.00103***	0.00105***	0.00105***
	(0.0000810)	(0.0000811)	(0.0000478)	(0.0000478)
Local - National unemployment		0.000469***		0.0000271***
		(0.000105)		(0.0000430)
Age controls	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Market area dummies	Yes	Yes	No	No
Household dummies	No	No	Yes	Yes
N	3761544	3762136	3762136	3761544
R-sq	0.039	0.019	0.005	0.005

OLS regression with the dependent variable being the ratio of value of coupon usage/total expenditure. Experienced unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Age controls are age and age squared of the male household heads. Household characteristics include unemployment status, household size, education, and race. The sample period runs monthly from 2004 to 2012. Regressions are weighted by household sampling weights from Nielsen. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.001, 0.01 and 0.05 levels, respectively.

Table A.2: **Store Brand Purchase and Lifetime Unemployment Experienced**

	(1)	(2)	(3)	(4)
Experienced unemployment	0.0171***	0.0171***	0.00905***	0.00902***
	(0.00461)	(0.00481)	(0.00282)	(0.00282)
National unemployment	0.000405	0.000392	0.000348	0.000347
	(0.000274)	(0.000275)	(0.000172)	(0.000172)
Local - National unemployment		0.0000371		0.00000239
		(0.000156)		(0.0000978)
Age controls	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Market area dummies	Yes	Yes	No	No
Household dummies	No	No	Yes	Yes
N	3731874	3731285	3731874	3731285
R-sq	0.026	0.014	0.005	0.005

OLS regression with the dependent variable being the ratio of value of generic store brand items/value of all items bought. Experienced unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Age controls are age and age squared of the male household heads. Household characteristics include unemployment status, household size, education, and race. The sample period runs monthly from 2004 to 2012. Regressions are weighted by household sampling weights from Nielsen. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.001, 0.01 and 0.05 levels, respectively.

Table A.3: **Product Ranking and Lifetime Unemployment Experienced**

	(1)	(2)	(3)	(4)
Experienced unemployment	-0.0551**	-0.0642**	-0.04133***	-0.0425***
	(0.0258)	(0.0263)	(0.01449)	(0.0145)
National unemployment	-0.0028***	-0.0026***	-0.00300***	-0.00296***
	(0.0009)	(0.00130)	(0.0007)	(0.0007)
Local - National unemployment		-0.0023**		-0.00086
		(0.0009)		(0.00062)
Age controls	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Market area dummies	Yes	Yes	No	No
Household dummies	No	No	Yes	Yes
N	2994923	2994434	2994923	2994434
R-sq	0.087	0.078	0.05	0.05

OLS regression with the dependent variable being a transformed ranking of goods constructed based on the unit prices of goods in specific product modules, markets and month, where lower value represents lower-priced goods. The original dependent variable continuously ranges from 0 to 1, and the transformation ln(y/(1-y)) maps the original variable to the real line. Experienced unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Age controls are age and age squared of the male household heads. Household characteristics include unemployment status, household size, education, and race. The sample period runs from 2004 to 2012. Regressions are weighted by household sampling weights from Nielsen. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.001, 0.01 and 0.05 levels, respectively.

Table A.4: **Sale Item Purchase and Lifetime Unemployment Experienced**

	(1)	(2)	(3)	(4)
Experienced unemployment	0.119***	0.115***	0.00978***	0.0107***
	(0.0165)	(0.0156)	(0.00466)	(0.00468)
National unemployment	0.00275***	0.00294***	0.00276***	0.00279***
	(0.000306)	(0.000310)	(0.00016)	(0.000161)
Local - National unemployment		0.00157**		0.000548***
		(0.000601)		(0.00018)
Age controls	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Market area dummies	Yes	Yes	No	No
Household dummies	No	No	Yes	Yes
N	3771876	3771284	3771876	3771284
R-sq	0.073	0.017	0.005	0.005

OLS regression with the dependent variable being the ratio of quantity of on-sale items purchased/total number of items purchased. Experienced unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Age controls are age and age squared of the male household heads. Household characteristics include unemployment status, household size, education, and race. The sample period runs monthly from 2004 to 2012. Regressions are weighted by household sampling weights from Nielsen. Robust standard errors in parentheses are clustered by household. ***, **, * denote significance at 0.001, 0.01 and 0.05 levels, respectively.