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SCARRED CONSUMPTION

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ABSTRACT

We show that personal experiences of economic shocks can “scar'” consumer behavior in the long run. We first illustrate the effects of experience-based learning in a simple stochastic life-cycle consumption model with time-varying financial constraints. We then use data from the Panel Study of Income Dynamics (PSID), the Nielsen Homescan Panel, and the Consumer Expenditure Survey (CEX) to estimate the long-term effects of lifetime experiences on consumption. We show that households who have lived through times of high local and national unemployment, or who have experienced more personal unemployment, spend significantly less on food and total consumption, after controlling for income, wealth, employment, demographics, and macro-economic factors, such as the current unemployment rate. The reverse holds for past experiences of low unemployment. We also estimate significant experience-based variation in consumption within household, i. e., after including household fixed effects. At the same time, lifetime experiences do not predict individuals' future income. The Nielsen data reveals that households who have lived through times of high unemployment are particularly likely to use coupons and to purchase sale items or lower-end products. As predicted by the experience-based learning model, the effects of a given macro shock are stronger for younger than for older cohorts. Finally, past experiences predict beliefs about future economic conditions in the Michigan Survey of Consumers (MSC), implying a beliefs-based channel. Our results suggest a novel micro-foundation of fluctuations of aggregate demand, and explain long-run effects of macroeconomic shocks.

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

1 Introduction

Ever since the seminal work of Modigliani and Brumberg (1954) and Friedman (1957), the life-cycle permanent-income model has been the workhorse to study consumption behavior. A number of the empirical findings, however, remain hard to reconcile with the predictions of the model, such as consumers' excess sensitivity to predictable income changes, or excessive smoothness after permanent income shocks.[1] These empirical puzzles have given rise to a debate about additional determinants of consumption, ranging from traditional explanations such as liquidity constraints (Gourinchas and Parker 2002) to behavioral approaches such as hyperbolic discounting (Harris and Laibson 2001), expectations-based reference dependence (Pagel 2017; Olafsson and Pagel 2018), and myopia (Gabaix and Laibson 2017).[2]

One new empirical fact, which could help clarify the underlying determinants of consumption, has not gotten as much attention yet in the academic literature: macroeconomic crises appear to leave long-term "scars" on consumer behavior, as suggested in the above quote by Blanchard. Such persistent effects of crises are also hard to reconcile with traditional models. The existing literature, if it explores persistent effects at all, mostly points to the loss of worker skills and reduced private investment during recessions, as for example in the research on hysteresis and secular stagnation.[3] In this paper, we turn to the micro-level evidence on consumption and ask whether personal experiences of macroeconomic shocks can have a lasting influence on individual consumers. Does the personal experience of an economic

[1] See, for example, Kaplan, Violante, and Weidner (2014); Deaton (1991); Aguiar and Hurst (2015).

[2] See also Dynan (2000) and Fuhrer (2000) on habit formation.

[3] Blanchard and Summers (1986) introduce the term "hysteresis effects" to characterize the high and rising unemployment in Europe. "Secular stagnation" goes back to Hansen (1939) who conjectured a protracted period of low growth following the Great Depression. Both terms have been used in recent work, such as Delong and Summers (2012), Summers (2014a), and Summers (2014b), to describe potential scarring effects of the Great Recession. See also Cerra and Saxena (2008), Reinhart and Rogoff (2009), Ball (2014), Haltmaier (2012), and Reifschneider, Wascher, and Wilcox (2015).

downturn induce more cautious consumption in the long-run, even when times have become better? Does extended exposure to prosperous times have the opposite effect?

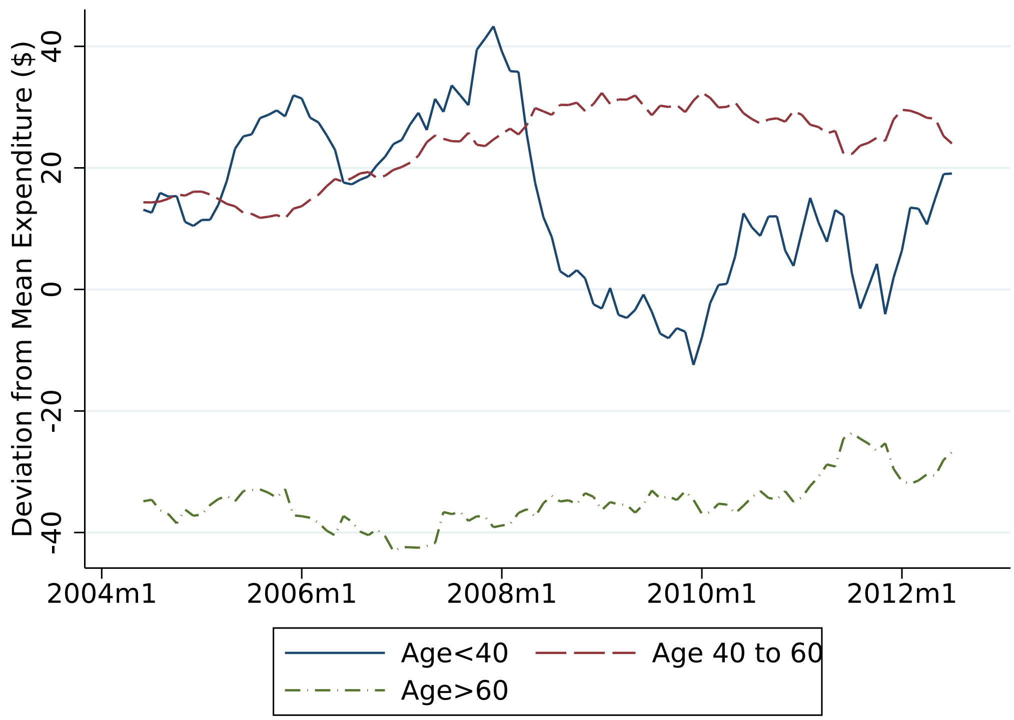
We document significant and long-lasting effects of crisis experiences on consumer spending in multiple consumption data sets, both across households and within households over time, and controlling for time effects, age, income, wealth, and an array of demographic and macroeconomic factors. This holds even though lifetime experiences do not predict future income after including the same set of controls. Experiences do, however, affect individuals' beliefs about future economic conditions. Hence, persistent effects of personal experiences might provide a micro-foundation of fluctuations of aggregate demand, and explain long-run effects of macroeconomic shocks.

Our approach builds on a growing literature in macro-finance documenting that personal exposure to macroeconomic shocks has a lasting effect on individual expectations and willingness to take risk. Based on the psychological underpinnings of availability and recency bias (Kahneman and Tversky (1974) and Tversky and Kahneman (1974)), empirical studies have shown that individuals' lifetime experiences of stock-market, bond-market, and inflation outcomes exert a persistent influence on their beliefs and risk-taking behavior. Experience-based learners overweight realizations that have occurred during their lifetimes, and in particular more recent ones, with roughly linearly declining weights going into the past (see, e. g., Malmendier and Nagel (2011, 2015)).[4]

Applied to consumption choices, we conjecture that individuals who have lived through difficult economic times spend less and reduce the quality of their consumption. The opposite holds for positive economic experiences. We consider both macro-economic experiences (national and local unemployment) and individual experiences (personal unemployment). A key implication of experience-based learning is that it gives rise to heterogeneity in consumption behavior in the cross section as well as over time: Households that have experienced extended periods of economic downturn and, within cohorts, higher local unemployment rates

[4] For further evidence on experience effects, see also Kaustia and Knüpfer (2008), Strahilevitz, Odean, and Barber (2011), and Kaustia and Knuepfer (2012).

Figure I: **Monthly Consumption Expenditure by Age Group**



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

or personal unemployment, spend less than those who have lived through mostly good times and always had jobs, controlling for income, wealth, and other household characteristics. Moreover, the cross-sectional differences vary over time as households accumulate different experiences and as younger cohorts react more strongly to a given shock than older cohorts since the shock makes up a larger fraction of their life histories so far.

To illustrate the hypothesized effect, Figure I plots the raw time-series data of household consumption expenditures from the Nielsen database, expressed as deviations from the cross-sectional mean (in the respective month). The plot shows that the spending of younger cohorts (below 40) is more volatile than that of older cohorts, consistent with younger cohorts exhibiting greater sensitivity. Zooming in on the Great Recession period, we also see that their spending was significantly more negatively affected than those of the other age groups.

Our analysis starts from a simple simulation exercise. We provide the basic intuition for experience effects in consumption using a stochastic life-cycle consumption framework with financial constraints. First, we show that the main empirical features of experience effects—over-weighing lifetime experiences and recency bias—are not generated in the standard consumption framework where consumers have full information and know the true probability of being unemployed next period. Next, we introduce experience-based learning (EBL) and show that lifetime experiences significantly affect EBL agents' consumption, controlling for their income and wealth. The model disentangles the role of EBL from potentially confounding factors such as income and wealth, thus providing guidance for the empirical analysis.

We then turn to formal tests of the hypothesis that individuals who have experienced different unemployment conditions exhibit different consumption behavior. Our main data sources are the Panel Study of Income Dynamics (PSID) (1999-2013) and the Nielsen Homescan Data (2004-2013), both of which are detailed panel datasets on consumption purchases by representative households in all U.S. markets. The PSID has the advantage of containing information on wealth, a key variable in consumption models, and of providing a long time series of data that can be used to construct individuals' lifetime experiences. The Nielsen data has the advantage of containing rich high-frequency data on both quantitative and qualitative margins of household purchases. In addition, we check the robustness of our findings in the Consumer Expenditure Survey (CEX), which contains a more comprehensive list of product categories. We construct a synthetic panel that combines CEX and Nielsen data using a nearest-neighbor matching estimator (following Rosenbaum and Rubin (1983), Abadie and Imbens (2011)). The synthetic panel allows us to shed light on the impact of unemployment experience on durable consumption and total consumption.[5]

[5] We have also explored the Health and Retirement Survey (HRS) as an additional data source. While the data contains information on consumption (from the Consumption and Activities Mail Survey) and wealth on a biennial basis since 2001, it mainly consists of people older than 50. Given that cross-cohort variation is central to our identification, the lack of young cohorts makes the HRS is not suitable for the analysis.

We employ six measures of household consumption: i) total consumption expenditure, ii) total food consumption, iii) use of coupons, iv) a ranking of purchases based on the unit price of goods (within product module, market, and month), and vi) purchase of on-sale products. To construct measures of unemployment experiences, we apply the linearly declining weights estimated in prior work to national and local unemployment rates individuals have experienced during their lifetimes so far, and to their personal unemployment. The measure simultaneously accounts for all experiences accumulated during an individual's lifetime and allows for experience effects to decay over time, e. g., as memory fades or structural change renders early experiences less relevant.

All estimations control for age, income, wealth, contemporaneous labor market status, household demographics, and time fixed effects. The inclusion of age effects differentiates experience effects from the link between consumption and age through life-cycle effects, such as increasing precautionary motives and risk aversion with age (cf. Caballero (1990), Carroll (1994)) or declining income and liquidity constraints during retirement (cf. 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 inclusion of time fixed effects controls for common shocks and common available information such as the current national unemployment rate.

The panel structure of the data also allows for the inclusion of 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 both from the differences in the consumption choices and unemployment histories across households, and how these differences vary over time, after accounting for time effects (year dummies for PSID data, year-month dummies for Nielsen data, and year-quarter dummies for CEX data) and life-cycle stages (age dummies). In the latter case, the estimation controls for differences in households' average consumption, even though these differences might reflect lifetime experiences, and solely relies on how within-household consumption varies over time in response to lifetime experiences.[6]

We find a significant relationship, of sizable economic magnitude, between personal experiences of macroeconomic fluctuations and consumption behavior. Households who have experienced higher unemployment spend less on food and on total consumption, after controlling for income and other household characteristics. Our estimates indicate that a one standard deviation increase in the macro-level experience measure is associated with a 4.6% ($395) decline in annual food consumption, and a 1.3% ($582) decline in annual total consumption in the PSID. The estimated magnitudes in the Nielsen data and the CEX are very similar. Even more strongly, a one standard deviation increase in personal unemployment experiences is associated with a 12.0% ($1,035) and 9.7% ($4,492) decreases in annual spending on food and total consumption respectively. We also find that past experiences of unemployment outcomes significantly increase the use of coupons and the purchase of sale items and products of lower quality. For example, households who have experienced unemployment rates at the 90th percentile of sample purchase 9% more sale items annually than respondents in the 10th percentile.

As predicted by experience-based learning, macroeconomic shocks have particularly strong effects on the young, who increase their consumption expenditure significantly more than older cohorts during economic booms, and lower it significantly more during busts. Importantly, these experiences do *not* predict individuals' actual future income after inclusion of our usual set of control variables.

[6] As an intermediate step, we have also re-estimated the empirical model including cohort fixed effects. In that case, our identification controls for cohort-specific differences in consumption, which might also reflect cohort-specific experiences. The estimation results are very similar to those from specifications without cohort fixed effects. Note that the experience measure is not absorbed by cohort fixed effects as the consumption data sets contains substantial within-cohort variation in experiences, differently from most of the prior literature on experience effects (Malmendier and Nagel (2011), Malmendier and Nagel (2015)). The unemployment experience measure of a given cohort varies over time depending on where the cohort members have resided over their lifetimes until time t. Relatedly, we note that the well-known identification issues of including age, time, and cohort effects (collinearity) do not affect the estimation of experience effects. Our goal is not to separately identify the effects of age, time, and cohort but to control for them (see Deaton (1997), Hall, Mairesse, and Turner (2007), Schulhofer-Wohl (2017)). The latter also applies for the estimation including household fixed effects.

Our empirical analysis speaks both to the "excess smoothness" puzzle (underreaction to innovations in permanent income, Campbell and Deaton (1989)) and to the "excess sensitivity" puzzle (overreaction to anticipated income increases, West (1989) and Flavin (1993)) mentioned above. The evidence on experience-based learning suggests that a potential reason for the failure of the standard consumption model is the lasting impact of the lifetime income histories that consumers have experienced up to the time of the (anticipated or unanticipated) shock on their future consumption choices.

We also provide some insight into the channel through which past experiences affect consumption. Using microdata from the Michigan Survey of Consumers (MSC) from 1953 to 2012, we find that people who have experienced higher unemployment rates over their lifetimes so far tend to expect worse financial conditions in the future. This evidence is consistent with a belief-based channel through which past experiences affect consumption decisions. Additionally, we explore whether preferences also play a role in driving the relationship between household past experiences and consumption. Do households prefer to be more frugal after having lived through economically hard times, controlling for their current conditions? Specifically, we include lagged consumption into the estimation model to capture potential habit formation. We find that the significant effects of past experiences on current consumption remain.

Our results suggest that experience effects could constitute a novel micro-foundation underlying fluctuations in aggregate demand and long-run effects of macroeconomic shocks. To that end, we provide suggestive evidence on the aggregate level pointing to experience effects as a factor of macroeconomic significance. We construct an aggregate measure of lifetime experiences using national unemployment rates and U.S. population data from the Census (as weights), and explore its correlation to real personal consumption expenditure (PCE) from the U.S. Bureau of Economic Analysis (BEA) from 1965 to 2013. The resulting plot shows a negative relationship between the two measures: times of higher aggregate unemployment experience in the population coincide with times of lower aggregate consumer spending. This relation suggests that changes in household consumer behavior may reflect not only responses to labor markets adjustments but also changes in belief formation due to first-hand experiences of economic shocks. Overall, our findings imply that the potential benefits of dampened macroeconomic fluctuations can be significant, thus calling for more discussion on optimal monetary and fiscal stabilization policy to control unemployment and inflation (Woodford (2003), Woodford (2010)).

Related Literature Our work connects several strands of literature and entails clear policy implications. Foremost, the paper contributes to a long, rich literature on consumption. In the life-cycle permanent-income framework, consumption decisions are treated as an intertemporal allocation problem in which agents smooth marginal utility of wealth across predictable income changes. Subsequent variants build upon the original formulation with more rigorous treatments of the assumptions about uncertainty, time-separability, and the curvature of the utility function (see Deaton (1992) and Attanasio (1999) for an overview). We view our paper as complementary to this literature: Experience effects describe household consumption behavior after taking into account the established features of the life-cycle framework. Our results explain why two individuals with similar income profiles, demographics, and household compositions may still make different consumption choices if they lived through different macroeconomic or personal employment histories.

Our findings are somewhat reminiscent of consumption models with intertemporal nonseparability, such as habit formation models (Meghir and Weber (1996), Dynan (2000), Fuhrer (2000)). 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, and they suffer a loss of utility if they do not attain their habitual consumption level. In a model of experience-based learning, instead, households adjust consumption patterns based on inferences they draw from their past experiences, without direct implications for utility gains or losses.

Another related strand of the consumption literature provides evidence on the quality margin of consumption reallocation. When faced with negative economic shocks, households reallocate expenditures toward goods that are on sale and of lower quality. For example, Nevo and Wong (2015) 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. The key element to identifying this additional, experience-based source of consumption adjustment are the inter-cohort differences and the differences in those differences over time. Relatedly, Coibion, Gorodnichenko, and Hong (2015) show that consumers also store-switch, as they reallocate expenditures toward lower-end retailers when economic conditions worsen.

The key idea of our paper, the notion of experience effects, builds on a growing literature in macro-finance, labor, and political economy documenting that individuals' lifetime exposure to macroeconomic, cultural, or political environments strongly affect their economic choices, attitudes, and 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 event likelihoods by the ease with which certain past occurrences come to mind. Taking these insights from social psychology to the data, Malmendier and Nagel (2011) show that investors' lifetime stock market experiences predict future risk taking in the stock market, and bond market experiences explain risk taking in the bond market. Malmendier and Nagel (2015) show lifetime 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)). In the political realm, Alesina and Fuchs-Schündeln (2007), Lichter, Löffler, and Siegloch (2016), Fuchs-Schuendeln and Schuendeln (2015), and Laudenbach, Malmendier, and Niessen-Ruenzi (2018) provide evidence of the long-term consequences of living under communism, its surveillance system, and propaganda on the formation of preferences and norms, and financial risk-taking. Fuchs-Schuendeln and Schuendeln (2015), for example, argue that the amount of time a person has lived under a democratic system determines her political preferences for democracy. Our findings on experience effects in consumption point to the relevance of such effects in a new context and reveal a novel link between consumption, life-cycle, and the state of the economy. A novelty of our empirical analysis, compared to the existing literature on experience effects, 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 (2015) rely solely on time variation in cross-sectional differences between cohorts to identify experience effects.

In the remainder of the paper, we first introduce a stochastic life-cycle consumption framework to illustrate the differences between the consumption choices of rational agents and experience-based learners (Section 2). We then provide evidence of signficant experience effects in consumption choices in the PSID (Section 3), the Nielsen data (Section 4), and the CEX (Section 5), with outcome variables ranging from total consumption and food consumption (PSID) to the quality of consumption including the purchase of on-sale, lower-quality, and coupon items (Nielsen) and durable consumption (CEX). In Section 6, we provide evidence on experience-based beliefs about future unemployment rates and consumer spending, as well as the role of habit formation. Section 7 indicates the aggregate implications of experience-based learning for consumer spending and concludes.

2 Consumption Model with Experience-based Learning

To provide intuition for the empirical estimation of experience effects in consumption, we first model and simulate experience-based learning in the context of a standard stochastic life-cycle consumption framework. We study the relationship between unemployment experience and consumption for two classes of consumers, rational agents and experience-based learners. Rational consumers use all available historical data to update their beliefs on the probability of being unemployed next period. Experience-based consumers overweight their own unemployment experiences when forming beliefs. We simulate the intertemporal consumption-saving decisions and estimate the relation between personal experiences and consumption for both types of consumers. The simulate-and-estimate exercise not only illustrates the basic idea of experience-based learning in consumption, but also distinguishes experience-based learning from features of the standard consumption model that might confound our estimation results, such as wealth or liquidity constraints. It thus provides guidance on the regression specifications for the empirical part of the paper.

Standard Model with Labor Income Uncertainty. We start from a standard life-cycle consumption model with borrowing constraints and income uncertainty, formulated as an extension of the model proposed by Carroll, Hall, and Zeldes (1992) and Carroll (1997). The consumer is born[7] at time $t = 1$ and works until T, earning labor income Y_t at each $t = 1, ..., T$. After time T, the consumer retires and lives until $T + N$, receiving a fixed retirement income $Y_t = \bar{Y} \geq 0$ (e. g., a pension) at each $t = T + 1, ..., T + N$.

At each point in time t, the consumer aims to maximize his expected and time-separable lifetime utility by optimally choosing consumption C_t. He enters each period with wealth A_t from the previous period and receives income stream of Y_t. He then consumes C_t and receives real interest r on net wealth $(A_t + Y_t - C_t)$. The individual's intertemporal optimization

[7] "Birth" corresponds to the beginning of economically independent life, for instance, to age 25.

problem can be stated as

$$\max_{C_t,\dots,C_{T+N}} \sum_{k=0}^{T+N-t} \delta^k E_t \left[u\left(C_{t+k}\right)\right] \tag{1}$$

$$\text{s.t.} \qquad A_{t+1} = (1+r)\left(A_t + Y_t - C_t\right) \tag{2}$$

$$A_t \geq 0 \tag{3}$$

where (2) is the the dynamic budget constraint, (3) is the borrowing constraint, and parameter δ is the discount factor. Note that the specification rules out borrowing, which simplifies the model, but also helps to address concerns that financial constraints (especially of younger cohorts) may confound the estimated relation between experience and consumption.[8] We assume that flow utility takes the standard CRRA form, $u(C) = C^{1-\rho}/(1-\rho)$, where ρ is the coefficient of relative risk aversion, which induces a precautionary savings motive.

Income Y_t in this model is determined by an exogenous process widely employed in the life-cycle consumption literature (Carroll, Hall, and Zeldes (1992); Carroll (1997); Cocco, Maenhout, and Gomes (2005)). Prior to retirement, stochastic labor income develops as

$$Y_t = P_t U_t = P_t W_t S_t \tag{4}$$

where P_t is the permanent component of the income process and U_t is the transitory component, each mutually independent to the other. The permanent component of income P_t can be any Markov process, as long as $\Pr\left(P_t > 0\right) = 1$. We follow Gourinchas and Parker (2002) and specify P_t as the product of an age-specific drift G_t, log-normal shocks to income N_t (with mean 1), and previous permanent income, P_{t-1}, i.e., $P_t = P_{t-1} G_t N_t$, and hence $\ln P_t \sim MA(1)$. We decompose the transitory component, U_t, into two factors, $U_t = W_t S_t$. W_t is an indicator variable for employment that has the Bernoulli distribution with parameter p, $W_t \sim \text{Bernoulli}(p)$ with $p \in (0,1)$, and S_t is a non-negative process with $E[S_t] = 1$.

[8] Younger cohort are predicted to react more strongly to a given shock than older cohorts under the experience effects hypothesis and also tend to be more constrained in their borrowing ability relative to older cohorts. By ruling out borrowing altogether, we conduct the analysis under the most stringent scenario.

Thus, the consumer is either unemployed at time t ($W_t = 0$), earning income $Y_t = 0$, or he is employed ($W_t = 1$) and receives $Y_t = P_t S_t > 0$.

Belief Formation. We consider two types of consumers, standard rational agents and experience-based learners. Both types know the model but differ in their belief about the probability p of being employed next period.

Rational consumers hold a constant belief p during their lifetime. They can be viewed as Bayesian learners who have used all available data on unemployment rates to update their belief. If they have lived long enough, they know (or closely approximate) the true p.

Experience-based learners, instead, form their belief p_t at time t about their employment next period (in $t+1$) based on the history of realizations in their lives so far including the current period, $W_{1:t} = (W_1, ..., W_t)$. Moreover, they apply a weighting scheme that differentiates recent experiences from those in the distant past,

$$p_t = \sum_{k=0}^{t-1} w\left(\lambda, t, k\right) W_{t-k}, \tag{5}$$

where $w(\lambda, t, k)$ denotes the weight assigned to the realization of W exactly k periods before period t and where λ is a shape parameter for the weighting function. Following Malmendier and Nagel (2011), we parametrize the weighting function as

$$w(\lambda, t, k) = \frac{(t-k)^{\lambda}}{\sum_{k=0}^{t-1} (t-k)^{\lambda}}. \tag{6}$$

The specification of experience weights is parsimonious in that it introduces only one additional parameter to capture different possible weighting schemes for past experiences. If $\lambda > 0$, then past observations receive less weight than more recent realizations, i. e., weights are declining in time lag k. This choice of weighting scheme emphasizes individuals' recent experiences, letting them carry higher weights, while still allowing for some impact of earlier life histories. For example, consider a 30-year-old living in the early 1980s, when the national unemployment rate reached over 10%. While the experience of living through relatively low unemployment during the early 1970s (around 5-6%) as a 20-year-old may still have some influence on his behavior, the influence is likely to be smaller relative to more recent experiences. In our main empirical analyses, we will apply linearly declining weights ($\lambda = 1$), which approximate the weights estimated in Malmendier and Nagel (2011, 2015). For robustness, we also conduct the analysis using weight parameter, $\lambda = 0$ and $\lambda = 3$.

Model Estimates on Experience Effects in Consumption. We relegate the details of the model solution to Appendix A.1, and show here the simulated consumption-saving decisions for the two classes of consumers. We also conduct a simple estimation exercise to compare the relationship between experience effects and consumption.

Table I: **Simulation Parameters**

Parameter		Benchmark value
Preference parameters		
Relative risk aversion coefficient	ρ	4
Discount factor	δ	0.97
Interest rate	r	1%
Lifetime parameters		
Retirement age		65
Age at death		75
Income process (iid)		
Variance of transitory shock		0.08
Variance of permanent shock		0.01

Table I reports the benchmark parameter values we use to simulate the model. We choose values in the range typically employed in the literature. The parameter values for the income process are from Cocco et al. (2005). The consumption path derived from the model under the standard rationality assumption is shown in Figure A.1 and resembles the usual hump-shaped profile.[9]

[9] In the Appendix, we also compare the consumption path derived from our model with that simulated from the more elaborate consumption-saving model using the Heterogeneous Agents Resources and toolKit (HARK) by Carroll, Kaufman, Low, Palmer, and White, available at https://github.com/econ-ark/HARK, as well as one constructed based on coefficients from regressions of consumption expenditures on age dummies

Table II: **Estimations with Model-Simulated Data**

	(1) Rational	(2) Rational	(3) EBL	(4) EBL
Income	0.029	0.061	0.061	0.077
	(0.001)	(0.001)	(0.003)	(0.002)
Wealth		0.078		0.063
		(0.001)		(0.001)
Unemployment Experience	-0.028	-0.021	-0.115	-0.068
	(0.232)	(0.092)	(0.002)	(0.001)

Notes. Estimations with the simulated consumption values as the dependent variable and the simulated income and wealth values as the regressors for rational consumers in columns (1) and (2), and experienced-based learning (EBL) consumers in columns (3) and (4), based on the model given by equations (1)-(4). Rational consumers hold a constant belief p about the probability of being employed next period, and EBL consumers form beliefs based on their employment history in their lifetime as specified in (5)-(6). All estimations control for age fixed effects. Simulations based on a sample size of 10,000.

Using the simulated values, we estimate the relationship between consumers' unemployment experience and consumption behavior, controlling for income and wealth. The corresponding OLS regressions are in Table II. In column 1, we do not include the wealth control in order to illustrate the possible confound. While income has the expected positive sign and significance level, lifetime experiences of unemployment does not appear to predict consumption. As expected, the coefficient becomes insignificant (and smaller) when we add the control for wealth. Thus, the results in columns 1 and 2 show that the negative influence of past unemployment experiences on long-run consumption choices is not captured by a standard consumption framework, once income and wealth are taken into account. If consumers use all available historical data to update their belief on the probability of being unemployed next period and, in the limit, know the true probability of being unemployed next period, past unemployment experiences do not have predictive power.

We then alter the belief-formation process to experience-based learning, and re-estimate the relationship between unemployment experience and consumption again both without and with wealth control (columns 3 and 4). The coefficient estimate on the experience variable is

and time dummies from the PSID (cf. Figures A.2 and A.3). Again we obtain the usual hump-shaped profile.

negative and highly significant in both cases. That is, lifetime experiences appear to strongly affect the consumption behavior of experience-based learners, even after taking into account their income and wealth.

These estimates help to disentangle the role of experience-based learning from two potentially confounding factors, income and wealth, and provide guidance for the empirical analyses. In particular, we will employ the following empirical specification for the estimation of lifetime-experience effects on consumption:

$$C_{it} = \alpha + \beta UEP_{it}(\lambda) + \gamma' x_{it} + error, \tag{7}$$

where C_{it} represents our various measures of consumption expenditures for consumer i at time t, $UEP_{it}(\lambda)$ denotes measures of unemployment experience, and x_{it} is a vector of control variables, including income and wealth controls. In the subsequent sections, we will estimate the empirical model in (7) using micro-data from three different sources, the PSID, the Nielsen Homescan Panel, and the CEX.

3 Empirical Analysis using the PSID

In this section, we test the experience effects hypothesis using the PSID. Do lifetime experiences of unemployment predict consumption spending in the long run?

The PSID is a longitudinal survey that contains comprehensive information on household consumption, income, wealth, and demographics. Compared to other consumption datasets, the PSID has the advantage of containing rich information on household wealth, a key variable in the consumption model we outlined in the previous section.

3.1 Data and Variable Construction

One of the main data sources we use for our empirical analysis is the Panel Survey of Income Dynamics (PSID). It contains comprehensive longitudinal data on consumption, income, and wealth at the household level since 1999. Its rich set of variables and long time series coverage allow us to test our hypothesis with wealth and demographic controls.

The PSID started its original survey in 1968 on a sample of $4,802$ family units who, along with their splitoff families, were repeatedly surveyed each year until 1997, when the PSID surveys became biennial.[10] We focus on data since 1999 when the PSID started to cover more consumption items (in addition to food), as well as information on household wealth. The additional consumption variables include spending on childcare, clothing, education, health care, transportation, and housing, and approximately 70% of the items in the CEX survey (Andreski, Li, Samancioglu, and Schoeni (2014)). Regarding household wealth, the survey asks about checking and saving balances, home equity, and stock holdings. Those wealth variables allow us not only to control for consumption responses to wealth shocks but also to tease out the effects of experiences on consumption for different wealth groups.

We conduct our empirical analysis both with food consumption as the dependent variable, following the earlier consumption literature, and with total consumption.[11] We control for liquid and illiquid wealth separately, using the definitions of Kaplan, Violante, and Weidner (2014): Liquid wealth includes checking and savings account, money market funds, certificates of deposit, savings bonds, treasury bills, and stock shares in publicly held corporations, mutual funds or investment trusts; illiquid wealth covers net value of home equity, net value of other real estate, net value of vehicles, private annuities or IRAs, as well as other investments in trusts or estates, bonds funds and life insurance policies.

The PSID also collects information on household demographics, including years of education (ranging from 0 to 17), age, gender, race (White, African American or Others), marital

[10] The PSID introduced a Latino sample with roughly $2,000$ Latino households from 1990 till 1995. From 1997 to 1999, the PSID also included an immigrant sample with approximately 500 families who arrived in the United States after 1968. We drop both the Latino sample and immigrant sample in our analysis because the surveys do not contain information on their unemployment experiences before they came to the U.S.

[11] Food consumption has been most widely used in the consumption literature largely because food spending used to be the only available consumption variable in the PSID before the 1999 survey wave. We are separating out the results on food consumption post-1999 partly for comparison, but also in case the data is more accurate as some researchers have argued. Food consumption and total consumption come directly from the PSID Consumption Data Package 1999-2013.

status, and family size. While the PSID collects some data for each family member, the information on the head of household is signficantly more detailed and complete. Therefore, while the family unit is our unit of analysis, we focus on the experiences and demographic variables of the heads of the family in our estimations, including our key explanatory variable measuring unemployment experiences.

Experience Measures. We measure the lifetime experiences of each household head in our PSID sample at time t as the weighted average of her lifetime unemployment experience as defined in equations (5) and (6), i. e., as the sum of all $w(\lambda, t, k) W_{t-k}$ over her lifetime so far, where W_{t-k} is the unemployment experience in year $t-k$, and k denotes how many years ago the unemployment was experienced.[12] The weights w are a function of t, k, and λ, where λ is a shape parameter for the weighting function. In our main analysis, we apply linearly declining weights ($\lambda = 1$), which approximate the weights estimated in Malmendier and Nagel (2011, 2015).[13] As discussed above, this construction of lifetime experience has the advantage that it emphasizes individuals' recent experiences, letting them carry higher weights, while still allowing for some impact of earlier life histories.

We employ both macroeconomic and personal unemployment experience measures. The macro measure captures the experience of living through various spells of unemployment rates. The personal measure captures the personal employment situations that the household heads experienced over their lifetimes so far.

To construct the macroeconomic experience measure, we need to combine information on where a family has been living (since the birthyear of the household head) with information about historical unemployment rates. Ideally, both sets of information would be available

[12] In the empirical lifetime experience measure, we utilize unemployment information from birth up to year $t-1$ while the theoretical p_t is constructed based on realizations of W_{t-k} for $k = 0, ..., t-1$, i. e., from the birth year to the realization in the current period. It is somewhat ambiguous what corresponds best to the theoretical set-up as, in practice, only backward looking information becomes available. However, since we do control for (macroeconomic and personal) contemporaneous unemployment status in all regressions, the inclusion or exclusion of the current realization of personal or macro-level unemployment in the experience measure does not make a difference to estimation results.

[13] For robustness, we also use weight parameter $\lambda = 0$ and $\lambda = 3$; see Appendix-Table A.1.

since the 1920s, when the oldest generation of heads of household in the PSID survey waves we utilize were born. The PSID does provide information about the region (state) where a family resides in a given PSID survey wave, but only since 1968, the start year of the PSID. Historical data on state-level unemployment rates is available from the Bureau of Labor Statistics (BLS) from 1976 on.[14] These data restrictions imply that, if we were to work with "all available" data to construct the experience measure, the values for family units from the later periods would be systematically more precise than those constructed for earlier periods, biasing the regression estimates. Hence, we have to make a trade-off between restricting the sample such that all family units have sufficient location and employment rate data, and restricting the length of the experience measure to only more recent years in order to have sufficient sample.

For our main specification, we choose to use state-level unemployment rates from year $t-5$ to $t-1$ for each family unit and construct the state-level macro measure either based solely on those most recent five years, or alternatively, complemented with national unemployment rate data from birth to year $t-6$. In the former case, we first weight the past experiences as specified in equation (6) (applied to $k = 1, ..., 5$), and then renormalized the weights to 1. In the latter case, we again use weights exactly as delineated in (6). For the data on national unemployment rates, we combine several historical unemployment series, a) the unemployment data from Romer (1986) for the period 1890-1930; b) the unemployment data from Coen (1973) for the period 1930-1939; c) the BLS series that counts persons aged 14 and over in the civilian labor force for the period 1940-1946; and d) the BLS series that counts persons aged 16 and over in the civilian labor force for the period 1947-present.[15] We also construct a macro experience measure based solely on the US-wide unemployment rate. The

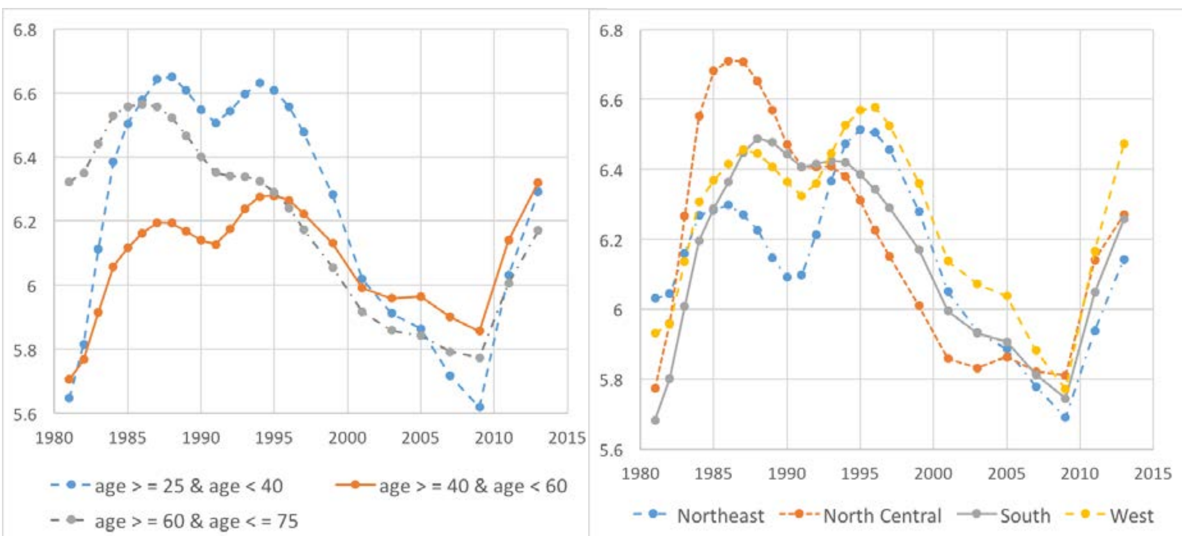
[14] There do not appear to be reliable sources of earlier historical unemployment data for all US states.

[15] An alternative and widely cited source of historical 1890-1940 data is Lebergott (1957, 1964). Later research has identified multiple issues in Lebergott's calculations and has sought to modify the estimates to better match the modern BLS series. Romer (1986) singles out Lebergott's assumptions that (1) employment and output in some sectors move one-to-one, and (2) the labor force does not vary with the business cycle, as invalid and generating an excessively volatile time series. Coen (1973) 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.

estimation results under all three measures of macroeconomic unemployment experience are very similar. We will show the measure combining the available local (state-wide) data with earlier national data in our main regressions.

To construct the personal experience measure, we first create a set of dummy variables indicating whether the respondent is unemployed at the time of each survey, using the reported employment status.[16] Mirroring the macro economic measure, we use the personal-experience dummy variables from year $t-5$ to $t-1$ and national unemployment rates from birth to year $t-6$, with weights calculated according to equation (6). As in the construction of the state-level experience measure, this hybrid construct addresses the limited sample period, with 1968 as the start year of the PSID.

Figure II: Unemployment Experience by Age Group and by Region



Notes. The left graph shows the unweighted means of local unemployment experiences of different age groups. The right graph shows the unweighted means of local unemployment experiences in different regions.

[16] The PSID reports eight categories of employment status: "working now," "only temporarily laid off," "looking for work, unemployed," "retired," "permanently disabled," "housewife; keeping houses," "student," and "other". We treat "other" as missing, and "looking for work, unemployed" as "unemployed." We code all other categories as "not unemployed." One caveat here is that the PSID is biennial during our sample period. For all gap years t, we assume that the families stay in the same state and have the same employment status as in year $t-1$. Alternatively, we average the values of $t-1$ and $t+1$, as discussed in Appendix A.2. The corresponding regression results are in Appendix-Table A.2.

Figure II illustrates the heterogeneity in lifetime experiences using our macroeconomic experience measure, both in the cross-section and over time, for the PSID families in our sample. The left panel of Figure II plots the unweighted mean experiences of young (below 40), middle-aged (between 40 and 60), and old individuals (above 60), while the right panel of Figure II plots the measures for individuals in the Northeast, North Central, South, and West. The plots highlight the three margins of variation that are central to our identification strategy: at a given point in time, people differ in their lifetime experience given their cohort group and residential location, and these differences in experiences evolve over time.

Table III: **Summary Statistics (PSID)**

Variable	Mean	SD	p10	p50	p90	N
Age	47.65	12.03	32	47	65	37,156
Experience (Macro) [in %]	6.00	0.28	5.67	5.97	6.37	37,156
Experience (Personal) [in %]	5.77	16.57	0.00	0.00	20.00	37,156
Household Size	2.73	1.45	1	2	5	37,156
Household Food Consumption [in $]	8,559	5,630	2,600	7,608	15,451	37,156
Household Total Consumption [in $]	46,256	36,497	14,733	39,559	82,765	37,156
Household Total Income [in $]	93k	133k	17k	69k	178k	37,156
Household Liquid Wealth [in $]	65k	718k	-22k	0k	117k	37,156
Household Illiquid Wealth [in $]	282k	1,268k	0k	72k	606k	37,156
Household Total Wealth [in $]	346k	1,545k	-3k	73k	762k	37,156

Notes. Summary statistics for the estimation sample, which covers the 1999-2013 PSID waves. Age, Experience (Macro), and Experience (Personal) are calculated for the heads of households. Household total income includes transfers and taxable income of all household members from the last year. Liquid wealth and illiquid wealth are defined following Kaplan, Violante and Weidner (2014). All values are in 2013 dollars using the PCE. Observations are annual and not weighted.

Summary Statistics. Table III shows the summary statistics for our sample. We focus on household heads who are between (and including) ages 25 and 75.[17] After dropping the individuals for whom we cannot construct the experience measures (due to missing information about location or employment status in any year from t to $t-5$), and observations with

[17] With the control for lagged income in our main estimations, the actual minimum age becomes 27. Additionally, we also conduct the analysis on a subsample that excludes retirees (households over the age of 65) since they likely earn a fixed income, which would not be affected by beliefs about future economic fluctuations. The results are similar.

missing demographic controls or that only appear once, we have 37,156 observations in the sample. The mean of the macroeconomic experience measure is 6.0%, and that of the personal experience measure is 5.4%. The average household food consumption and the average household total consumption in our sample are \$8,559 and \$46,256, respectively, measured in 2013 dollar.

3.2 Empirical Methodology

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

$$C_{it} = \alpha + \beta UE_{it} + \psi UEP_{it} + \gamma' x_{it} + \eta_t + \varsigma_s + \upsilon_i + \varepsilon_{it}, \tag{8}$$

where C_{it} is consumption, UE_{it} macroeconomic unemployment experience, UEP_{it} personal unemployment experience measure and x_{it} a vector of control variables including wealth controls, income controls, age dummies, and household characteristics (unemployment status as denoted by an indicator variable that equals 1 if the household head is currently unemployed, family size, gender, years of education (ranging from 0 to 17), marital status, and races (White, African American and others)). Finally, η_t are time (year) dummies, ς_s are state dummies, and υ_i are household dummies.[18] The standard errors are clustered at the cohort level.[19]

Our main coefficients of interest are β and ψ. The rational null hypothesis is that both coefficients are zero. The alternative hypothesis, generated by our model of experience-based learning, is that consumers who have experienced higher unemployment spend less on average,

[18] We have also estimated the model including region∗year fixed effects, and the results remain very similar. Note that we do not include state∗year fixed effects in the model since one of the key margins of variation in our main regressor of interest, macroeconomic unemployment experience (UE_{it}), is at the state∗year level.

[19] All the regression results are quantitatively and qualitatively similar when clustered by household, household-time, and cohort-time, and two-way clustered at the cohort and time level. Results and discussions for regressions with standard errors clustered at different levels are shown in Appendix-Table A.3. We also vary the weighting of observations by applying the PSID family weights, shown in Appendix-Table A.4. Note we do not use PSID family weights in the main regression due to efficiency concerns.

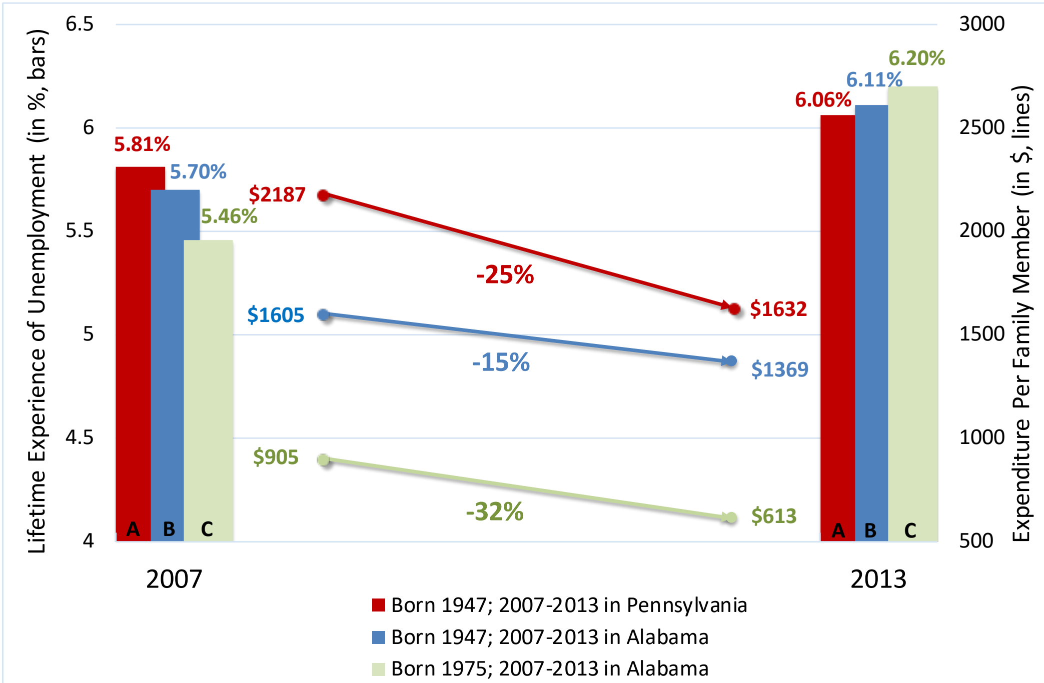
and hence that both coefficients are negative.

We estimate the model both with and without the inclusion of household dummies. In the former case, we identify experience effects in consumption solely from time variation in the within-household co-movement of consumption and unemployment histories. In the latter case, our identification also comes from time variation in cross-sectional differences in consumption and unemployment histories between households.

We illustrate the three sources of identification with a simple example of three individuals in our PSID data and their unemployment experiences and household consumption over the course of the Great Recession. We pick three individuals, A, B, and C, two of which (A and B) have the same age (both born in 1948) but live in different states during the 2007-2013 period (Pennsylvania and Alabama); and two of them (B and C) live in the same state (Alabama) but differ in age (with C born in 1975).

The two sets of bars in Figure III illustrate their lifetime experiences of unemployment at the beginning and at the end of the 2007-2013 period, based on the weighting scheme in (6) and their states of residence. Person A enters the crisis period with a higher macroeconomic unemployment experience than Person B (5.81% versus 5.70%), but her lifetime experience becomes more favorable by 2013 (6.06% versus 6.11%) because unemployment rates were lower in Pennsylvania than in Alabama during the crisis period. Similarly, Person B enters the crisis period with higher macroeconomic unemployment experience than Person C (5.70% versus 5.46%); but being the older person, B is less affected by the crisis, leading to a reversal of the lifetime unemployment experience between old and young by the end of the crisis (6.11% versus 6.20%). Furthermore, Figure III relates these differences-in-differences of lifetime experience over the crisis period to their consumption behavior. As indicated by the connecting lines, the increase in unemployment experiences of Person A, B, and C by 0.25%, 0.41%, and 0.74%, respectively, were accompanied by decreases in their consumption expenses in the same relative ordering, by 15%, 25%, and 32%, respectively.

Figure III: **Examples of Unemployment Experience Shock from Recession, PSID**



Notes. The red (darkest) bars depict the 2007 and 2013 unemployment experiences of Person A, and the red (darkest) line reflects the corresponding change of total consumption per family member in Person A's family. Similarly, the blue (medium dark) bars and line show Person B's unemployment experiences and consumption. The green (light) bars and line present Person C's unemployment experiences and consumption. All consumption expenditures are measured in 2013 dollars, adjusted using PCE. Person A's ID in the PSID is 15930; Person B's ID in the PSID is 53472; Person C's ID in the PSID is 54014.

3.3 Regression Results

Table IV shows our main estimation results with (log) food consumption as the dependent variable in the upper panel, and log total consumption in the lower panel. Columns (1)-(3) show results without household fixed effects, and columns (4)-(6) with household fixed effects. All the regressions control for (log) income, liquid wealth, and illiquid wealth. We also include all other control variables listed above, as well as the fixed effects indicated at the bottom of the table. The estimated coefficients on the control variables (not shown) have the expected sign, consistent with prior literature.

Table IV: **Experience Effects and Annual Consumption (PSID)**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Food Consumption						
Experience (Macro)	-0.181***		-0.165***	-0.174**		-0.166**
	(0.052)		(0.050)	(0.068)		(0.069)
Experience (Personal)		-0.761***	-0.757***		-0.430***	-0.426***
		(0.114)	(0.114)	(0.136)	(0.136)	
R-squared	0.198	0.203	0.204	0.542	0.542	0.542
Dependent Variable: Total Consumption						
Experience (Macro)	-0.058*		-0.045	-0.080**		-0.074**
	(0.031)		(0.028)	(0.032)		(0.031)
Experience (Personal)		-0.608***	-0.607***		-0.331***	-0.329***
		(0.074)	(0.074)		(0.082)	(0.081)
R-squared	0.494	0.505	0.505	0.755	0.756	0.756
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	Yes	Yes	Yes
Observations	37,156	37,156	37,156	37,156	37,156	37,156

Notes. Consumption variables come from the 1999-2013 PSID Consumption Expenditure Data package. We include all consumption items recorded throughout the sample period. We take the logarithm of consumption, income, and wealth; non-positive values are adjusted by adding the absolute value of the minimum plus 0.1 before being logarithmized. "Experience (Macro)" is the macroeconomic experience measure of unemployment, and "Experience (Personal)" is the personal experience measure. Demographic controls include family size, heads' gender, race, marital status, and education level, and a dummy variable indicating whether the respondent is unemployed at the time of the survey. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Turning to the coefficients of interest, the results indicate that macroeconomic and personal unemployment experiences significantly reduce consumption expenditures in the long-run. In the estimations predicting food consumption, shown in the upper half of the table, we find a highly significant negative effect of both macroeconomic and personal experiences, controlling for the current unemployment status. The economic magnitude of the effects remain the same whether we include the two types of experience measures separately (in columns 1 and 2) or jointly (in column 3). Based on the estimates in column (3), a one standard-deviation increase in macroeconomic unemployment experience leads to a 4.6% decrease in food consumption, which translates to approximately $395 less annual spending. Hence, the economic magnitude of the macro experience effect alone on food consumption is large, particularly considering that the estimates reflect behavioral change due to fluctuation in the macro-economy, not direct income shocks. Furthermore, it remains unaltered when we include household fixed effects, though with a slight reduction in statistical significance.

The estimated effect of personal unemployment experiences on consumption appears to be even larger, relative to the sample variation. A one standard-deviation increase predicts a 12.0% decrease in food consumption, which is approximately $1,035 in annual spending. Note, however, that the 2.5-fold economic magnitude of the personal experience effect, relative to the macro experience effect, reflects the much larger variation in personal experiences, with one standard deviation amounting to additional unemployment of about 20% of a consumer's lifetime. Given the large cross-sectional heterogeneity in personal experiences, we also use the average of the standard deviations of personal experience for each individual across time, which amounts to 5%. A corresponding increase in experienced unemployment by the average within-person standard deviation of 5%, then, implies a reduction in food consumption by $324 annually, and hence a similar order of magnitude as the macro experience effect.

As expected, the estimated experience effects become somewhat smaller in columns (4) to (6) (by about 40-45% for personal experiences), where we introduce household fixed effects. The decrease reflects that experience effects (also) predict cross-sectional differences in consumption between households with "mostly good" versus "mostly bad" lifetime experiences, and this component of experience effects is now differenced out.

When we use total consumption as the dependent variable, in the lower half of the table, the economic magnitude of the macro-economic experience effect increases (given the larger size of total consumption), though the statistical significance decreases. When we include household fixed effects, however, in columns (4) to (6) of the table, the estimations are again as precise as in the case of food consumption.

In terms of economic magnitude, our estimates indicate that a one standard-deviation increase in macroeconomic experience lowers total consumption by 1.3% or approximately $582 in annual spending, based on the estimated coefficient from column (3).[20] A one standard-deviation increase in personal lifetime unemployment experience lowers total consumption by 9.7%, or $4,492 annually. Using the mean of the standard deviations of personal experience for each individual across time, we find a one standard-deviation increase in the average standard deviation in personal lifetime experience leads to a 3.0% decrease in total consumption, or $1,406 in yearly spending.

Overall, the results robustly show people with more adverse macroeconomic and personal unemployment experience tend to consume less, both in terms of food consumption and total consumption, while controlling for wealth accumulation, income level account, family structures, and demographics.

Robustness. We chose the PSID, and in particular the survey waves since 1999, as one of our main sources of data largely because it provides detailed information about household wealth. Indeed, comparing the wealth variables in the PSID to the wealth information reported in the Survey of Consumer Finances (SCF), which is often regarded as the gold standard for wealth information in survey data, Pfeffer, Schoeni, Kennickell, and Andreski (2016) assess their quality to be generally quite comparable. The exceptions are "business

[20] We use the column (3) estimate for consistency with the calculations regarding food consumption above, and also because it is the lowest (most conservative) estimate, even though it is insignificant. As shown in Table IV, all other estimates of the effect are significant.

assets" and "other assets," for which the PSID tend to have lower values.

To address remaining concerns that wealth might be mis-measured and that the mis-measurement would affect our coefficient estimates of experience effects, we re-estimate our empirical model using varying constructs of wealth measures. Specifically, we replace the controls for liquid and illiquid wealth with four variants: (1) log total wealth, (2) wealth decile dummies, separately for liquid and illiquid wealth, (3) log home equity value (home price minus mortgage) and log non-housing wealth, and (4) log total debt and log positive wealth separately. All results are shown in Appendix-Table A.5. The estimated coefficients of interest remain very similar, both in terms of economic magnitude and in terms of statistical significance.

A related concern regards the role of liquidity. Even if our results are robust to various constructs of the overall wealth proxy, might the result on the impact of household unemployment experience on consumption still be confounded with the presence of (unmeasured) liquidity constraints? Our separate controls for liquid and illiquid wealth, both in the baseline estimations in Table IV and in columns (2) and (6) of Appendix-Table A.5, ameliorate these concerns. As a further step, we test whether the consumption of households that are disproportionately likely to be liquidity constrained, as proxied by their low liquid-assets position, are more affected by their unemployment experience. Following prior literature, such as Parker, Souleles, Johnson, and McClelland (2013), we sort households year by year into two groups based on whether their liquid wealth lies above or below the median liquid-wealth level in the sample. We then construct an indicator variable that takes the value 1 if a household's wealth position falls into the below-median group. Expanding equation (8), we interact the low-liquidity indicator and the experience variables. As shown in Appendix-Table A.6, households in the bottom half of the liquid-wealth group tend to spend less relative to households in the top half on average. However, their consumption expenditure does not exhibit a significantly stronger reaction to unemployment experience. All coefficient estimates are either insignificant or point in the opposite direction. This suggests that the negative effect of households' unemployment experiences on consumption is not explained by liquidity constraints.

Another concern might be measurement errors in the PSID income variable. Gouskova and Schoeni (2007) evaluate the quality of the family income variable in the PSID by comparing it to family income reported in the Current Population Survey (CPS), which is used for compiling the government's official estimates of income and poverty. The comparison shows that the income distributions from the two surveys closely match for incomes between the 5th and 95th percentiles. However, there is less consensus in the upper and lower five percentiles of the income distributions. In light of this finding, we re-estimate our empirical model from equation (8) with the sample restricted to households whose incomes fall between the 5th and 95th percentiles. The results are presented in Appendix-Table A.7. With this restriction, we still observe significantly negative coefficients on both the macroeconomic and personal experience measures across all six specifications. In the estimations without household fixed effects, the estimated coefficients are somewhat smaller, and in the estimations with household fixed effects, they are very similar.

Placebo tests. The PSID data also allows us to directly address the concern that our results may be driven by unobserved determinants of households' *future* income, which could be correlated with past unemployment experiences. For instance, one might be concerned that a longterm reduction in consumption after having experienced unemployment in the past might reflect a consumer's (rational) expectations about reduced future employment and earnings prospects. The detailed panel information on households' income allows us to test this hypothesis directly. We re-estimate the baseline model from equation (8), substituting consumption with future income as the dependent variable. As shown in Table V, we estimate the relationship between future income and unemployment experience using family income one, two, and three survey waves in the future, i. e., two, four, and six years ahead, respectively. The estimation results suggest that unemployment experiences do not play a significant role in explaining future household income. After controlling for the same set of

Table V: **Experience Effects and Future Income**

	Income_{t+2}	Income_{t+4}	Income_{t+6}
Experience (Macro)	-0.030	-0.044*	-0.050
	(0.020)	(0.023)	(0.030)
Experience (Personal)	0.010	0.021	0.017
	(0.013)	(0.013)	(0.021)
Income controls	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Observations	15,710	11,258	7,641
R-squared	0.865	0.884	0.903

Notes. The dependent variables are future income in two, four, and six years, respectively. All independent variables are defined as in Table IV. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

household characteristics and fixed effects as in the baseline estimation, including current employment status, the estimated coefficients of personal unemployment experiences are all positive, small, and insignificant. For macroeconomic experiences, we estimate small negative coefficients, which are also insignificant with the exception of the estimation predicting income four years ahead, where it is marginally significant. In summary, our results do not appear to be driven by unmeasured future earnings prospects.

Relatedly, one also may be concerned that the experiences we are capturing are correlated with future income volatility. To alleviate this concern, we again change the dependent variable in our baseline model from equation (8), this time employing measures of income volatility. Following Meghir and Pistaferri (2004) and Jensen and Shore (2015), we construct two measures of income volatility, one reflecting the variance of permanent income and one reflecting the variance of transitory income. The permanent-income variance measure is the product of two-year changes in excess log income (between years t and $t-2$) and six-year changes (between years $t + 2$ and $t - 4$) in excess log income. The transitory-variance measure is the squared two-year change in excess log income, where excess log income is defined as the residual from an OLS regression of (the natural log of) income on our full slate of control variables. Re-estimating the regressions with either measure of income volatility as the dependent variable, we do not find any significant correlation between unemployment experiences and income volatility.

Wealth Build-up. Given the significant and sizable estimated effects of lifetime unemployment experiences on consumption, one may wonder whether household experiences may affect even the build-up of wealth. In the case of negative lifetime experiences, for example, our findings suggest that consumers restrain from consumption expenditures more than "required" by their income and wealth position. Their frugality should predict, then, more future wealth. Vice versa, consumers who have lived through mostly good times are predicted to be spenders, and should thus end up with less wealth.

In order to test whether experience effects are also detectable in long-run wealth accumulation, we relate households' lagged experiences to their wealth. (This analysis also ameliorates potential concerns about the quality of the consumption data.) We consider the effect of lifetime experiences on wealth up to seven survey waves (14 years) into the future, and we consider both liquid wealth and total wealth.

Appendix-Figure A.1 summarizes the coefficients of interest graphically for 10 regressions, namely, the cases of wealth at $t + 6$, $t + 8$, $t + 10$, $t + 12$, and $t + 14$. The upper part shows the coefficient estimates when studying the potential impact on the build-up of liquid wealth, and the lower part shows the estimates for total wealth. All coefficient estimates are positive, though the impact of macro experiences is smaller and (marginally) significant only in a few cases, namely, the more recent years for total wealth and the years further in the future for liquid wealth. The estimates of the role of personal lifetime experiences are also all positive, much larger, and typically signficant, with coefficients ranging from 0.02 to 0.03 for liquid wealth and from 0.08 to 0.10 for total wealth. These estimates imply that a one-standard deviation increase of personal lifetime experiences of unemployment will lead to additional precautionary savings and resulting wealth build-up of about 1.3% or $4,500 10 years later. Appendix-Table A.8 provides the details on the coefficient estimates of both experience measures.

In conclusion, we see evidence of a positive relationship between past experience and wealth. Households who have experienced high unemployment tend to accumulate more wealth down the road.

4 Empirical Analysis using Nielsen Data

In this section, we use a second source of consumption data, the Nielsen Homescan Dataset, to test the experience-effect hypothesis. The goal of this analysis is not only to provide a robustness check of the estimation results on the effects of unemployment experiences on overall and food consumption from the PSID, but also to examine whether people's experiences affect the quality margins of their consumption. While the Nielsen data does not contain the same detailed information on wealth as the PSID data, it contains rich high-frequency micro-level information on purchases and products that capture both the quantitative and qualitative margins of household consumption.

4.1 Data

The Nielsen Homescan Dataset contains information on product purchases made by a panel of more than 100,000 U.S. households from 54 geographically dispersed markets, each roughly corresponding to a Metropolitan Statistical Area (MSA), over the period 2004-2013. The households in the sample provide detailed information about the products they purchase. For each product, the data reports 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, at the Universal Product Code (UPC) level. The level of detail provided within product modules is such that we can distinguish, for example, between regular milk, flavored milk, and buttermilk. Furthermore, the households record whether the purchase involves coupon use or sale items. When coupons were used, the households record the dollar value of the coupons. An item is defined as being on sale if the household recorded that the item purchased involved a deal from the retailer. 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.[21]

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. Note that the geographic information is more precise than the state-level identification in the PSID, as it allows us to control for the local (county-level) unemployment rate U_{mt}. 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, as in the PSID sample.[22]

We construct five monthly measures of consumption, which reflect both the quantitative and the qualitative margins of household purchases: (1) total expenditure (in \$) net of coupon use, (2) coupon use, normalized by total expenditures, (3) the ranking of purchased products, constructed based on their unit price within each given product module, market, and month, and normalized between 0 and 1, where lower value represents lower-priced goods, and (4) number of on-sale products purchased, normalized by the total number of products purchased.

As in the analysis of the PSID data, we link the measures of consumption in the Nielsen data to measures of households' lifetime unemployment experiences. As before we construct lifetime experiences as the weighted average of experienced unemployment outcomes since birth, using linearly declining weights. We also use the same combination of historical data

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

[22] As in the PSID data, we also conduct the analysis on a subsample that excludes households over the age of 65 (retirees) whose expectation of their future income should be immune to beliefs about future economic fluctuations. The results from both sets of regressions are similar.

sets on unemployment. Note that, on the one hand, the high-frequency nature of the Nielsen data allows us to construct more precise experience measures than the PSID, which vary at monthly frequency. On the other hand, we are not able to construct the same type of macro and personal unemployment experience measures as in the PSID because Nielsen provides neither information on where households resided prior to the sample period nor on their prior employment status. The data limitations necessitate that we re-construct the macro-level experience measure based on national unemployment rates (rather than state-level unemployment rates for the more recent years). For the personal experience measure, we can, at best, construct a variable that accounts for unemployment experiences since the beginning of the Nielsen data set. Such a measure is necessarily biased, as it is less precise at the beginning of the sample and for shorter household spells. We therefore choose to report the estimations employing only the macro-experience measure in the main text.[23]

Our data sample consists of 3,171,833 observations of 105,061 households. The top panel of Table VI 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 VI provides summary statistics on the monthly consumption measures. We note that the average consumption expenditure from Nielsen approximately corresponds to the food consumption expenditures in the PSID, which cross-validates the quality of the data sets as the Nielsen data cover mostly food products.

As mentioned above, the Nielsen data lack information about consumers' wealth, which is an important component of consumption analyses. Our prior estimations using the PSID data allow us to gauge potential biases (and alleviate such concern) to some extent, given the comparable consumption outcome variables across the two data sets. To further address the issue of the missing wealth control, we follow recent advancements in the literature, such as Stroebel and Vavra (2017) and Dube, Hitsch, and Rossi (2018), and use ZIP-code level house

[23] We have re-estimated our model using such a proxy for personal unemployment experience, constructed as a binary variable that takes the value 1 at time t if the head of household has ever been unemployed since the beginning of the sample period up to time $t-1$, and 0 otherwise. The results on our main coefficient of interest remain similar.

Table VI: **Summary Statistics (Nielsen)**

Variable	Mean	SD	p10	p50	p90	N
Age of male head of HH	50	12	33	49	67	3,171,833
Income	\$50k-\$60k		\$20k-\$25k	\$50k-\$60k	\$100k+	3,171,833
Household size	2.8	1.5	1	2	5	3,171,833
Total expenditure	714	537	205	586	1,366	3,171,833
Coupon use	0.03	0.05	0	0.01	0.09	3,171,833
Product ranking	0.47	0.11	0.34	0.47	0.61	3,171,833
Purchase of sale items	0.24	0.24	0	0.17	0.62	3,171,833
Experience (Macro)	6.0	0.2	5.8	5.9	6.3	3,171,833

Notes. Coupon use is the value of coupons used divided by total expenditures. Product ranking ranges from 0 to 1 based on the unit price of a good within its product module and market in the given month, where a lower value represents a lower-priced good. Purchase of sale items is the number of sale items divided by the total number of items bought. Experience (Macro) is the household's lifetime experience of national unemployment rates. Nielsen reports income in 13 brackets. The sample period runs monthly from 2004 to 2013.

prices as a measure of housing wealth. According to these studies, consumption responds strongly to house price movements, suggesting an important role for housing wealth in consumption dynamics (see, e. g., Mian, Rao, and Sufi (2013), Stroebel and Vavra (2017), and Berger and Vavra (2015)). Empirical analyses can exploit this insight since better measures of housing prices have now become available. Specifically, we extract Zillow's Home Value Index at the local ZIP code level,[24], and merge the data with the Nielsen Homescan sample. The match rate lies around 75%, and the resulting data set contains almost 3.2 million observations. We include this proxy for local housing prices, as well as an indicator variable for being a homeowner and its interaction with the Home Value Index in all of our estimations to partially address the concern about the lack of direct controls for total wealth.[25]

[24] Zillow Inc. collects detailed data on individual housing values across the U.S. and constructs ZIP-code level indices on a monthly bases, using the median value for a ZIP code. The calculations use Zillow's estimates of housing values ("Zestimates"), which aims to provide a realistic market value given the size, rooms, and other known attributes of the house, recent appraisals, geographic location, and general market conditions. (The exact formula is proprietary.) More details about the data and the quality of Zillow coverage across the U.S. are provided in Dube, Hitsch, and Rossi (2018).

[25] We also conduct the analysis without including the set of wealth controls in the regressions, and the coefficient on unemployment experience remains significant and of very similar magnitude.

4.2 Empirical Methodology

Using the weighted experience measure and data on consumption, we re-estimate the sensitivity of consumption to experienced unemployment conditions in the Nielsen data. The estimation model closely mirrors the PSID model from equation (8), but accounts for the additional details as well as the limitations of the Nielsen data as follows:

$$C_{it} = \alpha + \beta UE_{it} + \kappa U_{mt} + \gamma^{'} x_{it} + \eta_t + \varsigma_m + \upsilon_i + \varepsilon_{it}. \tag{9}$$

C_{it} represents the measures of consumption and UE_{it} denotes the lifetime (macro) experience of unemployment rates. U_{mt} is the current county-level unemployment rates; x_{it} is a vector of control variables including income controls, wealth controls, household characteristics (unemployment status, household size, education, race, and a dummy variable indicating whether the respondent is unemployed at the time of the survey), and age dummies; η_t are time (year-month) dummies; ς_m are local-market dummies[26]; and υ_i are household dummies. The standard errors are clustered at the cohort level.[27]

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. As before, we present results from equation 8 estimated both without and with the inclusion of household dummies. In the former case, our identification comes from time variation in cross-sectional differences in consumption and unemployment histories between cohorts as well as from time variation in within-household evolvement in consumption and unemployment histories. In the latter case, we fully exploit the panel structure of the dataset and identify experience effects in consumption solely from time variation in within-household evolvement in consumption and unemployment histories.

[26] Local markets denote the Nielsen designated market areas (DMAs). They are slightly bigger than county but smaller than MSA. We control for location at the local market level instead of county level because people may travel outside of counties to purchase goods. The results are similar if we use county fixed effects instead.

[27] All regression results are quantitatively and qualitatively similar when clustered by household, household-time, cohort-time, or two-way clustered at the cohort and time level.

4.3 Empirical Results

Table VII present results from regression specification (9). Columns (1) and (2) show estimates from pooled OLS regressions, and columns (3) and (4) report the estimates from regressions with household fixed effects, thus controlling for time-invariant unobserved heterogeneity at the household level. We find that, exactly as in the PSID data, households who have experienced higher unemployment conditions during their lifetimes so far 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 one standard deviation increase in lifetime experience of unemployment is associated with a \$59 decline in monthly consumption of non-durable goods, which amounts to around 8% of average monthly spending for the households in our sample. When we introduce household fixed effects, the estimated experience effects become smaller, as expected given the differencing out of the cross-sectional differences in consumption between households with "mostly good" versus "mostly bad" lifetime experiences. With household fixed effects, a one standard deviation increase in lifetime experience of unemployment is associated with a \$25 decline in monthly consumption of non-durable goods, comparable to the estimates from regressions using the PSID.

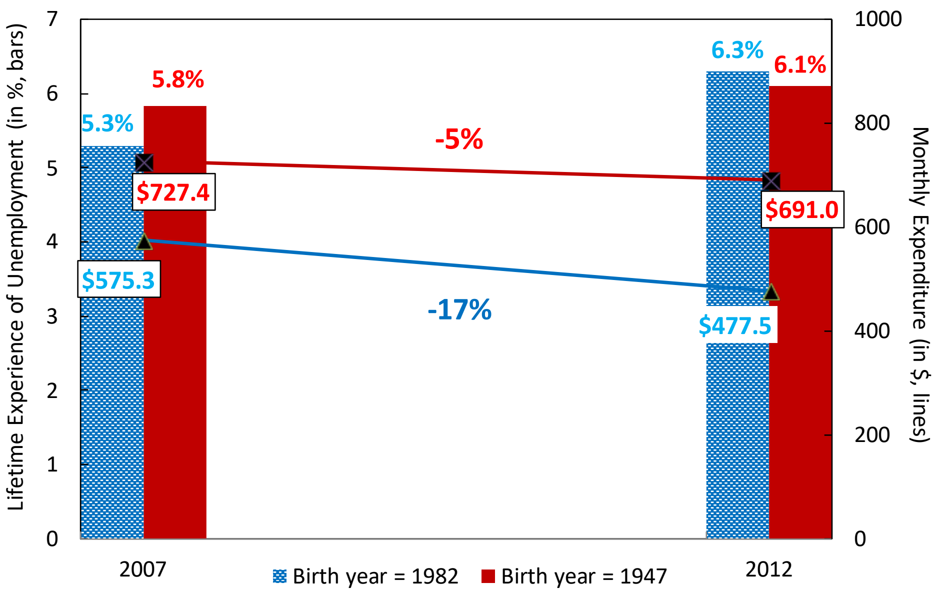
In Figure IV, we illustrate the economic magnitude of the estimates in the context of unemployment conditions during the Great Recession, which falls in the Nielsen sample period. The average monthly unemployment rate from 2008-2012 was 8.1%, with the maximum during the period being 10%. Comparing these numbers with historical averages, the average unemployment rate during the 60 years prior to 2008, from 1947-2007, was 5.6%. Now consider two individuals, a 25-year-old and a 60-year-old as of December 2007. Their lifetime unemployment experience, based on our experience weighting scheme, was 5.3% and 5.8%, respectively, when they entered the crisis in 2008. By the end of 2012, their lifetime unemployment experience was 6.3% vs. 6.1%, respectively. In other words, the unemployment experience for the 25-year-old increased by 1%, whereas that for the 60-year-old increased by

Table VII: **Experience Effects and Monthly Consumption (Nielsen)**

	(1)	(2)	(3)	(4)
Experience (Macro)	-0.415***	-0.415***	-0.178***	-0.177***
	(0.044)	(0.044)	(0.034)	(0.034)
Unemployment rate (county)		-0.002		-0.005***
		(0.003)		(0.001)
Income control	Yes	Yes	Yes	Yes
Wealth control	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Market-area fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	No	No	Yes	Yes
Observations	3,171,833	3,171,833	3,171,833	3,171,833
R-squared	0.116	0.116	0.526	0.526

Notes. Pooled OLS and fixed effects regression with (log) total consumption expenditure as the dependent variable. Experience (Macro) is the macroeconomic experience measure of unemployment (household's lifetime experience of national unemployment rates). Wealth controls include the ZIP-code level house-price index from Zillow, an indicator variable for households that own at least one house, and an interaction term between the house price index and the homeowner dummy. Household characteristics include unemployment status, household size, education, race, and a dummy variable indicating whether the respondent is unemployed at the time of the survey. Time fixed effects are year-month fixed effects. Regressions are weighted using the household sampling weights from Nielsen. The sample period runs from 2004 to 2013. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Figure IV: **Example of Unemployment Experience Shock from Recession, Nielsen**



Notes. Example of the impact of the Great Recession on weighted lifetime experiences of unemployment rates and monthly consumption expenditure of a 25-year-old vs. a 60-year-old (as of 2007) from December 2007 to December 2012. The bars show the weighted lifetime experiences of unemployment rates based on a linearly-declining weighting scheme. The lines show the monthly expenditures: the values for 2007 are from actual data, and the values for 2012 are calculated based on model estimates.

0.3%. Relating these experiences to consumption behavior, our model estimates imply that the monthly consumption expenditure of the 25-year-old decreased by approximately 18% while that of the 60-year-old decreased by approximately 5%.

Next, we turn to the more fine-grained measures of consumption quality, which are our main motivation for including the Nielsen data in the analysis. We explore the effect of lifetime unemployment experience on coupon use, the purchase of lower-end products (within a product category), and the purchase of sale items. Other than the switch in outcome variable, the estimation model is exactly the same as delineated in equation (9).

The estimates are shown in Table VIII. We display only the main coefficients of interest but include the same battery of controls as in Table VII. We find that households who have lived through periods of worse employment conditions are more likely to use coupons, pur-

Table VIII: **Experience Effects and Monthly Consumption Quality (Nielsen)**

	(1)	(2)	(3)	(4)
A: Coupons				
Experience (macro)	0.036***	0.035***	0.005*	0.005*
	(0.005)	(0.005)	(0.003)	(0.003)
Unemployment rate (county)		0.001***		0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.040	0.041	0.690	0.690
B: Product Ranking				
Experience (macro)	-0.104***	-0.104***	0.004**	0.004**
	(0.0338)	(0.0338)	(0.002)	(0.002)
Unemployment rate (county)		-0.001**		-0.009***
		(0.001)		(0.002)
R-squared	0.083	0.083	0.680	0.680
C: On-sale Items				
Experience (macro)	0.159***	0.156***	0.009**	0.009*
	(0.018)	(0.018)	(0.004)	(0.004)
Unemployment rate (county)		0.003***		0.005***
		(0.000)		(0.001)
R-squared	0.073	0.074	0.830	0.830
Income control	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Market area fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	No	No	Yes	Yes
Observations	3,171,833	3,171,833	3,171,833	3,171,833

Notes. OLS regressions with the ratio of coupons used over total expenditure as the dependent variable in Panel A; the (transformed) ranking of goods, based on their unit price in their specific product modules, markets, and months in Panel B (where we use the logit transformation ln(y/(1-y)) to map the original ranking, which ranges from 0 to 1, to the real line); and with the ratio of on-sale items purchased over the total number of items purchased as the dependent variable in Panel C. Experience (macro) is the household's lifetime experience of national unemployment rates. Other controls are as in Table VII. The sample period runs from 2004 to 2013. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

chase lower-end products, and allocate more expenditures toward sale items. For example, considering the inter-decile range of unemployment experiences, our estimates suggest that households who have experienced unemployment rates at the 90th percentile of the sample experiences use \$13 more in coupon and purchase 8% more sale items monthly than respondents at the 10th percentile. This set of results show that people who have lived through large fluctuations in unemployment adjust the quality margins of their consumption accordingly. This suggests a thorough study on the long-term impact of macroeconomics shocks on consumption calls for analysis not only based on aggregate spending figures but also evidence on product substitution and consumption reallocation—margins that entail important welfare implications.

4.4 Heterogeneity Across Cohorts

The analyses of consumption decisions in the PSID and Nielsen data indicate that people overweight their lifetime experiences, which naturally gives rise to heterogeneity in consumption behavior across cohorts. In particular, we see that consumers overweight more recent experiences, and the experience-effect hypothesis implies that younger cohorts do so more strongly than older cohorts. One implication of our findings, then, is that a given unemployment shock should have a stronger effect on cohorts with shorter lifetime histories so far. In other words, we predict that the young lower their consumption expenditure to a greater degree than older cohorts during economic busts and, vice-versa, increase their spending significantly more than older cohorts during booms.

We test this implication directly, regressing the log change in consumption in the Nielsen data on the interaction of age with the log change in unemployment conditions from month t to $t-1$, controlling for the same battery of controls as in Table VII. We do so separately for positive and negative changes (in absolute value) in unemployment rates in order to identify possible asymmetries in the reaction to improving versus tightening economic conditions. Moreover, as we focus on the most recent unemployment experience and know where a household resides during that period, we can use either changes in the national unemployment rate or changes in the local (county-level) unemployment rate as our proxy for the experienced unemployment shock, controlling for the respective other rate change.[28]

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

	(1)	(2)	(3)	(4)	(5)
	Δln(C)	Δln(C)	Δln(C)	Δln(C)	Δln(C)
Age * Δln(National unemp-down)	-0.023***	-0.023***			-0.021***
	(0.005)	(0.005)			(0.005)
Age * Δln(National unemp-up)	-0.006***	-0.007***			-0.000
	(0.002)	(0.002)			(0.003)
Age * Δln(Local unemp-down)			-0.002*	-0.003**	-0.002
			0.00121)	(0.00135)	(0.00138)
Age * Δln(Local unemp-up)			-0.008***	-0.008***	-0.009***
			(0.001)	(0.001)	(0.001)
Local unemployment control	Yes	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Market area fixed effects	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	Yes	No	Yes	Yes
Observations	3,171,833	3,171,833	3,171,833	3,171,833	3,171,833
R-squared	0.005	0.005	0.005	0.005	0.005

Notes. OLS regression with dependent variable being the log change in monthly total consumption expenditure and the main regressors being the interaction term between age and 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 $t-1$. Local unemployment controls are the log change in local unemployment rate separated into two variables depending on whether the change is positive or negative. Household characteristics include household size, education, and race. Time fixed effects include year-month fixed effects. The sample period runs monthly from 2004 to 2012. Regressions are weighted by Nielsen household weights. Robust standard errors in parentheses are clustered by cohort and time. *, **, *** denote 10%, 5%, and 1% significance, respectively.

[28] Note that it would be more difficult to estimate the relationship between changes in consumption and recent changes in unemployment experience in the PSID. The low (biannual rather than monthly) frequency of survey waves makes it harder to define the “most recent” experience in a uniform way, and also drastically reduces statistical power as we have only eight waves.

The results are shown in Table IX. We interact age with the national-rate shock in columns (1) and (2), and with the local (county-level) rate shock in columns (3) and (4). We include all interactions in column (5). Note the log changes in the national unemployment rate are absorbed by the time (year-month) fixed effects, and we include the positive and negative log changes in the local unemployment rate across all specifications.

We find that unemployment shocks, whether positive or negative, have a smaller effect on expenditures as age increases, as shown by the estimated effects of the age-unemployment interaction. Both when we consider the most recent change in national unemployment rates (columns 1 and 2) and local unemployment rates (columns 3 and 4), the coefficients on the interaction between age and the most recent change in unemployment are significant and negative. The effects are a bit stronger for increases in national unemployment and for decreases in local unemployment. When we include all four interaction effects, their coefficient sizes remain similar, with the exception of the interaction of age with lower national employment, where the estimated coefficient becomes smaller and insignificant. Overall, the results support our prediction of a significantly stronger response to recent experiences among the young than among the old.

This finding also helps further distinguish the experience-effect hypothesis from alternative theories in the existing consumption literature such as liquidity constraints of the young (e.g. Zeldes (1989), Gourinchas and Parker (2002)). Models with liquidity constraints predict that the young react more strongly to negative unemployment shocks than the old, as they are more likely to hit liquidity constraints; but they do not easily predict a more positive reaction to positive shocks. To generate the latter prediction, these models need to rely on the argument that the young were previously constrained, and a positive shock allows them to adjust to their permanent-income optimum. However, our identification also exploits the differences in consumption of the young at better and worse economic times. Here, an adjustment to the PIH optimum would predict the opposite outcome relative to the experience effect hypothesis: the young with more negative prior experiences would exhibit a stronger reaction to recent good outcomes according to the PIH.[29] Thus, our findings highlight experience effects as a distinct force in affecting people's consumption behavior.

5 CEX

As a final source of data on consumption choices, we turn to the Consumer Expenditure Survey (CEX). So far, we have estimated strong experience effects both on food and total consumption in the PSID data, and on grocery items and their quality in the Nielsen data. We now enlarge the set of consumption items further to include durable consumption as well as the CEX measure of total consumption, which has been widely used in the literature and which encompasses further categories of expenditures, in addition to durables and non-durable items, including healthcare and education expenses.[30]

The CEX is a repeated cross-sectional survey that contains household spending data across a comprehensive list of product categories at the quarterly frequency and is considered to be the benchmark dataset in the consumption literature. Compared to our other data sources, the PSID and Nielsen, its main disadvantage is the lack of panel structure as the ability to study experience effects within households, i. e., after including household fixed effects, is one of the advances in this paper over prior studies of experience effects in different contexts.

In order to keep the advantages of panel analysis but also exploit the comprehensiveness of the CEX, we match the two datasets and create a synthetic panel.[31] Specifically,

[29] To that end, we ran a set of regressions that augments the specifications from Table IX with a triple interaction regressor involving age, positive and negative national or local unemployment shocks, and a dummy variable for negative experience that takes the value 1 if the respondent's unemployment experience is above the median unemployment experience for her age. The results show that for a given age, positive national and local unemployment shocks have weaker effects on the consumption of respondents with worse unemployment experiences, as predicted by experience-based learning but not by a standard PIH framework.

[30] Note that estimations involving durable consumption may be partly affected by the timing of household durable purchases. Prior research such as Bar-Ilan and Blinder (1992) and Berger and Vavra (2015) shows that durable purchases tend to be discontinuous and go down during recessions. However, these concerns do not apply to our estimates of experience effects on food and other non-durable consumption items.

[31] We have also analyzed the CEX separately. Appendix-Table A.9 shows the results of estimating regression model (9) on the repeated cross-section CEX data. For all outcome variables – durable, non-durable, and total consumption – we continue to estimate highly significant negative experience effects.

Table X: **Summary Statistics (Nielsen-CEX Matched Data)**

Variable	Mean	SD	p10	p50	p90	N
Total consumption expenditure	4,508	4,919	1,838	3,371	7,111	866,819
Durable consumption	1,078	4,466	0	117	1,460	866,819
Non-durable consumption	2,612	1,178	1,423	2,400	4,025	866,819
Non-durable consumption (Nielsen)	2,139	1,602	618	1,757	4,083	3,171,833
Experience (Macro)	5.9	0.2	5.8	5.9	6.2	866,819

Notes. The sample period runs quarterly from 2004 to 2012. Observations are quarterly and not weighted.

we match a household i from the CEX data with a household j from Nielsen on a set of common covariates (characteristics) $x_i = (x_{i,1}, x_{i,2}, ..., x_{i,p})$ and $x_j = (x_{j,1}, x_{j,2}, ..., x_{j,p})$, which include age, income, marital status, household size, education, race, region of residency, employment status, as well as their consumption of non-durable items, using the nearest-neighbor matching estimator from Rosenbaum and Rubin (1983) and Abadie and Imbens (2011). The distance between x_i and x_j is parameterized by the vector norm $\parallel x_i - x_j \parallel_S = ((x_i - x_j)' S^{-1} (x_i - x_j))^{1/2}$, where S is a given symmetric, positive-definite matrix. We find that the set of nearest-neighbor indices for observation i from the CEX in Nielsen as $\Omega_i = (j | t_j = 1 - t_i, \parallel x_i - x_j \parallel_S < \parallel x_i - x_l \parallel_S, t_l = 1 - t_i, l \neq j)$. In words, the nearest-neighbor propensity-score matching chooses for each observation in the CEX an observation in Nielsen that has the closest estimated propensity score.

Table X provides summary statistics on the matched sample. Note durable consumption and non-durable consumption do not add up to total consumption because total consumption encompasses categories of expenditure that are not considered durable or non-durable, including healthcare and education expenses. In the matched dataset, the distributions on total and durable consumption are comparable to those from the underlying CEX data, which is indicative of successful matching. The average durable and non-durable consumption spending amount to 23.9% and 29.2% of the mean total consumption expenditures, respectively. Note durable spending and nondurable spending are weakly positively correlated, with durable spending being much more volatile than non-durable spending. For an average household, its share of durable consumption makes up 10% of total spending, while non-durable consumption amounts to 69% of total spending.

Table XI shows results from re-estimating specification (9) using the matched CEX-Nielsen sample. In columns (1) and (4) we use total expenditures as the outcome variable, in columns (2) and (5), we focus on durable consumption spending, and in columns (3) and (6) we focus on non-durables. As before we show the results both without household fixed effects (columns 1 to 3) and with fixed effects (columns 4 to 6).

The results strongly confirm our prior findings and reveal new quantitative implications for the different components of total consumption. All experience effect coefficients are negative and typically highly significant. In other words, households who have experienced worse unemployment conditions during their lifetime spend significantly less in total (on all goods), and also specifically on durable and on non-durable items. One exception are non-durables in the case where we identify only within household; here the coefficient becomes small and insignificant. Otherwise, the coefficients are stable across specifications, and the economic magnitudes are large: a one standard deviation increase in lifetime unemployment experience is associated with a \$38 decline in monthly non-durable consumption and \$108 decline in monthly total consumption (using the estimates of columns 3 and 1 respectively). The estimate on non-durable consumption is largely in line with the estimate from the PSID as the earlier set of results shows that a one standard deviation increase in lifetime experience is associated with a \$33 decline in monthly food consumption, while the estimate on total consumption is larger than the one from the PSID (\$76 decline in monthly total consumption), which may be attributed to the fact that total consumption in the CEX encompasses more categories of goods. The new estimate for durable consumption is large and highly significant across specifications. A one standard deviation increase in lifetime unemployment experience is associated with a \$57 decline in monthly durable consumption.

Table XI: **Experience Effects and Quarterly Consumption (Nielsen-CEX Matched Sample)**

	Total	Durables	Non-durable	Total	Durables	Non-durable
Experience (Macro)	-0.358***	-0.797***	-0.220**	-0.266***	-0.796***	-0.033
	(0.038)	(0.122)	(0.019)	(0.051)	(0.145)	(0.028)
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Market-area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	Yes	Yes	Yes
Observations	866,819	866,819	866,819	866,819	866,819	866,819
R-squared	0.183	0.053	0.257	0.020	0.008	0.069

Notes. Regressions with (log) total consumption expenditure, durable consumption, and non-durable consumption as the dependent variables. Experience (Macro) is the macroeconomic experience measure of unemployment (household's lifetime experience of national unemployment rates). Household characteristics include unemployment status, household size, education, and race. Time fixed effects include year-quarter fixed effects. 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 cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

6 Mechanism: Evidence on the Beliefs Channel

Thus far, we have presented robust findings of a negative and significant relationship between people's lifetime experiences of economic conditions and their consumption behavior. We have estimated consistent coefficients across three sets of consumption data. What these estimations do not pin down is the channel through which lifetime experiences affect consumption choices. Specifically, we may ask to what extent personal lifetime experiences color beliefs about future outcomes, and to what extent they alter consumer preferences. In this section, we explore both the beliefs and the preference channel, and provide some suggestive evidence for the former.

First, we test whether lifetime experiences of economic fluctuations affect consumption behavior through the channel of altering beliefs about future economic prospects. We use microdata on expectations from the Reuters/Michigan Survey of Consumers (MSC). The MSC has been conducted by the Survey Research Center at the University of Michigan since the early 1950s. It has been conducted quarterly until Winter 1977, and monthly since 1978. The dataset is in repeated cross-section format and includes a total of 213,177 observation. On average, 630 individuals are surveyed each month (or quarter).

Among the multitude of belief elicitations, we identify two questions that capture expectations about economic conditions and that are related to unemployment and consumption. The first question elicits beliefs about future unemployment rates: "Now looking ahead–do you think that a year from now you will be better off financially, or worse off, or just about the same as now?" We relate the answers to this question to the lifetime experiences of the surveyed individuals. If the experience effect on consumption works through a beliefs channel, then worse lifetime experiences should predict more pessimistic beliefs about future financial conditions. If experience effects work through a preference channel, then beliefs would remain unaffected, after controlling for all historical data, current unemployment and other macro conditions. (Note, however, that evidence for a beliefs channel does not rule out that unstable preferences are an additional channel through which experience effects operate.

And vice versa, failure of lifetime experiences of unemployment to predict general beliefs about unemployment rates does not rule out that experience effects operate through tilting beliefs about individual employment prospects.)

The second question is about expenditures for (durable) consumption items and individuals' current attitudes towards buying such items: "About the big things people buy for their homes – such as furniture, refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?" If the experience effects in consumption operate through a beliefs channel, then individuals with worse lifetime experiences might consider times to be generally bad for spending on durables. The idea is that, while the individual sensitivity of spending to personal lifetime experiences might reflect either pessimistic beliefs about the future or more frugal preferences, induced by those experiences, only the former is easily consistent with a more general assessment of times to be "good or bad" for spending of other people.

For the regression analysis, we construct two binary dependent variables. The first indicator takes the value of 1 if the respondent expects better or about the same personal financial conditions over the next twelve months (first question), and 0 otherwise. The second indicator variable takes the value of 1 if the respondent answers "Good" or "About the same" to the second question, i. e., assesses times to be good or the same for durable consumption purchases, and 0 otherwise. We also extract income and all other available demographic variables, including education, marital status, gender, race, and age of the respondent. Using the information on respondents' birth years, we construct our usual measure of lifetime experiences of unemployment for each survey respondent at each point in time during the sample. We then regress the dummy indicating higher expectation of higher unemployment or a positive buying attitude on lifetime experiences of unemployment, controlling for current unemployment, income, household demographics, age fixed effects and year fixed effects.

Table XII: **Experience Effects and Expectations**

	Expected financial condition coming year (1 = Better or Same, 0 = Worse)			Good/bad time to buy major household items (1 = Good or Same, 0 = Bad)		
	(1)	(2)	(3)	(4)	(5)	(6)
Lifetime experience of unemployment (rates)	-0.017***	-0.015***	-0.014***	-0.059***	-0.050***	-0.046***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Unemployment rate	-0.015***	-0.015***	-0.015***	-0.044***	-0.044***	-0.043***
	(0.004)	(0.005)	(0.005)	(0.001)	(0.001)	(0.002)
Income		0.017***	0.021***		0.051***	0.039***
		(0.001)	(0.001)		(0.001)	(0.002)
Demographic controls	No	No	Yes	No	No	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	209,786	197,129	193,483	203,492	191,420	187,909
R-squared	0.047	0.048	0.048	0.057	0.065	0.069

Notes. Dependent variable in column 1-3 is response to the question "Now looking ahead–do you think that a year from now you will be better off financially, or worse off, or just about the same as now?" (1 = Better off or about the same, 0 = Worse off) reported by individual respondents in the Michigan Survey of Consumers. Dependent variable in column 4-6 is response to the question "About the big things people buy for their homes– such as furniture, refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?" (1 = Good (or Same), 0 = Bad) reported by individual respondents. Estimation is done with least squares, weighted with sample weights. Lifetime experience of unemployment is a lifetime linearly-declining weighted national unemployment rate experienced by households. Demographic controls include education, marital status, gender, and race. Age controls are dummy variables for each age. The sample period runs from 1953 to 2012. Standard errors, shown in parentheses, are robust to heteroskedasticity. *, **, *** denote 10%, 5%, and 1% significance, respectively.

The estimation results are shown in Table XII. In columns (1) to (3), we present the estimates of the effect of lifetime experiences on unemployment forecasts. We find that people who have experienced greater unemployment rates during their lifetimes so far expect significantly worse future financial conditions. The statistical and economic significance of the estimated experience effect is robust to variations in the set of controls included. Whether we include only the fixed effects (age and time dummies), or add a control for income, or include also all other above-mentioned demographic variables, we always estimate a highly significant coefficient between -0.017 and -0.014 of lifetime unemployment experiences. In terms of economic magnitude, we can consider the inter-decile range of lifetime experiences: Respondents who have experienced unemployment rates at the 90th percentile of sample are around 2.5 percent more likely to say financial conditions will be worse in the next 12 months than respondents in the 10th percentile.

The estimation results based on the second question are shown in columns (4) to (6) of Table XII. We use the same estimation model and variation in control variables, but substitute the dependent variable with our indicator for "buying attitude." Here, we estimate a significantly negative effect of lifetime experiences of unemployment. The coefficient is again fairly stable, ranging from -0.059 to -0.0046. Respondents who have experienced unemployment rates at the 90th percentile of sample are around 8.5 percent more likely to say now is a bad time to buy major household items than respondents in the 10th percentile.

Hence both sets of estimations from the MSC provide evidence in support of the view that past experiences affect beliefs, in this case beliefs about future economic conditions and buying attitudes. This evidence on the beliefs channel is consistent with prior literature on experience effects, including Malmendier and Nagel (2011) and Malmendier and Nagel (2015). While the results do not rule out that past experiences affect preferences as well, the beliefs channel appears to be an important component of experience effects.

It is difficult to further distinguish the relative importance of experience-based learning (beliefs channel) and the hypothesis of experience-based taste changes (preference channel).

There are many possible specifications of the preference-based interpretation, and it is thus impossible to conclusively reject the instable-preferences explanation. As in the case of the beliefs-based channel, we can at best aim to provide evidence in favor of specific formalizations.

In an attempt to do so, we explore one preference specification that has garnered significant support in prior empirical literature: We study whether our findings on the significant relationship between consumption and lifetime experience may be correlated with habit persistence in consumption. To that end, we estimate an alternative version of the empirical model in equation (9) that includes a lagged consumption measure on the right hand side. This dynamic specification, with the lagged dependent variable included, 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 the specification 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.[32] 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.

The results, presented in XIII, show that the effects of unemployment experience on consumption remain highly significant after taking into account consumption habit. The estimation results both confirm the robustness of experience effects and indicate that they do not operate through the channel of habit formation.

[32] Note that 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 XIII: **Experience Effects and Consumption, GMM regressions**

	PSID	Nielsen	Nielsen-CEX
Experience (macro)	-0.181***	-0.266***	-0.227***
	(0.0628)	(0.0506)	(0.0616)
Experience (personal)	-0.635**	—	—
	(0.120)		
Income control	Yes	Yes	Yes
Wealth control	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes
Observations	29,813	3,016,952	693,467
R-squared	0.45	0.41	0.49

Notes. System GMM regressions with food consumption (in logarithm) as the dependent variable. "Experience (Macro)" is the macroeconomic experience measure, "Experience (Personal)" is the personal experience measure, specified as described above for the respective datasets. Time fixed effects include year fixed effects for the PSID sample, and year and month fixed effects for the Nielsen and Nielsen-CEX sample. Location fixed effects include state fixed effects for the PSID sample and market area fixed effects for the Nielsen and Nielsen-CEX sample. The sample period runs from 1999-2013 for the PSID and 2004 to 2013 for the Nielsen and Nielsen-CEX matched sample. Robust standard errors in parentheses are clustered on cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

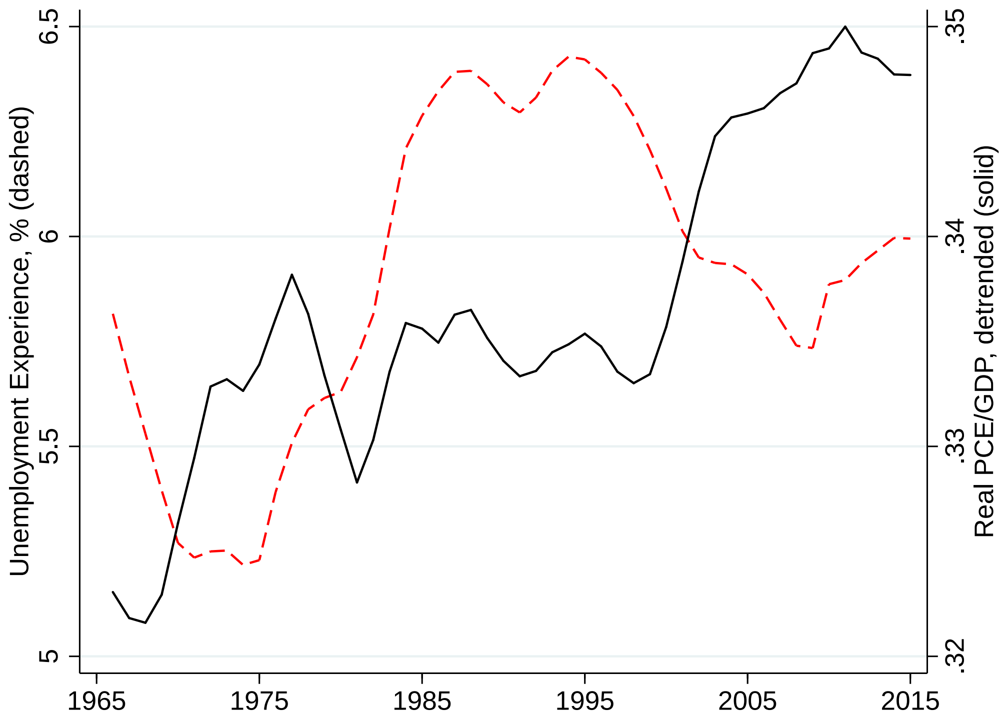
7 Aggregate Implications and Conclusion

While it has been a decade since the start of the Great Recession, effects of the crisis still linger, and 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 have put forward the idea that experiences of macroeconomic and personal unemployment shocks play a significant role in affecting household consumption and thereby serve as an important force in determining the long-term consequences of macroeconomic shocks. Estimation results from detailed household panel data and three different data sources confirm this conclusion. Households who have experienced times of higher local and national unemployment rates and more personal unemployment spend significantly less, after controlling for income, wealth and demographics, and they tend to choose lower-quality items.

Our results on the lasting effects of past experiences on consumption suggest that experience effects could constitute a novel micro-foundation underlying fluctuations in aggregate demand and long-run effects of macroeconomic shocks. While a thorough investigation of the macroeconomic implications of experience effects is beyond the scope of this paper, we provide some suggestive evidence on the aggregate level to point to experience effects as a factor of macroeconomic significance.

Specifically, we relate an aggregate measure of lifetime experiences in the U.S. population to a measure of aggregate consumption expenditure in the U.S. from 1965 to 2013. For the former measure, we take a weighted average of national unemployment experience, as defined in Equation (5), using data on U.S. population broken down by age (age 25 to 75) from the Census as weights. For aggregate consumer spending, we use data on real personal consumption expenditure (PCE) from the U.S. Bureau of Economic Analysis (BEA) normalized by real gross domestic product (GDP). As shown in Figure V, there exists a negative relationship between the two measures: times of higher aggregate unemployment experience coincide with times of lower aggregate consumer spending. The strong negative correlation pattern not only adds credibility to our micro-level estimates but also suggests the

Figure V: **Aggregate Unemployment Experience and Consumer Spending**



Notes. Aggregate unemployment experience calculated as a weighted average of national unemployment experience, as defined in Equation 5, with the weights being U.S. population by age (restricted to age 25 to 75) from the Census. Aggregate consumer spending is measured as real personal consumption expenditure (PCE) from the U.S. Bureau of Economic Analysis (BEA) normalized by real gross domestic product (GDP), detrended by removing a linear time trend from the series.

possibility that personally experienced labor market conditions may be a significant granular source of aggregate fluctuations.

Thus, the evidence on experience effects in consumption has potentially important policy implications. They appear to significantly dampen macroeconomic fluctuations, which in turn calls for 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 undergone more drastic and 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.

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APPENDIX

A.1 Model Solution under Experience-Based Learning

The model given by Equations (1)-(6) has no closed-form solution that would characterize an individual's optimal consumption decision in each period. Instead, the consumer has to solve the life-time optimization model by backwards induction in each decision period. To solve the intertemporal optimization problem numerically, we apply the cash-on-hand approach by Deaton (1991) in the version developed by Carroll, Hall, and Zeldes (1992). Cash-on-hand X_t is the sum of the individual's current income and current assets, $X_t = A_t + Y_t$, and $x_t \equiv X_t/P_t$ is the ratio of cash-on-hand to the permanent component of income at t. The dynamic budget constraint in (2) can be rewritten as

$$x_{t+1} = (1+r)\left(x_t - c_t\right)\frac{P_t}{P_{t+1}} + U_{t+1}, \tag{A.1}$$

where lower-case letters indicate variables normalized by the permanent income in that period. The relevant state variables are the cash-on-hand ratio x_t and the belief p_t the consumer forms about her employment probability p in the next period $t+1$ after observing the realization of her employment status in t, W_t. With this notation, the value function in period t satisfies

$$V_t\left(x_t, p_t\right) = \max_{c_t} u(c_t) + \delta E_t\left[V_{t+1}\left(x_{t+1}, p_{t+1}\right) \mid p_t\right], \tag{A.2}$$

where p_{t+1} is a deterministic function of W_{t+1} and p_t, with the functional form specified in equation (5) in the main text, and x_{t+1} satisfies (A.1) for $t < T+N$. The terminal condition is $x_{T+N+1} \geq 0$.

We make the simplifying assumption that, at time t, the consumer applies her belief about her employment probability next period also to all subsequent periods until retirement. That is, when optimizing at time t, she assigns the current value p_t also to all future probabilities

p_{t+k} for $0 < k \leq T - t$.[33] Under this assumption, the expectation term in expression (A.2) can be simplified as follows:

$$
\begin{aligned}
& E_t\left[V_{t+1} \mid p_t\right] \\
= & p_t E_t\left[V_{t+1}\left(\frac{A_{t+1}}{P_{t+1}}+U_{t+1}, p_{t+1}(p_t, 1)\right) \mid W_{t+1}=1\right]+\left[\left(1-p_t\right) V_{t+1}\left(\frac{A_{t+1}}{P_{t+1}}, p_{t+1}(p_t, 0)\right)\right. \\
= & V_{t+1}\left(\frac{A_{t+1}}{P_{t+1}}, p_{t+1}(p_t, 0)\right)+p_t E_t\left[V_{t+1}\left(\frac{A_{t+1}}{P_{t+1}}+U_{t+1}, p_{t+1}(p_t, 1)\right)-V_{t+1}\left(\frac{A_{t+1}}{P_{t+1}}, p_{t+1}(p_t, 0)\right)\right] \\
= & V_{t+1}(a_{t+1}, p_t)+p_t E_t\left[V_{t+1}\left(a_{t+1}+U_{t+1}, p_t\right)-V_{t+1}\left(a_{t+1}, p_t\right)\right],
\end{aligned}
$$

where the substitution $p_{t+1}(p_t, 0) = p_{t+1}(p_t, 1) = p_t$ in the last row reflects the above-mentioned simplifying assumption that the consumer does not take into account that the belief held in the next and any subsequent period is a function of future employment outcomes. Instead, she believes that she will apply the estimate p_t in all future periods.

Hence, the consumer's value function satisfies

$$
V_t\left(x_t, p_t\right)=\max_{c_t} u(c_t)+\delta\Big(V_{t+1}(a_{t+1}, p_t)+p_t E_t\big[V_{t+1}\left(a_{t+1}+U_{t+1}, p_t\right)-V_{t+1}\left(a_{t+1}, p_t\right)\big]\Big), \tag{A.3}
$$

subject to the dynamic budget constraint (A.1) and the terminal condition $V_{T+N+1} \equiv 0$. After p_t is updated every period based on Equation 5, this is a one-dimensional problem in x_t, which we solve numerically using backward induction. Increasing the belief p_t raises the expected net present value of future income. Hence $V(x_t, p_t)$ is strictly increasing in p_t and x_t.

Note the consumer's problem after entering retirement in period $T + 1$ is deterministic as income is fixed at $\bar{Y} > 0$ every period from then until $T + N$. To derive the optimal consumption policy function for the retirement period, we apply the Euler equation $u'(C_t) = (1 + r)\delta u'(C_{t+1})$, which gives $C_{t+1}/C_t = [(1 + r)\delta]^{\frac{1}{\rho}}$ since $u'(c) = C^{-\rho}$. If we know C_{T+1},

[33] This assumption merely serves to simplify the calculation. Without the assumption, we have to estimate the consumption policy for different possible realizations of future p_{t+k}'s on a finite grid on $[0, 1]$.

then we can compute $C_{T+k} = [(1+r)\delta]^{\frac{k}{\rho}} C_{T+1}$ for $1 < k \leq N$. We can pin down C_{T+1} by equating the net present-value of consumption $C_{T+1}, \ldots, C_{T+N}$ with the net present-value of resources at the time of retirement $T+1$:

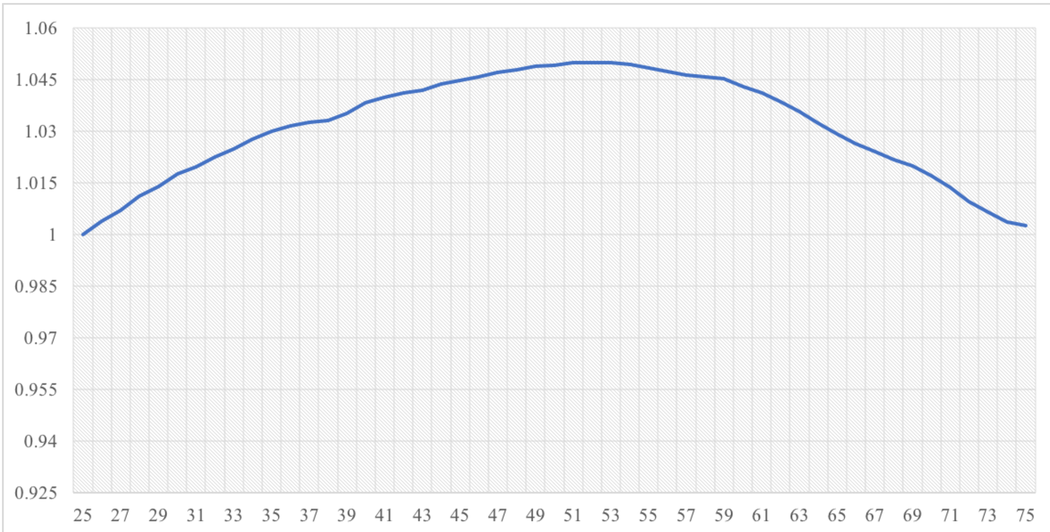
$$\sum_{k=0}^{N} \frac{1}{(1+r)^k} [(1+r)\delta]^{\frac{k}{\rho}} C_{T+1} = A_{T+1} + \bar{Y} \sum_{k=0}^{N} \frac{1}{(1+r)^k} \tag{A.4}$$

We thus know the optimal consumption policy for the retirement as a function of the assets at the time of retirement, $C_{T+k}(A_{T+1})$ for $1 < k \leq N$.

Model Comparison We check the validity of our model outlined in Section 2 by comparing the simulated life-cycle consumption path for the rational consumers in our model (Figure A.1) with that from an augmented consumption model with perfect-foresight consumers and income shocks from the Heterogeneous Agents Resources and toolKit (HARK) written by Christopher Carroll, Alexander Kaufman, David Low, Nathan Palmer, and Matthew White (https://github.com/econ-ark/HARK), as well as the food and total consumption paths constructed using the PSID data.

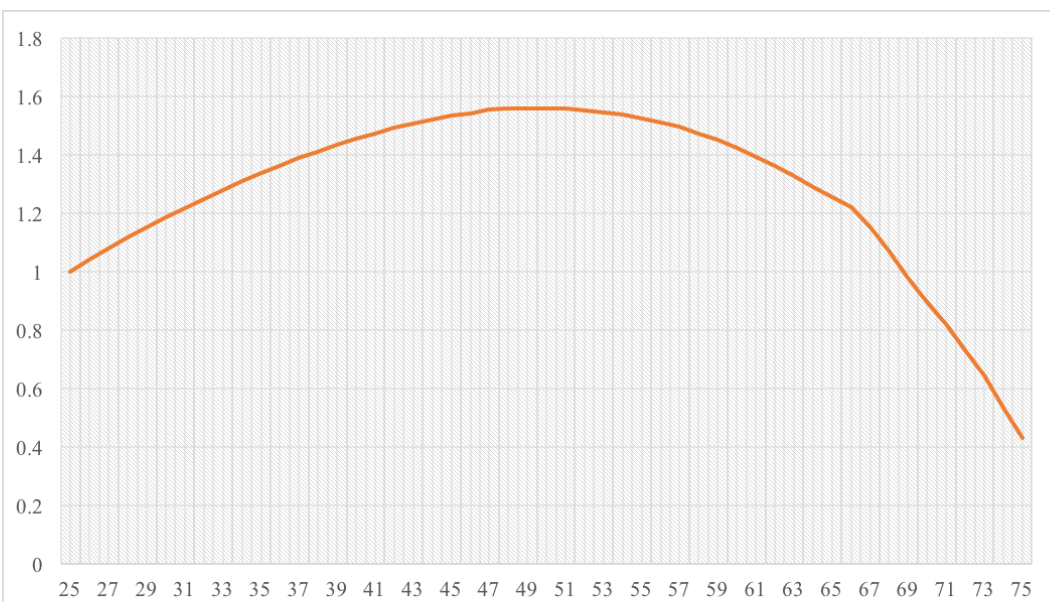
To simulate the consumption model from HARK, we input the same parameters as in our simple model whenever possible. For the survival probabilities in each period, a key parameter in the HARK model and not spelled out in our model, we also set them to be linearly declining from 1 in the first period to 0.51 in the last period. (There are 50 periods total.) The consumption path derived from the PSID data are constructed based on coefficients from regressions of consumption expenditures on age dummies and time dummies using the raw data. The corresponding figures based on simulations from the model using HARK and estimations using the PSID are presented in Figure A.2 and Figure A.3, respectively. Overall, the figures show that the life-cycle pattern derived from our model sample closely resemble the usual hump-shaped profile from a standard life-cycle model and from the raw data in one of the most commonly-used consumption datasets.

Figure A.1: **Consumption Path in Baseline Model Simulation**



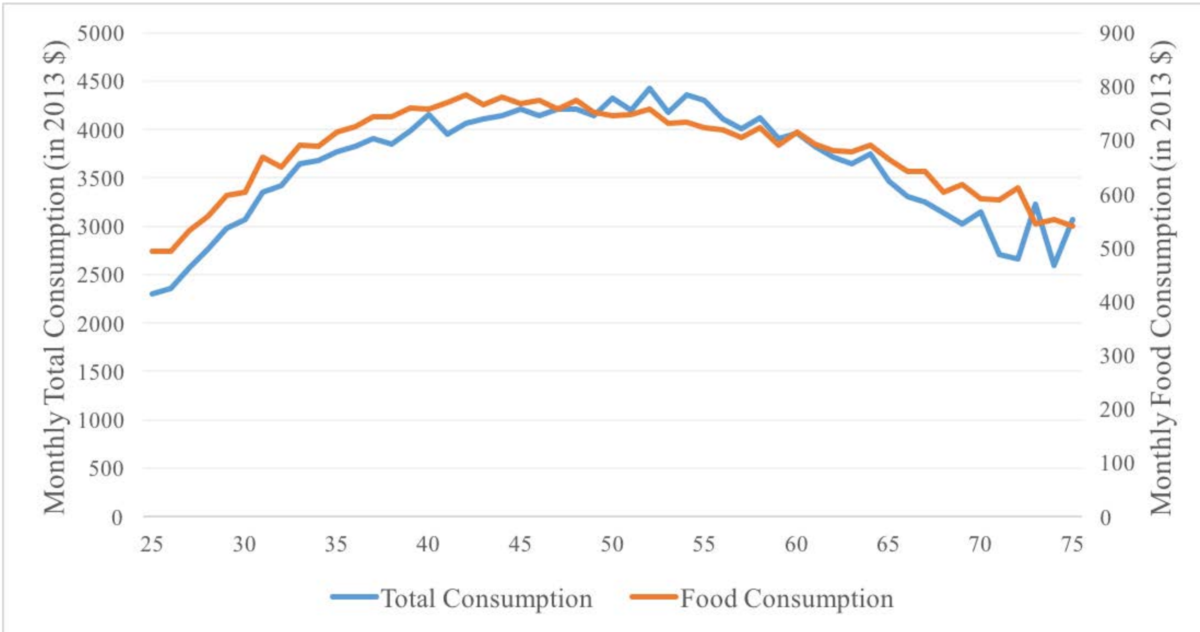
Notes. Simulations based on model outlined in Section 2 for rational consumers using parameters in Table I.

Figure A.2: **Consumption Path in Augmented Model Simulation**



Notes. Simulation based on a consumption model with perfect foresight consumers and income shocks from HARK using the same parameters used in our model simulation and additional parameters outlined in the text.

Figure A.3: **Average Household Expenditures of Different Age Groups**



Notes. The graph is depicted using the regression sample and "age" here refers to the age of the head of each household. The vertical axis on the left indicates total consumption per month and and the vertical axis on the right indicates for monthly food consumption. All consumption numbers are measured in 2013 dollars, adjusted using PCE.

A.2 PSID

In this section of the Appendix, we present a series of robustness tests of the estimations using the PSID data.

In Appendix-Table A.1, we re-estimate the regression models of Table IV but use experience measures that are constructed with weighting parameters $\lambda = 0$ and $\lambda = 3$ instead of $\lambda = 1$ (in the main text). Higher λ means individuals put more emphasis on their more recent experiences. When $\lambda = 0$, individuals are weighing all their past experiences equally. Note that experience-based learners with $\lambda = 0$ differ from Bayesian learners even though both assign equal weights to past realizations. Bayesian learners use all information to update their beliefs, while experience-based learners focus on information that occurred during their lifetime. As shown in Table A.1, the coefficients become larger in magnitude as λ increases, but the results remain qualitatively similar. Hence, the significant relation between experience and consumption appears to be robust to the choice of the weighting parameter.

In Appendix-Table A.2, we construct the experience measures for the gap years between the PSID biennial surveys in an alternative way. Recall that, for our measure of macroeconomic experience in the main text, we fill in the unemployment rate in a gap year t by assuming that the family lived in the same state as in year $t-1$. Here, we assume that respondents spend half of year t in the state in which they lived in year $t-1$ and the other half in the state in which they lived in year $t+1$. This alternate construction does not change the value if respondents live in the same state in years $t-1$ and $t+1$. Similarly for the personal experience measure, we reconstruct respondents' employment status in year t as the average of their status in years $t-1$ and $t+1$, rather than applying the value from year $t-1$. For example, if a person is unemployed in $t-1$ and is employed in $t+1$, the personal experience in t will be denoted as 0.5. We then re-estimate the model in (8) using these alternative constructs of experience. The results are very similar to those in Table 4 in the main text.

Appendix-Table A.3 shows the results when using different clustering units. Instead of clustering the standard errors by cohort as in Tables IV, we cluster the standard errors by cohort∗year, household, household∗year, and we two-way cluster by cohort and year. The pooled regressions in Appendix-Table A.3 correspond to the specification in column (3) in Table 4, and the specifications with household fixed-effects correspond to column (6) in Table 4. As shown, the statistical significance of our results are not affected in most cases. The one notable difference is that, with Total Consumption as the dependent variable and when not including household fixed effects (pooled regressions), the macro-level experience variable becomes insignificant while the personal experience variable remains highly significant. Once we included household fixed effects, both experience variables are significant.

In Appendix-Table A.4, we apply the PSID longitudinal family weights. Note that some families are given zero weight and are thus dropped from the estimation, which explains the lower number of observations in the weighted regressions. As before the results remain very similar in the specifications with household fixed effects. When we do not include the fixed effects (pooled regressions), the coefficient on the personal experience variable becomes larger in magnitude and remains highly significant while the coefficients of macro experience variable remain of similar magnitude but become marginally or not significant.

Appendix-Table A.5 presents results from estimations using alternative wealth controls. Column (1) shows the results if we control for log total wealth instead of separating liquid and illiquid wealth. In column (2), we use decile dummies, separately for liquid and illiquid wealth. In column (3), we control for log home equity value (home price minus mortgage) and log non-housing wealth. In column (4), we control for log total debt and log positive wealth separately. The coefficients of interest remain stable, again with the exception of the macro-level experience measure in the specification without household fixed effects.

Next, we test whether households that are more liquidity constrained are more affected by their unemployment experience. Closely following the practice in the consumption literature such as Johnson, Parker, and Souleles (2006) and Parker, Souleles, Johnson, and McClelland (2013), we sort households into two groups based on whether their liquid wealth is above or below the sample median in the respective year. We then add an indicator for below-median liquid wealth as well as its interactions with the experience variables to the estimating equation in (8). As shown in Appendix-Table A.6, households in the bottom half of liquid wealth tend to spend less, but do not exhibit a stronger reaction to unemployment experience. This suggests households' experience significantly affect consumption above and beyond potential liquidity constraints.

In Appendix-Table A.7, we restrict the analysis to households between the 5^{th} and 95^{th} percentiles of the income distribution. As mentioned in the main text, this exercise aims to address concerns about measurement error in the reported income in the PSID. The estimated coefficients remain significantly negative for both the macro and the personal experience measures.

In Appendix-Table A.8, we study the effects of lifetime experiences on household wealth accumulation. This analysis tests whether, given the significant impact of unemployment experiences on consumption, we can also detect experience effects in the build-up of wealth. The dependent variables are either liquid wealth or total wealth, and the main regressors are lagged experience measures. We lag the experience measures by six, eight, ten, twelve, and 14 years, instead of using the contemporary experience measures, recognizing that the effects of experience on wealth may take time to realize. We include the same set of control variables as in our main analyses, including controls for income in years $t-1$ and $t-2$, and add a control for the average family income between year $t-2$ and the year in which the lagged experience measures are based on (six, eight, ten, twelve, and 14 years ago, respectively). For example, when six-year lagged experience is the main regressor, we control for the average income between $t-2$ and $t-6$. This average-income control addresses the concern that previous experiences of economic boom or crisis may have implications for future income (Oyer (2008); **?**); Oreopoulos, von Wachter, and Heisz (2012)).[34] In the Appendix-Figure A.1, we plot the estimated coefficients on the lagged experience measures. In Appendix-Table A.8, we show the estimates of the coefficients on the 10-year, 12-year, and 14-year lagged experience measures. We find a significant role of past experiences for the build-up of wealth and liquid wealth, especially in the context of personal experiences.

[34] The results are similar if, instead of having an average-income control, we include the incomes for all years between year $t-2$ and the year in which the lagged experience measures are based on.

Table A.1: **Consumption (PSID), Different Weighting Parameters (λ)**

Dependent Varariable:	Food Consumption			Total Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)
Weighting Parameter $\lambda = 0$						
Experience (Macro)	-0.308**		-0.293**	-0.145**		-0.133**
	(0.127)		(0.129)	(0.060)		(0.058)
Experience (Personal)		-0.430***	-0.425***		-0.334***	-0.332***
		(0.137)	(0.137)		(0.082)	(0.082)
R-squared	0.542	0.542	0.542	0.755	0.756	0.756
Weighting Parameter $\lambda = 3$						
Experience (Macro)	-0.104**		-0.100**	-0.045**		-0.042**
	(0.039)		(0.040)	(0.018)		(0.018)
Experience (Personal)		-0.427***	-0.423***		-0.324***	-0.322***
		(0.134)	(0.134)		(0.080)	(0.080)
R-squared	0.542	0.542	0.542	0.755	0.756	0.756
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,156	37,156	37,156	37,156	37,156	37,156

Notes. All variables other than the experience measures are defined as in Table IV. The experience measures are constructed using $\lambda = 0$ in the upper part of the table, and $\lambda = 3$ in the lower part. Robust standard errors in parentheses are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.2: **Consumption (PSID), Alternative Constructions of Experience Measures**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Food Consumption						
Experience (Macro)	-0.186***		-0.170***	-0.178**		-0.171**
	(0.053)		(0.052)	(0.069)		(0.069)
Experience (Personal)		-0.800***	-0.796***		-0.429***	-0.424***
		(0.122)	(0.121)		(0.140)	(0.141)
R-squared	0.198	0.203	0.203	0.542	0.542	0.542
Dependent Variable: Total Consumption						
Experience (Macro)	-0.059*		-0.047	-0.082**		-0.077**
	(0.031)		(0.029)	(0.032)		(0.031)
Experience (Personal)		-0.634***	-0.633***		-0.327***	-0.325***
		(0.078)	(0.078)		(0.082)	(0.082)
R-squared	0.494	0.504	0.504	0.755	0.756	0.756
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	Yes	Yes	Yes
Observations	37,156	37,156	37,156	37,156	37,156	37,156

Notes. All variables other than the experience measures are defined as in Table IV. The construction of the experience measures differs as follows: For any gap year t (between PSID survey waves in $t-1$ and $t+1$), the baseline experience measures in the main text assume that families reside in the same state as in year $t-1$. The alternative construction used in this Appendix-Table assumes that families reside half of year t in their (t-1)-state of residence, and half of the year in their (t+1)-state of residence. (The different assumption does not matter when a family does not move between surveys.) Hence, the macro experience measure in this Appendix-Table uses the average of the year t unemployment rates of the (t-1)-state of residence and the (t+1)-state residence as gap year t's unemployment rate. Similarly, for the personal experience measure, we fill in the employment status of a household head in a gap year with the average of the years before and after. For example, if a person is unemployed in $t-1$ and is employed in $t+1$, then his personal experience in year t is denoted as 0.5. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.3: **Consumption (PSID), Alternative Clustering Units**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Food Consumption								
Experience (Macro)	-0.165***	-0.165**	-0.165***	-0.165***	-0.166***	-0.166	-0.166***	-0.166***
	(0.048)	(0.062)	(0.053)	(0.048)	(0.062)	(0.090)	(0.060)	(0.056)
Experience (Personal)	-0.757***	-0.757***	-0.757***	-0.757***	-0.426***	-0.426***	-0.426***	-0.426***
	(0.091)	(0.142)	(0.112)	(0.091)	(0.112)	(0.108)	(0.124)	(0.114)
R-squared	0.204	0.204	0.204	0.204	0.542	0.542	0.542	0.542
Dependent Variable: Total Consumption								
Experience (Macro)	-0.045*	-0.045	-0.045	-0.045*	-0.074***	-0.074**	-0.074**	-0.074***
	(0.023)	(0.028)	(0.030)	(0.024)	(0.023)	(0.029)	(0.035)	(0.025)
Experience (Personal)	-0.607***	-0.607***	-0.607***	-0.607***	-0.329***	-0.329***	-0.329***	-0.329***
	(0.052)	(0.092)	(0.074)	(0.050)	(0.054)	(0.079)	(0.068)	(0.051)
R-squared	0.505	0.505	0.505	0.505	0.756	0.756	0.756	0.756
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	37,156	37,156	37,156	37,156	37,156	37,156	37,156	37,156

Notes. All variables are defined as in Table IV. Standard errors in columns (1) to (4) are clustered by cohort∗year, cohort and year (two-way clustering), household and household∗year, respectively, and the same for columns (5) to (8). *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.4: **Consumption (PSID) with PSID Weights**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Food Consumption						
Experience (Macro)	-0.128*		-0.107	-0.146**		-0.145**
	(0.072)		(0.068)	(0.071)		(0.070)
Experience (Personal)		-0.961***	-0.959***		-0.349**	-0.349**
		(0.241)	(0.240)		(0.167)	(0.168)
R-squared	0.221	0.229	0.229	0.566	0.566	0.566
Dependent Variable: Total Consumption						
Experience (Macro)	-0.070		-0.052	-0.084**		-0.084**
	(0.053)		(0.048)	(0.039)		(0.038)
Experience (Personal)		-0.878***	-0.877***		-0.357***	-0.357***
		(0.235)	(0.234)		(0.103)	(0.103)
R-squared	0.477	0.493	0.493	0.764	0.765	0.765
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	Yes	Yes	Yes
Observations	36,789	36,789	36,789	36,789	36,789	36,789

Notes. All variables are defined as in Table IV, but observations are now weighted by the PSID family weights. The family with zero weights are dropped. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.5: **Consumption (PSID), Alternative Wealth Controls**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Food Consumption								
Experience (Macro)	-0.165***	-0.133***	-0.161***	-0.140***	-0.167**	-0.143**	-0.162**	-0.130*
	(0.050)	(0.049)	(0.051)	(0.050)	(0.070)	(0.069)	(0.069)	(0.070)
Experience (Personal)	-0.756***	-0.553***	-0.756***	-0.475***	-0.426***	-0.408***	-0.426***	-0.359**
	(0.114)	(0.112)	(0.114)	(0.115)	(0.136)	(0.136)	(0.136)	(0.143)
R-squared	0.204	0.223	0.204	0.230	0.542	0.545	0.543	0.552
Dependent Variable: Total Consumption								
Experience (Macro)	-0.046	-0.017	-0.044	-0.017	-0.075**	-0.057*	-0.076**	-0.040
	(0.028)	(0.029)	(0.029)	(0.030)	(0.031)	(0.030)	(0.031)	(0.027)
Experience (Personal)	-0.606***	-0.454***	-0.606***	-0.344***	-0.329***	-0.316***	-0.329***	-0.278***
	(0.074)	(0.071)	(0.074)	(0.073)	(0.081)	(0.080)	(0.081)	(0.079)
R-squared	0.504	0.543	0.504	0.578	0.756	0.761	0.756	0.776
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	37,156	37,156	37,156	35,206	37,156	37,156	37,156	35,070

Notes. The pooled regressions and the regressions with household fixed effects here are only different from the regressions in Table 4 in terms of the wealth controls. Column (1) controls for log total wealth instead of log liquid wealth and log illiquid wealth. Column (2) controls the decile dummies of liquid wealth and illiquid wealth instead of taking their logarithms. Column (3) controls for housing wealth and other wealth (total wealth minus housing wealth). Column (4) controls for positive wealth and debt. Columns (5) – (8) have the same wealth controls as columns (1) – (4) respectively. Robust standard errors are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.6: **Consumption (PSID) by Liquid Wealth**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Food Consumption						
Experience (Macro)	-0.254***		-0.238***	-0.217***		-0.204**
	(0.057)		(0.057)	(0.079)		(0.079)
Experience (Personal)		-0.842***	-0.827***		-0.615***	-0.604***
		(0.145)	(0.143)		(0.165)	(0.166)
Low Liquid Wealth	-0.937**	-0.009	-0.949**	-0.590	-0.035*	-0.567
	(0.380)	(0.018)	(0.388)	(0.358)	(0.018)	(0.361)
Experience (Macro) * LLW	0.157**		0.157**	0.096		0.089
	(0.064)		(0.065)	(0.059)		(0.060)
Experience (Personal) * LLW		0.159	0.135		0.339*	0.324*
		(0.157)	(0.158)		(0.190)	(0.191)
R-squared	0.197	0.202	0.202	0.542	0.543	0.543
Dependent Variable: Total Consumption						
Experience (Macro)	-0.071**		-0.063*	-0.071**		-0.068*
	(0.034)		(0.032)	(0.035)		(0.035)
Experience (Personal)		-0.555***	-0.553***		-0.324***	-0.322***
		(0.094)	(0.093)		(0.112)	(0.112)
Low Liquid Wealth	-0.028	0.033***	-0.087	0.122	0.002	0.089
	(0.187)	(0.008)	(0.169)	(0.150)	(0.005)	(0.156)
Experience (Macro) * LLW	0.010		0.020	-0.020		-0.014
	(0.032)		(0.028)	(0.025)		(0.026)
Experience (Personal) * LLW		-0.107	-0.110		-0.013	-0.013
		(0.127)	(0.125)		(0.097)	(0.098)
R-squared	0.489	0.500	0.500	0.755	0.756	0.756
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	Yes	Yes	Yes
Observations	37,156	37,156	37,156	37,156	37,156	37,156

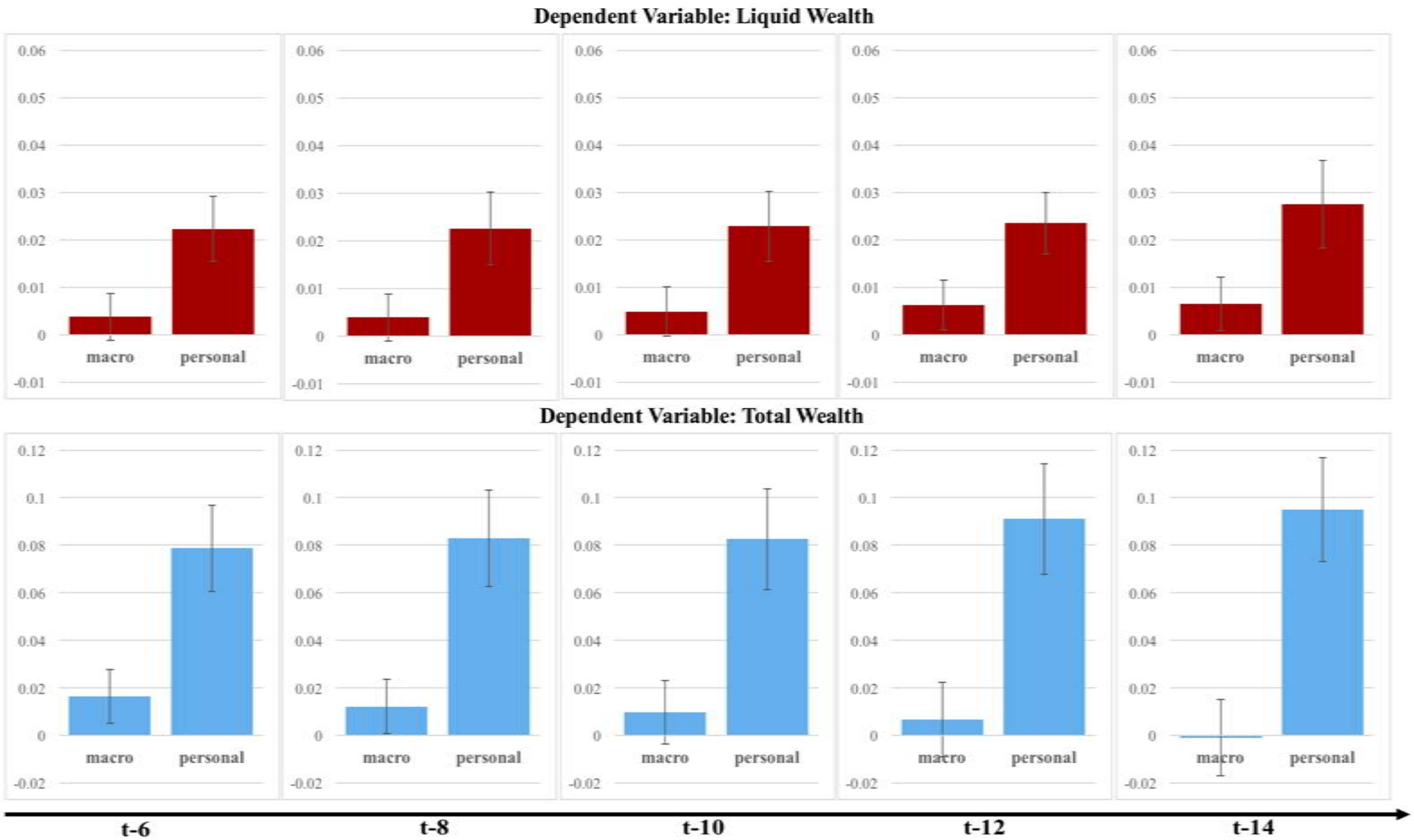
Notes. Consumption variables come from the 1999-2013 PSID Consumption Expenditure Data package. We include all consumption items recorded throughout the sample period. We take the logarithm of consumption, income, and wealth; non-positive values are adjusted by adding the absolute value of the minimum plus 0.1 before being logarithmized. "Experience (Macro)" is the macroeconomic experience measure of unemployment, and "Experience (Personal)" is the personal experience measure. Low Liquid Wealth (LLW) is an indicator variable equal to 1 for households whose liquid wealth falls below the sample median of liquid wealth each year. Wealth controls include liquid and illiquid wealth. Demographic controls include employment status, family size, the household heads' gender, race, marital status, and education level. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.7: **Consumption (PSID), Households in the 5^{th}-95^{th} Income Percentiles**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Food Consumption						
Experience (Macro)	-0.110**		-0.102**	-0.119**		-0.116**
	(0.048)		(0.048)	(0.056)		(0.056)
Experience (Personal)		-0.441***	-0.439***		-0.302**	-0.300**
		(0.098)	(0.098)		(0.119)	(0.120)
R-squared	0 0.177	0.179	0.180	0.542	0.543	0.543
Dependent Variable: Total Consumption						
Experience (Macro)	-0.033*		-0.029	-0.066***		-0.064***
	(0.020)		(0.019)	(0.022)		(0.022)
Experience (Personal)		-0.240***	-0.239***		-0.170***	-0.169***
		(0.031)	(0.031)		(0.030)	(0.030)
R-squared	0.552	0.555	0.555	0.786	0.786	0.786
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	Yes	Yes	Yes
Observations	32,957	32,957	32,957	32,957	32,957	32,957

Notes. All variables are defined as in Table IV, but we remove all observations with total family income below the 5^{th} or above the 95^{th} percentile in each wave from 1999 to 2013, as well as the pre-sample 1997 wave (because we control for lagged income). Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Figure A.1: **Estimated Coefficients and Confidence Intervals for Experience Measures**



Notes. The upper five graphs (red bars) present the estimates when we use liquid wealth as the dependent variable. The lower five graphs (blue bars) show the estimates when we use total wealth as the dependent variable. The five graphs in horizontal order show the estimated coefficients when we use 6-year lagged, 8-year lagged, 10-year lagged, 12-year lagged and 14-year lagged experience measures respectively. All the confidence intervals are at 90% confidence level.

Table A.8: **Wealth Accumulation and Unemployment Experiences**

Dependent Var.:	Liquid Wealth at time t						Total Wealth at time t					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exp. (Macro)$_{t-10}$	0.006*		0.005	0.003		0.003	0.012		0.010	0.018***		0.019***
	(0.003)		(0.003)	(0.003)		(0.003)	(0.008)		(0.008)	(0.006)		(0.006)
Exp. (Personal)$_{t-10}$		0.023***	0.023***		-0.000	-0.001		0.083***	0.083***	-0.003	-0.005	
		(0.004)	(0.004)		(0.002)	(0.002)		(0.013)	(0.013)		(0.014)	(0.014)
R-squared	0.048	0.048	0.048	0.332	0.332	0.332	0.292	0.294	0.294	0.714	0.714	0.714
Observations	21,691	21,691	21,691	21,691	21,691	21,691	21,691	21,691	21,691	21,691	21,691	21,691
Exp. (Macro)$_{t-12}$	0.007**		0.006*	0.008**		0.007**	0.010		0.007	0.020***		0.020***
	(0.003)		(0.003)	(0.003)		(0.003)	(0.009)		(0.009)	(0.007)		(0.007)
Exp. (Personal)$_{t-12}$		0.026***	0.026***		0.002	0.001		0.092***	0.091***		0.003	0.001
		(0.005)	(0.005)		(0.002)	(0.003)		(0.014)	(0.014)		(0.014)	(0.014)
R-squared	0.049	0.050	0.050	0.333	0.333	0.333	0.294	0.296	0.296	0.730	0.730	0.730
Observations	19,427	19,427	19,427	19,427	19,427	19,427	19,427	19,427	19,427	19,427	19,427	19,427
Exp. (Macro)$_{t-14}$	0.008**		0.007*	0.008**		0.008**	0.002		-0.001	0.011*		0.010
	(0.003)		(0.003)	(0.003)		(0.003)	(0.009)		(0.010)	(0.006)		(0.006)
Exp. (Personal)$_{t-14}$		0.028***	0.028***		0.003	0.002		0.095***	0.095***		0.010	0.009
		(0.005)	(0.005)		(0.003)	(0.003)		(0.013)	(0.013)		(0.009)	(0.009)
R-squared	0.052	0.052	0.052	0.331	0.331	0.331	0.378	0.380	0.380	0.827	0.827	0.827
Observations	17,151	17,151	17,151	17,151	17,151	17,151	17,151	17,151	17,151	17,151	17,151	17,151
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes

Notes. "Exp. (Macro)" is the macroeconomic experience measure, and "Exp. (Personal)" is the personal experience measure. Liquid wealth and total wealth are defined in the way as in the main draft. We separately use the $t-10$, $t-12$ experience measures, and $t-14$ experience measures. Income controls include the $t-1$ family total income and the average family total income between $t-2$ and the year we use the experience measures. For gap years (between PSID survey waves), we use the assumption from baseline analysis and use prior-year income. Demographic controls include family size, the household heads' gender, race, marital status, education level, and employment status. We take the logarithm of all income and wealth variables. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.9: **Experience Effects and Quarterly Consumption (CEX)**

	Total	Durables	Non-durable
Experience (Macro)	-0.077***	-0.085***	-0.086***
	(0.010)	(0.027)	(0.005)
Income control	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Observations	417,607	417,607	417,607
R-squared	0.390	0.126	0.409

Notes. Pooled regressions with (log) total consumption expenditure, durable consumption, and non-durable consumption as the dependent variables. Household characteristics include unemployment status, household size, education, and race. Time fixed effects include year-quarter fixed effects. Region fixed effects include dummies for the Northeast, Midwest, South, and West region. Regressions are weighted by household sampling weights from CEX. The sample period runs from 1980 to 2012. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.