Online Appendix

Scarred Consumption

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Appendix A Empirical Analysis

A.1 Robustness using PSID Data

We present a series of robustness tests of the estimations relating unemployment experiences to consumption, as well as of the estimations of the wealth build-up.

In Appendix-Figure A.1, we replicate the empirical exercise proposed in the job displacement literature, including Jacobson, LaLonde, and Sullivan (1993) and Couch and Placzek (2010), which estimates income loss around displacement. It plots the coefficients δ_k from the regression $y_{it} = \alpha_i + \gamma_t + \sum_{k\geq -m} D_{it}^k \delta_k + x_{it}\beta + \epsilon_{it}$, where y_{it} denotes earning of worker i in year t, D_{it}^k denotes dummy variables that take the value 1 if displacement occurred k years following the event and 0 otherwise; x_{it} denotes a set of controls including gender, martial status, race, education, and age; α_i denotes worker dummies; and γ_t denotes year dummies. The coefficients δ_k show the effect of displacement on a worker's earnings k years following its occurrence.

Our results show a persistent effect of displacement on earnings, which echoes the findings in the prior literature and supports the quality of our data on income. Our analyses differentiate experience effects from these known earnings implications of job loss in two ways: First, we control for earnings in the recent past. Second, we focus on the effects of unemployment experiences farther in the past, as we construct all measures of past experiences such that those from the recent past are excluded.

Appendix-Table A.1 presents the summary statistics of the full sample, i. e., including observations with total family income below the 10^{th} or above the 90^{th} percentile in each wave from 1999 to 2017, as well as the pre-sample 1997 wave (because we control for lagged income). Otherwise, we apply the same restrictions as in the construction of the main sample, namely, drop 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 missing demographic controls or that only appear once. The resulting sample has 42,167 observations, compared to 33,263 observations in the main sample. The sample statistics are very similar, with a mean personal experience of 6.21% and 6.23% based on weights of $\lambda = 1$ and $\lambda = 3$, respectively, a mean macroeconomic experience of 6.07% and 6.00% based on weights of $\lambda = 1$ and $\lambda = 3$, respectively, and average household total consumption of $38,898 (in 2017 dollars).

In Appendix-Table A.2, we re-estimate the regression model of Table 2 on the full sample. The results become even stronger. The estimated macroeconomic experience and personal experience effects are both larger and more significant than those estimated in Table 2.

In Appendix-Table A.3, we construct alternative experience measures for the gap years (between the PSID biennial surveys). For the macroeconomic measure 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 $t-1$ and $t+1$.) Similarly, for personal unemployment, 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. Re-estimating the model from equation (3), we find results very similar to those in Table 2 in the main text.

In Appendix-Table A.4, we present an alternative experience measure that incorporates the unemployment experiences of the spouses. For married households, we use the average of the household heads' and spouses' past exposure to unemployment, controlling for a married-couples indicator. All other variables are defined as in Table 2. The coefficients of interest remain very stable.

Appendix-Table A.5 shows the results for different clustering units. Instead of clustering by cohort as in Table 2, we two-way cluster the standard errors by cohort and year (columns 1 and 3) and cluster by household (columns 2 and 4). In columns (1) to (2), we use experience measures based on linearly declining weights (λ=1), and in columns (3) to (4), we use experience measures that shift more weight to recent observations (λ=3). The statistical significance of our results are not affected in most cases.

In Appendix-Table A.6, 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. The results remain similar to the baseline results in Table 2 in direction and significance.

In Appendix-Table A.7, we estimate an alternative version of the empirical model in equation (3) that includes a lagged consumption measure on the right-hand side, to take into account possible habit persistence in consumption. 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). More details about the estimation are provided in Section III.B. The results show that the effects of prior unemployment experience on consumption remain mostly significant after taking into account possible habit persistence in consumption. The estimation results both confirm the robustness of experience effects and indicate that they do not operate through the channel of habit formation.

Appendix-Tables A.8, A.9, A.10 and A.11 address concerns about unobserved wealth, liquidity, or income components.

Appendix-Table A.8 presents results from estimations using alternative wealth controls, in addition to the measures of liquid and illiquid wealth in Table 2: third- and fourth-order liquid and illiquid wealth (columns 1 and 5); decile dummies of liquid and illiquid wealth (columns 2 and 6); housing wealth and other wealth (columns 3 and 7); positive wealth and debt (columns 4 and 8). In columns (1) to (4), we use experience measures based on linearly declining weights (λ=1), and in columns (5) to (8), we use experience measures that shift more weight to recent observations (λ=3). The coefficients of interest remain stable and are statistically significant.

Appendix-Table A.9 uses alternative income controls, in addition to the first- and second-order controls for income and lagged income: third- and fourth-order income and lagged income (columns 1 and 5); quintile dummies of income and lagged income (columns 2 and 6); decile dummies of income and lagged income (columns 3 and 7); bottom-2, 2^{nd}- 4^{th}, 4^{th}- 6^{th}, 6^{th}- 8^{th}, 8^{th}- 10^{th}, 90^{th}- 92^{nd}, 92^{nd}- 94^{th}, 94^{th}- 96^{th}, 96^{th}-98^{th}, and top-2 percentile dummies of income and lagged income (columns 4 and 8). In columns (1) to (4), we use experience measures based on linearly declining weights (λ=1), and in columns (5) to (8), we use experience measures that shift more weight to recent observations (λ=3). The coefficients of interest remain stable. All of the estimates that were significantly negative before are still significant.

We display all coefficients of interest from Appendix-Tables A.8 and A.9 graphically in Appendix-Figure A.2.

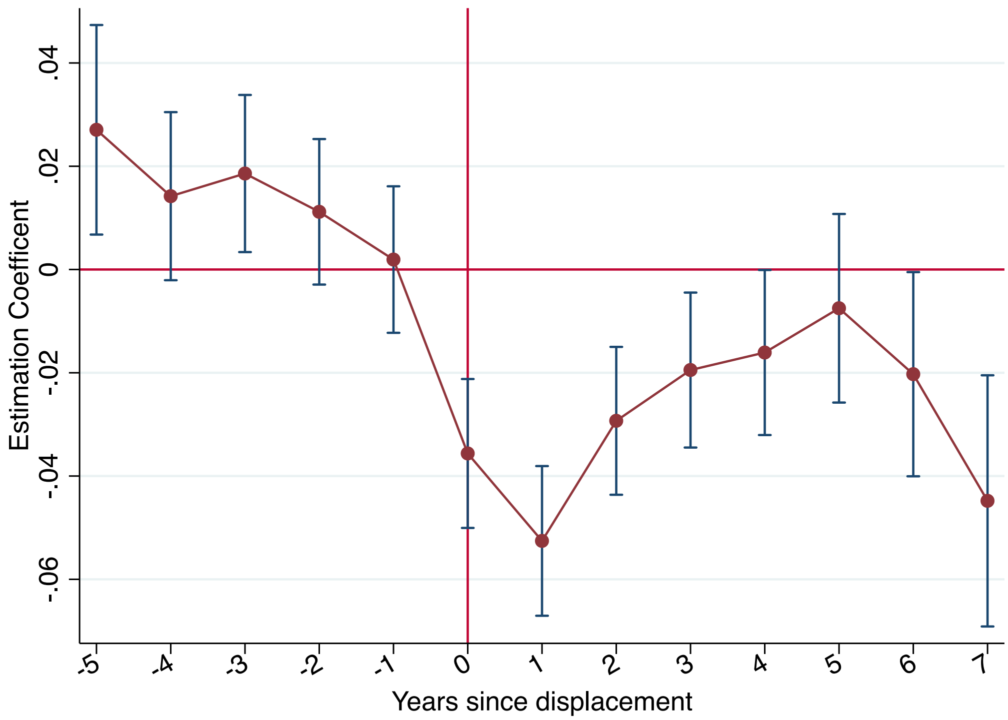
Table A.10 addresses the concern about measurement error in the income variable by incorporating estimates of the extent of measurement error into the income variable and assessing whether they affect our results, following the methodology in Romer (1986) and Cogley, Sargent, and Surico (2015). We apply the estimates of Bound, Brown, Duncan, and Rodgers (1994) on the share of variance associated with measurement error using a validation study for the PSID. While the validation study they use covers only a small fraction of the PSID sample, they extrapolate their findings to estimate the share of measurement errors in representative samples. We adopt their estimates for the share of measurement error in log earnings $var(\epsilon^y) = 0.04var(y)$. The results using the measurement-error-adjusted income are shown in Table A.10. They show that the coefficients of interest not only are similar in direction and significance but also increase in magnitude.

In Table (A.11), 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 (3). As Appendix-Table A.11 shows, households in the bottom half of liquid wealth do not exhibit stronger reactions to unemployment experience. This suggests households' experiences affect consumption beyond potential liquidity constraints.

In Appendix-Table A.12, we study the effects of lifetime exposure to unemployment on wealth accumulation. This analysis tests whether, given the significant impact of unemployment experiences on consumption, we can also detect a role of unemployement experience effects on the build-up of wealth. The dependent variable is total wealth, and the main regressors are lagged experience measures. We lag the experience measures by six, eight, ten, and twelve 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 total wealth in the corresponding lagged year and income in years $t-1$ and $t-2$ while adding 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, and twelve 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 booms or crises may have implications for future income (Oyer 2008; Kahn 2010; Oreopoulos, von Wachter, and Heisz 2012).[24] We find a significant role of past experiences for the build-up of wealth.

[24] 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.

Figure A.1: **Earnings Around Displacement**



Notes. The figure plots the coefficients δ_k from the regression $y_{it} = \alpha_i + \gamma_t + \sum_{k \geq -m} D_{it}^k \delta_k + x_{it}\beta + \epsilon_{it}$, where y_{it} denotes earning of worker i in year t, D_{it}^k denotes dummy variables that take the value 1 if displacement occurred k years following the event and 0 otherwise, x_{it} denotes a set of controls including gender, martial status, race, education, and age, α_i denotes worker dummies, and γ_t denotes year dummies. The coefficients δ_k show the effect of displacement on a worker's earnings k years following its occurrence. Data source: PSID.

Table A.1: **Summary Statistics (PSID), Full Sample**

Variable	Mean	SD	p10	p50	p90	N
Age	49.63	11.40	35	49	66	42,167
Household Size	2.70	1.45	1	2	5	42,167
Household Total Consumption [$]	38,898	30,637	11,905	32,872	70,833	42,167
Household Total Income [$]	78k	105k	14k	58k	151k	42,167
Household Liquid Wealth [$]	53k	585k	-21k	0.6k	100k	42,167
Household Illiquid Wealth [$]	250k	1,074k	0k	65k	540k	42,167
Household Total Wealth [$]	303k	1,300k	-2k	65k	671k	42,167
Experience (Personal), λ=1 [%]	6.21	3.88	4.41	4.96	11.08	42,167
Experience (Personal), λ=3 [%]	6.23	6.81	3.06	3.98	15.19	42,167
Experience (Macro), λ=1 [%]	6.07	0.29	5.73	6.04	6.47	42,167
Experience (Macro), λ=3 [%]	6.00	0.55	5.35	5.94	6.76	42,167

Notes. Summary statistics for the estimation sample, which covers the 1999-2017 PSID waves, as well as the pre-sample 1997 wave (because we control for lagged income). Age, Experience (Personal), and Experience (Macro) are calculated for the heads of households. Household Total Income includes transfers and taxable income of all household members from the last year. Liquid and Illiquid Wealth are defined following Kaplan, Violante, and Weidner (2014). Values are in 2017 dollars (using the PCE), annual, and not weighted.

Table A.2: **Experience Effects and Consumption (PSID), Full Sample**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)	-0.683***		-0.680***	-0.420***		-0.418***
	(0.194)		(0.193)	(0.112)		(0.112)
Experience (Macro)		-0.067**	-0.066**		-0.044***	-0.043***
		(0.029)	(0.029)		(0.017)	(0.017)
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3
Observations	42,167	42,167	42,167	42,167	42,167	42,167
R-squared	0.752	0.752	0.752	0.752	0.752	0.752

Notes. The consumption variables come from the 1999-2017 PSID Consumption Expenditure Data package. We include all observations (i.e., also observations with total family income below the 10^{th} or above the 90^{th} percentile in each wave from 1999 to 2017), as well as the pre-sample 1997 wave (because we control for lagged income). 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 (Personal)" is the personal experience measure of unemployment and "Experience (Macro)" is the macroeconomic experience measure, as defined in the text. In columns (1) to (3), we use experience measures based on linearly declining weights (λ=1), and in columns (4) to (6), we use experience measures that shift more weight to recent observations (λ=3). Demographic controls include family size, heads' gender, race, marital status, education level, and a dummy variable indicating whether the respondent is unemployed at the time of the survey. Income controls include the first and second order of the logarithm of income and lagged income. Wealth controls include the first and second order of the logarithm of liquid and illiquid wealth. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.3: **Consumption (PSID), Alternative Experience Measure: Gap Years**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)	-0.413***		-0.405***	-0.247***		-0.242***
	(0.123)		(0.124)	(0.069)		(0.070)
Experience (Macro)		-0.055***	-0.054***		-0.033***	-0.032***
		(0.018)	(0.018)		(0.010)	(0.011)
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3
Observations	33,263	33,263	33,263	33,263	33,263	33,263
R-squared	0.771	0.771	0.771	0.771	0.771	0.771

Notes. All variables other than the experience measures are defined as in Table 2. 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. In columns (1) to (3), we use experience measures based on linearly declining weights (λ=1), and in columns (4) to (6), we use experience measures that shift more weight to recent observations (λ=3). Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.4: **Consumption (PSID), Alternative Experience Measure: Spousal Experience**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)	-0.413***		-0.420***	-0.255***		-0.257***
	(0.098)		(0.098)	(0.058)		(0.058)
Experience (Macro)		-0.049***	-0.045***		-0.032***	-0.029***
		(0.017)	(0.017)		(0.010)	(0.010)
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3
Observations	39,085	39,589	38,737	39,085	39,589	38,737
R-squared	0.763	0.764	0.764	0.763	0.764	0.764

Notes. All variables other than the couple indicator and experience measures are defined as in Table 2. In columns (1) to (3), we use experience measures based on linearly declining weights (λ=1), and in columns (4) to (6), we use experience measures that shift more weight to recent observations (λ=3). Couple is an indicator equal to 1 for households who are married and is now included as a demographic control. The experience measures for the married households are constructed using an average of the household's head and the spouse. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.5: **Consumption (PSID), Alternative Clustering Units**

	(1)	(2)	(3)	(4)
Experience (Personal)	-0.275*	-0.275***	-0.169**	-0.169***
	(0.126)	(0.103)	(0.073)	(0.059)
Experience (Macro)	-0.055***	-0.055***	-0.033***	-0.033***
	(0.015)	(0.018)	(0.009)	(0.010)
Demographic controls	Yes	Yes	Yes	Yes
Income controls	Yes	Yes	Yes	Yes
Wealth controls	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Experience weighting	λ=1	λ=1	λ=3	λ=3
Clustering Unit	Cohort&Year	HH	Cohort&Year	HH
Observations	33,263	33,263	33,263	33,263
R-squared	0.771	0.771	0.771	0.771

Notes. All variables are defined as in Table 2. In columns (1) to (2), we use experience measures based on linearly declining weights (λ=1), and in columns (3) to (4), we use experience measures that shift more weight to recent observations (λ=3). Standard errors are clustered by cohort and year (two-way clustering) in columns (1) and (3) and by household in columns (2) and (4). Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.6: **Consumption (PSID), Alternative Weights: PSID Weights**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)	-0.281**		-0.276**	-0.173***		-0.170**
	(0.113)		(0.114)	(0.065)		(0.065)
Experience (Macro)		-0.055***	-0.054***	-0.033***	-0.032***	
		(0.018)	(0.018)	(0.011)	(0.011)	
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3
Observations	33,034	33,034	33,034	33,034	33,034	33,034
R-squared	0.770	0.770	0.770	0.770	0.770	0.770

Notes. All variables are defined as in Table 2, but observations are now weighted by the PSID family weights. The family with zero weights are dropped. In columns (1) to (3), we use experience measures based on linearly declining weights (λ=1), and in columns (4) to (6), we use experience measures that shift more weight to recent observations (λ=3). Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.7: **Experience Effects and Consumption, GMM regressions**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)	-0.485***		-0.368***	-0.258***		-0.274***
	(0.093)		(0.100)	(0.051)		(0.053)
Experience (Macro)		-0.016	-0.012		-0.022**	-0.017**
		(0.017)	(0.018)		(0.010)	(0.009)
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3
Observations	25,460	25,460	25,460	25,460	25,460	25,460
R-squared	0.590	0.589	0.560	0.570	0.519	0.588

Notes. System GMM regressions with total consumption (in logarithm) as the dependent variable and lagged dependent variable as a regressor. All other variables are defined as in Table 2. In columns (1) to (3), we use experience measures based on linearly declining weights (λ=1), and in columns (4) to (6), we use experience measures that shift more weight to recent observations (λ=3). Robust standard errors in parentheses are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.8: **Consumption (PSID), Additional Wealth Controls**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience (Personal)	-0.273**	-0.255**	-0.274**	-0.166*	-0.158**	-0.149**	-0.159**	-0.106*
	(0.114)	(0.110)	(0.114)	(0.097)	(0.070)	(0.060)	(0.063)	(0.056)
Experience (Macro)	-0.054***	-0.052***	-0.056***	-0.048**	-0.031***	-0.030***	-0.031***	-0.029***
	(0.018)	(0.018)	(0.018)	(0.019)	(0.013)	(0.011)	(0.011)	(0.011)
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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience weighting	λ=1	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3	λ=3
Observations	33,263	33,263	33,263	31,214	31,214	31,214	31,214	31,214
R-squared	0.771	0.774	0.771	0.789	0.775	0.778	0.775	0.789

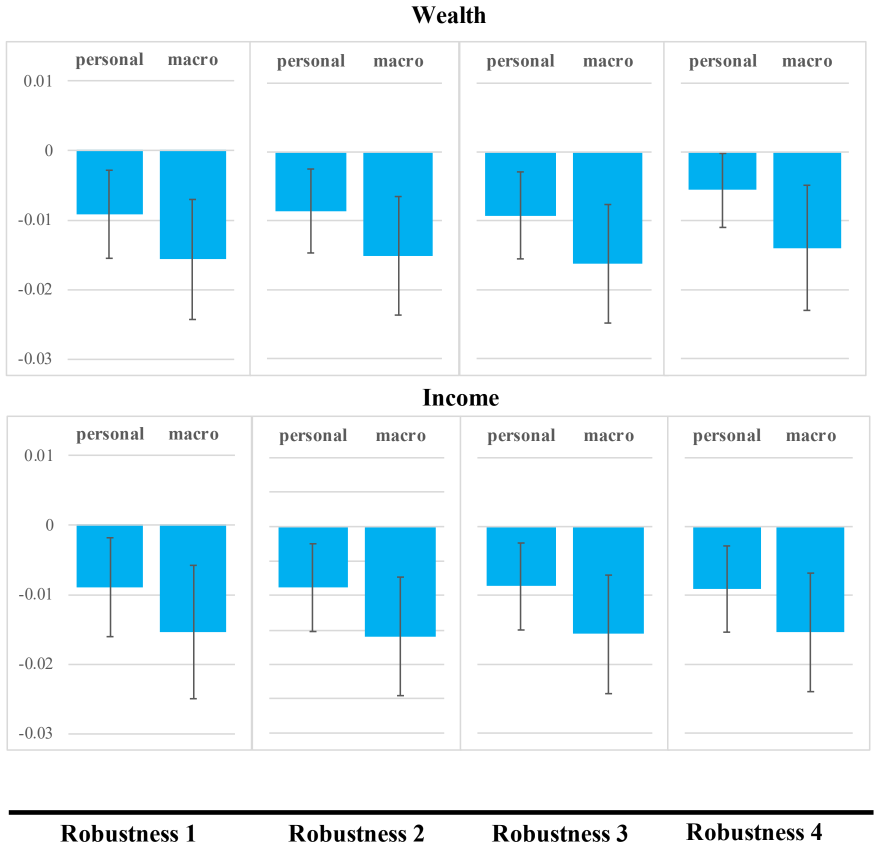
Notes. Regressions differ from those in Table 2 only in terms of the wealth controls. In columns (1) to (4), we use experience measures based on linearly declining weights (λ=1), and in columns (5) to (8), we use experience measures that shift more weight to recent observations (λ=3). Columns (1) and (5) control for third- and fourth-order liquid and illiquid wealth. Columns (2) and (6) include decile dummies of liquid wealth and illiquid wealth. Columns (3) and (7) control for housing wealth and other wealth (total wealth minus housing wealth). Columns (4) and (8) control for positive wealth and debt. All wealth controls are in addition to the controls of first- and second-order of liquid and illiquid wealth. Robust standard errors are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.9: **Consumption (PSID), Additional Income Controls**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience (Personal)	-0.266**	-0.264**	-0.259**	-0.270**	-0.164**	-0.163**	-0.160**	-0.166**
	(0.128)	(0.115)	(0.114)	(0.113)	(0.073)	(0.066)	(0.065)	(0.065)
Experience (Macro)	-0.053***	-0.055***	-0.054***	-0.053***	-0.031***	-0.032***	-0.032***	-0.032***
	(0.020)	(0.018)	(0.018)	(0.018)	(0.012)	(0.011)	(0.011)	(0.011)
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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience weighting	λ=1	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3	λ=3
Observations	33,263	33,263	33,263	33,263	33,263	33,263	33,263	33,263
R-squared	0.771	0.771	0.771	0.771	0.771	0.771	0.771	0.771

Notes. Regressions differ from those in Table 2 only in terms of the income controls. In columns (1) to (4), we use experience measures based on linearly declining weights (λ=1), and in columns (5) to (8), we use experience measures that shift more weight to recent observations (λ=3). Columns (1) and (5) control for third- and fourth-order of income and lagged income. Columns (2) and (6) include quintile dummies of income and lagged income. Columns (3) and (7) include decile dummies of income and lagged income. Columns (4) and (8) include separately for the bottom-2, $2^{nd}-4^{th}$, $4^{th}-6^{th}$, $6^{th}-8^{th}$, $8^{th}-10^{th}$, $90^{th}-92^{nd}$, $92^{nd}-94^{th}$, $94^{th}-96^{th}$, $96^{th}-98^{th}$, and top-2 percentile dummies of income and lagged income. All income controls are in addition to the controls of first- and second-order of income and lagged income. Robust standard errors are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Figure A.2: **Wealth and Income Controls: Effects of a One-Standard-Deviation Increase in Experience**



Notes. The top panel show the effects of a one-standard-deviation increase in unemployment experience (constructed using λ=1 weighting) on total consumption when we include four alternative wealth controls: (1) third- and fourth-order liquid and illiquid wealth, (2) decile dummies for liquid wealth and illiquid wealth, (3) housing wealth and other wealth (total wealth minus housing wealth), and (4) positive wealth and debt. All wealth controls are in addition to first- and second-order liquid and illiquid wealth. The bottom panel show the effects of a one-standard-deviation increase in experience (constructed using λ=1 weighting) on total consumption when we include four alternative income controls: (1) third- and fourth-order income and lagged income, (2) quintile dummies for income and lagged income, (3) decile dummies for income and lagged income, and (4) separate dummies for the bottom 2, $2^{nd}-4^{th}$, $4^{th}-6^{th}$, $6^{th}-8^{th}$, $8^{th}-10^{th}$, $90^{th}-92^{nd}$, $92^{nd}-94^{th}$, $94^{th}-96^{th}$, $96^{th}-98^{th}$, and top 2 percentiles of income and lagged income. All income controls are in addition to first- and second-order income and lagged income. All regressions include household fixed effects. Error bars show 90% confidence level.

Table A.10: **Experience Effects and Consumption (PSID), Accounting for Measurement Error in Income**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)	-0.373***		-0.367***	-0.228***		-0.225***
	(0.117)		(0.118)	(0.067)		(0.068)
Experience (Macro)		-0.062***	-0.060***	-0.036***	-0.036***	
		(0.018)	(0.018)	(0.010)	(0.011)	
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3
Observations	33,263	33,263	33,263	33,263	33,263	33,263
R-squared	0.768	0.768	0.768	0.768	0.768	0.768

Notes. Regressions differ from those in Table 2 only in terms of the income controls. As in Table 2, income controls include the first and second order of the logarithm of income and lagged income. In addition, we set a priori the amount of income variability that can be attributed to error, using the estimates of Bound, Brown, Duncan, and Rodgers (1994) based on the equation $var(\epsilon^y) = 0.04 var(y)$. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.11: **Consumption (PSID), Additional Liquidity Controls**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)	-0.144		-0.137	-0.103		-0.099
	(0.132)		(0.132)	(0.075)		(0.076
Experience (Personal) * LLW	-0.002		-0.002*	-0.121		-0.122
	(0.001)		(0.001)	(0.083)		(0.083)
Experience (Macro)		-0.058***	-0.059***		-0.032***	-0.033***
		(0.020)	(0.020)		(0.011)	(0.011)
Experience (Macro) * LLW		0.005	0.008		-0.002	0.000
		(0.014)	(0.014)		(0.008)	(0.008)
Low Liquid Wealth	0.020**	-0.022	-0.031	0.013**	0.016	0.012
	(0.009)	(0.087)	(0.087)	(0.006)	(0.045)	(0.045)
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3
Observations	33,263	33,263	33,263	33,263	33,263	33,263
R-squared	0.771	0.771	0.771	0.771	0.771	0.771

Notes. Low Liquid Wealth (LLW) is an indicator variable equal to 1 for households with liquid wealth below the sample-year median. All other variables are defined as in Table 2. Robust standard errors (in parentheses) are clustered by cohort. *, **, *** denote 10%, 5%, and 1% significance, respectively.

Table A.12: **Wealth Accumulation**

	(1)	(2)	(3)	(4)	(5)	(6)
Experience (Personal)$_{t-6}$	0.424***		0.419***	0.240***		0.238***
	(0.058)		(0.057)	(0.033)		(0.032)
Experience (Macro)$_{t-6}$		0.040***	0.038***		0.018***	0.016***
		(0.014)	(0.014)		(0.008)	(0.008)
Observations	17,918	17,918	17,918	17,918	17,918	17,918
R-squared	0.321	0.320	0.321	0.321	0.319	0.321
Experience (Personal)$_{t-8}$	0.465***		0.461***	0.262***		0.260***
	(0.062)		(0.061)	(0.034)		(0.034)
Experience (Macro)$_{t-8}$		0.043**	0.040**		0.022*	0.021
		(0.020)	(0.020)		(0.013)	(0.013)
Observations	13,754	13,754	13,754	13,754	13,754	13,754
R-squared	0.305	0.303	0.305	0.305	0.303	0.305
Experience (Personal)$_{t-10}$	0.497***		0.494***	0.282***		0.281***
	(0.077)		(0.077)	(0.043)		(0.043)
Experience (Macro)$_{t-10}$		0.049	0.047		0.025	0.024
		(0.030)	(0.031)		(0.018)	(0.018)
Observations	10,436	10,436	10,436	10,436	10,436	10,436
R-squared	0.286	0.285	0.286	0.286	0.284	0.286
Experience (Personal)$_{t-12}$	0.581***		0.581***	0.331***		0.331***
	(0.098)		(0.098)	(0.055)		(0.055)
Experience (Macro)$_{t-12}$		0.057	0.057		0.031	0.031
		(0.043)	(0.044)		(0.026)	(0.026)
Observations	7,525	7,525	7,525	7,525	7,525	7,525
R-squared	0.277	0.275	0.277	0.277	0.275	0.277
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
Experience weighting	λ=1	λ=1	λ=1	λ=3	λ=3	λ=3

Notes. The dependent variable is total wealth, as defined in the main text. In columns (1) to (3), we use experience measures based on linearly declining weights (λ=1), and in columns (4) to (6), we use experience measures that shift more weight to recent observations (λ=3). The top panel uses the $t-6$ experience measures; the subsequent three panels use experience measures from $t-8$, $t-10$, $t-12$, respectively. Income controls include the $t-1$ family total income and the average family total income between $t-2$ and the year of the experience measures. Wealth controls include total wealth from the year of the experience measures. For gap years between PSID survey waves, we use prior-year income. Demographic controls include family size, 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.

A.2 Robustness using Nielsen Data

Our second source of data on consumption choices is the Nielsen Homescan Dataset. This data contains detailed information on product purchases of a panel of more than 100,000 U.S. households from 54 geographically dispersed markets, including price, quantity, date of purchase, identifier of the store, as well as product characteristics, including brand, size and packaging, at the UPC level. Households record the dollar value of any coupons used and whether the purchase involved a deal from the retailer (sale item). The product categories are food and non-food grocery, health and beauty aids, and general merchandise, summing to approximately 3.2 million unique UPCs covering 125 general product categories.[25]

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.[26]

Our data sample consists of 3,168,445 observations of 79,837 households from 54 geographically dispersed markets, each roughly corresponding to a Metropolitan Statistical Area (MSA), from 2004-2013. Table A.13 provides the summary statistics. 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.

The high-frequency nature of the Nielsen data allows us to construct more fine-grained measures of consumption and unemployment exposure than the PSID. However, since Nielsen provides no information about households' prior residence or employment status (pre-sample period), we are not able to construct the same type

[25] Several studies have examined the quality of the data. For example, Einav, Leibtag, and Nevo (2010) compare the self-reported Nielsen 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.

[26] 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.

Table A.13: **Summary Statistics (Nielsen)**

Variable	Mean	SD	p10	p50	p90
Age	53.9	11.2	38	54	69
Household Size	2.72	1.28	1	2	4
Total Consumption [$]	722	541	209	594	1,380
Coupon Use [%]	0.03	0.05	0	0.01	0.09
Product Ranking	0.48	0.10	0.36	0.48	0.60
Purchase of Sale Items [%]	0.26	0.25	0	0.19	0.64
Household Income [$]	$50-$60k		$25-$30k	$60-$70k	$100k+
Experience (Macro), $\lambda = 1$ [%]	5.97	0.18	5.78	5.93	6.25
Experience (Macro), $\lambda = 3$ [%]	5.90	0.36	5.48	5.80	6.41

Notes. The table reports the summary statistics of the monthly Nielsen data from 2004-2013. Copon use is the value of coupons 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 a given month; lower-priced goods have lower values. Purchase of sale items is the number of sale items divided by the total number of items bought. Nielsen reports income in 13 brackets. Experience (Macro) is households' lifetime experience of national unemployment rates.

of macro and personal unemployment experience proxies as in the PSID. We thus construct the macro-level experience measure based on monthly national unemployment rates. For the personal experience measure, we can, at best, measure unemployment experiences since the beginning of the Nielsen data. Such a measure is biased as it is less precise at the beginning of the sample and less precise for households with shorter spells. We therefore report the estimations employing only the macro-experience measure, but re-estimate our model using a measure of personal unemployment experience 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.

To estimate the sensitivity of consumption quality to experienced unemployment conditions in the Nielsen data, we use an estimation model that mirrors the PSID model from equation (3) but accounts for the additional market-level information:

$$C_{it} = \alpha + \beta UE_{it} + \kappa U_{mt} + \gamma^{'} x_{it} + \eta_t + \varsigma_m + \upsilon_i + \varepsilon_{it}. \tag{A.1}$$

where C_{it} denotes total monthly consumption expenditure. The other new variables are the current county-level unemployment rate U_{mt} and local-market dummies ς_m, where local markets denote Nielsen's designated market areas (DMAs).[27] As before UE_{it} denotes the lifetime (macro) experience of unemployment rates based on a weighting scheme of $\lambda = 1.$ or $\lambda = 3$. The vector of controls x_{it} includes 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), age dummies, household dummies, and the time dummies η_t are now year-month-specific.

Nielsen lacks information about consumers' wealth, which is an important component of consumption analyses. Our prior estimations alleviate concerns about unobserved wealth to some extent, given the robustness of the estimates across a broad range of wealth, income, and liquidity proxies. To further address the issue of the missing wealth control in the Nielsen data, 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 prices as a measure of housing wealth. According to these studies, consumption dynamics respond strongly to house price movements and housing wealth (cf. also Mian, Rao, and Sufi (2013) and Berger and Vavra (2015)). Empirical analyses can exploit this insight since better measures of housing prices have become available. Specifically, we extract Zillow's Home Value Index at the local ZIP code level as a proxy for local housing prices and merge it with the Nielsen data.[28] The match rate lies around 75%, and the resulting data set contains almost 3.2 million observations. We include the Home Value Index, an indicator for being a homeowner, and their interaction in all of our estimations.[29]

Table A.14 presents results from regression specification (A.1) in the main text. In columns (1) to (2), we use macroeconomic experience measures based on linearly declining weights (λ=1), and in columns (3) to (4), we use experience measures that shift more weight to recent observations (λ=3). We find that, exactly as in

[27] DMAs are slightly bigger than a county but smaller than an MSA. We control for location at the local market level instead of the county level because people may travel outside of counties to purchase goods. The results are similar if we use county fixed effects instead.

[28] Zillow Inc. collects detailed data on home values across the U.S. and constructs monthly indices using the median value for a ZIP code. Zillow's estimates of home values ("Zestimates") aim to provide realistic market values given the size, rooms, and other known attributes of the house, recent appraisals, geographic location, and general market conditions. (The exact formula is proprietary.) For details about the data and Zillow's coverage across the U.S. see Dube, Hitsch, and Rossi (2018).

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

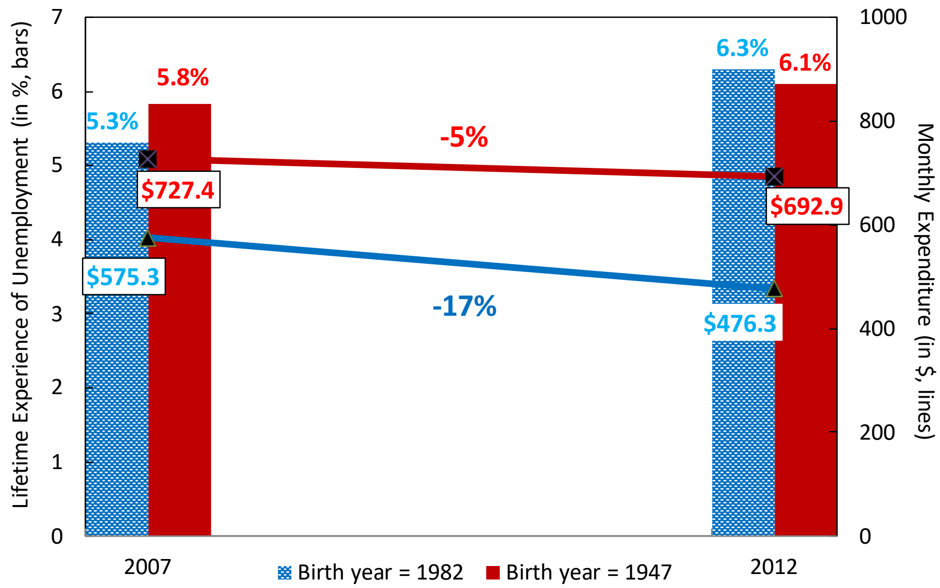
Table A.14: **Experience Effects and Monthly Consumption (Nielsen)**

	(1)	(2)	(3)	(4)
Experience (Macro)	-0.165***	-0.164***	-0.172***	-0.172***
	(0.055)	(0.055)	(0.027)	(0.027)
Unemployment rate (county)		-0.005***		-0.005***
		(0.001)		(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	Yes	Yes	Yes	Yes
Experience weighting	$\lambda = 1$	$\lambda = 1$	$\lambda = 3$	$\lambda = 3$
Observations	3,168,445	3,168,445	3,168,445	3,168,445
R-squared	0.526	0.526	0.526	0.526

Notes. Fixed effects regression with (log) total consumption expenditure as the dependent variable. Experience (Macro) is the macroeconomic experience measure of unemployment. In columns (1) to (2), we use macroeconomic experience measures based on linearly declining weights (λ=1), and in columns (3) to (4), we use experience measures that shift more weight to recent observations (λ=3). 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.

the PSID data, households who have experienced worse unemployment conditions during their lifetimes so far spend significantly less, controlling for contemporaneous macro conditions, local market conditions, and household controls. The economic magnitude is significant: based on the estimates in column (2), a one standard deviation increase in unemployment experiences is associated with a \$256 decline in annual consumption of non-durables, which amounts to around 3% of average spending for the households in our sample. All regression results are quantitatively and qualitatively similar when clustered by household or two-way clustered at the cohort and time level.

Figure A.3: **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- and 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 linearly-declining weights. 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.

In Figure A.3, 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 of $\lambda = 1$, 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 pp, whereas that for the 60-year-old increased by 0.3 pp. Relating these experiences to consumption behavior, our model estimates (from column (4) in Table A.14) imply that the monthly consumption expenditure of the 25-year-old decreased by approximately 17% while that of the 60-year-old decreased by approximately 5%.

A.3 Robustness using CEX

In this section, we turn to a third source of consumption data, the Consumer Expenditure Survey (CEX). We now enlarge the set of consumption items to include durable goods as well as the CEX measure of total consumption, which is widely used in the literature. It encompasses further categories of expenditures, including healthcare and education expenses.

The CEX is a repeated, cross-sectional survey of household spending across a comprehensive list of product categories at the quarterly frequency. It is considered the benchmark data in the consumption literature. Compared to the PSID, its two main disadvantages are the lack of wealth information and the lack of panel structure.

As in the analysis of the PSID, we link measures of consumption to households' lifetime unemployment experiences. In the CEX data, we are not able to construct the same type of macro and personal unemployment experience measures as in the PSID because the CEX does not provide information on where households resided prior to the sample period, nor on their prior employment status. We use the macro-level experience measure based on national unemployment rates at the quarterly frequency.

Table A.15 provides the summary statistics. The average income, \$49k, is in line with the average income at the national level. The sample period runs from 1980-2012. The average non-durable and durable spending amount to 67% and 33% of the mean total expenditures, respectively. Non-durable spending and durable spending are weakly positively correlated, with durable spending being much more volatile than non-durable spending.

We re-estimate the sensitivity of consumption to experienced unemployment conditions, using an estimation model that closely mirrors the PSID model from equation (3). Table A.16 shows the results for total, durable, and non-durable consumption, using macroeconomic experience measures based on linearly declining weights (λ=1).

The results strongly confirm our prior findings and reveal new quantitative implications for the different components of total consumption. All experience effect

Table A.15: **Summary Statistics (CEX)**

Variable	Mean	SD	p10	p50	p90	N
Age	51	17	30	49	75	439,312
Household Size	2.7	1.5	1	2	5	439,312
Total Consumption [$]	6,374	6,310	2,037	4,700	11,915	439,312
Durable Consumption [$]	2,092	4,575	130	822	4,210	439,312
Non-durable Consumption [$]	4,282	3,264	1,608	3,567	7,564	439,312
Household Income [$]	49,181	50,096	9,293	35,157	101,200	439,312
Experience (Macro) [%]	6.1	0.31	5.78	6.1	6.5	439,312

Notes. The table reports the summary statistics of quarterly CEX data from 1980-2012. Experience (Macro) is households' lifetime experience of national unemployment rates.

coefficients are negative and highly significant. Households who have experienced worse unemployment conditions during their lifetime spend significantly less in total, durable, and non-durable consumption. The economic magnitudes are large: A one standard-deviation increase in unemployment experience is associated with a decline of $711 in annual consumption and $467 in annual non-durable consumption. The estimates on annual total consumption and non-durable consumption are larger than the PSID and Nielsen estimates ($595 and $256 decline), respectively. This may reflect the fact that both total expenditures and non-durable expenditures in the CEX encompass more categories than the PSID and Nielsen, and spending on these categories could be more elastic. For example, compared to the Nielsen, non-durable consumption in the CEX includes categories such as clothing and entertainment, which tend to be elastic. The new estimate for durables indicates that a one-standard-deviation increase in past unemployment experience predicts a $283 decline in annual durable consumption.

Appendix B Additional Implications

B.1 Consumption Quality

Motivated by the robust results on the quantity of consumption spending, we investigate whether people's lifetime exposure to unemployment also affects the quality of their consumption. Does the personal experience of harder economic times also

Table A.16: **Experience Effects and Quarterly Consumption (CEX)**

	Total	Durable	Nondurable
Experience (Macro)	-0.090***	-0.109***	-0.088***
	(0.008)	(0.020)	(0.007)
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	439,312	439,312	439,312
R-squared	0.432	0.243	0.462

Notes. Pooled 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, constructed as a lifetime linearly-declining weighted national unemployment rate experienced by households. 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.

induce more cautious spending in terms of bargain hunting, coupon use, and lower quality of items purchased? To explore this question, we make use of the rich, micro-level information on purchases in the Nielsen data. We estimate equation A.1 using three monthly measures of consumption quality as the dependent variable: (1) coupon use, normalized by total expenditures, (2) the ranking of products based on their unit price (within module, market, and month), normalized between 0 and 1, where lower value represents lower-priced goods, and (3) number of on-sale products purchased, normalized by the total number of products purchased. The summary statistics are in Table A.13.

Table B.17 displays the main coefficients of interest. We find that households who have lived through worse employment conditions are more likely to use coupons, purchase lower-end products, and allocate more expenditures toward sale items. In other words, people who have lived through periods of high unemployment adjust the quality margins of their consumption accordingly.

Table B.17: **Experience Effects and Monthly Consumption Quality (Nielsen)**

	(1)	(2)	(3)	(4)
A: Coupons				
Experience (Macro)	0.047***	0.047***	0.025***	0.025***
	(0.006)	(0.006)	(0.005)	(0.005)
Unemployment rate (county)		-0.001***		0.001***
		(0.000)		(0.000)
Observations	2,869,000	2,869,000	2,869,000	2,869,000
R-squared	0.037	0.038	0.160	0.160
B: Product Ranking				
Experience (Macro)	-0.107***	-0.106***	-0.046**	-0.045**
	(0.037)	(0.037)	(0.019)	(0.020)
Unemployment rate (county)		-0.005***		-0.005***
		(0.002)		(0.002)
Observations	2,866,259	2,866,259	2,866,259	2,866,259
R-squared	0.089	0.089	0.355	0.355
C: On-sale Items				
Experience (Macro)	0.219***	0.219***	0.090***	0.090***
	(0.025)	(0.025)	(0.014)	(0.014)
Unemployment rate (county)		-0.002		0.001
		(0.001)		(0.002)
Observations	2,869,000	2,869,000	2,869,000	2,869,000
R-squared	0.062	0.062	0.210	0.210
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

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 macroeconomic experience measure of unemployment, constructed as a lifetime linearly-declining weighted national unemployment rate experienced by households. Column 2 and 4 include the regressor local unemployment. 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.

Our results echo findings in the existing literature such as Nevo and Wong (2015), who show that U.S. households lowered expenditures during the Great Recession by increasing coupon usage, shopping at discount stores, and purchasing more goods on sale, larger sizes, and generic brands. While they explain this behavior with the decreased opportunity costs of time, we show that experience effects is also at work. Key to identifying this additional source of consumption adjustment are the inter-cohort differences and the difference in those differences over time.

B.2 Heterogeneity Across Cohorts

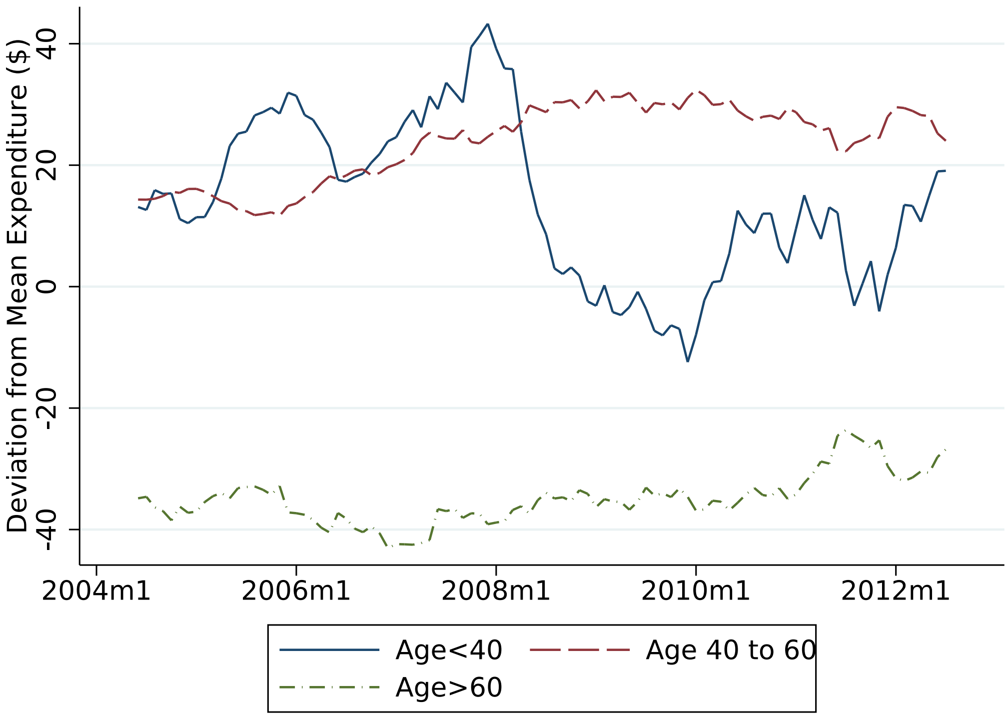
Experience effects from past exposure to unemploymentgive rise to heterogeneity in consumption choices. The experience-effect hypothesis links this heterogeneity to different histories of past experiences. Another, more subtle implication of the hypothesis is that there is heterogeneity in the response to the *same* recent experience: younger consumers will react more strongly to a new unemployment shock than older consumers. The reason is that an unemployment shock in the recent past alters the (weighted) lifetime average of a consumer more the shorter the history of past experiences is, i. e., the younger the consumer is. We can see this in the formula for experience-based beliefs, as defined in equations (1) and (2). The shorter a consumer's life is the more mass is assigned to the most recent realization. Hence, we predict that the young lower their consumption expenditure to a greater degree than older cohorts during economic busts and, vice-versa, increase it more during booms.

Indeed, as shown in Appendix-Figure B.4 using the Nielsen data, the consumption spending of younger cohorts is significantly more volatile and more sensitive to crises such as the Great Recession.

We further test the age heterogeneity prediction using the Nielsen data.[30] We regress the change in log monthly consumption on the interaction of age with the

[30] We continue to use the Nielsen data rather than switching back to the PSID data since the low frequency of survey waves in the PSID (biannual rather than monthly) does not allow to define the "most recent" past experience in a uniform and consistent way, challenging the interpretation of the corresponding estimations. When we nevertheless estimate an approximative model in the PSID, relating the (log) change in total consumption to the interaction between the change in annual unemployment (from time $t-1$ to t) and a dummy variable for the young, we find qualitatively similar effects.

Figure B.4: **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.

change in log unemployment conditions from month t to $t-1$, controlling for the same battery of controls as in Table B.17. We do so separately for positive and negative changes (in absolute value) in unemployment in order to identify possible asymmetries in the reaction to improving versus tightening economic conditions. Since we know where a household resided in $t-1$, we can use changes in either the national unemployment rate or the local (county-level) unemployment rate as our proxy for a recently experienced unemployment shock, controlling for the respective other rate change.

The results are in Table B.18. Columns (1)-(2) show the estimates when we interact age with the national-rate shock, and columns (3)-(4) show the estimates when using the local (county-level) rate shock. We include both sets of interactions in columns (5)-(6). Note that the level effect of log national unemployment rate changes is absorbed by the time (year-month) fixed effects, and that we include the positive and negative changes in log local unemployment rate across all specifications.

The estimation results in columns (1) to (4) reveal that the coefficients of all age-unemployment interactions are significantly negative. That is, recent unemployment shocks, whether positive or negative, have a smaller effect on the consumption expenditures of older cohorts.

The effects are a bit stronger for decreases in national unemployment and for increases in local unemployment. When we include all four interaction effects, in columns (5) and (6), the coefficient sizes remain similar, though the estimated coefficient of the interaction of age with higher national unemployment and with lower local unemployment become smaller and insignificant. Overall, the results support our prediction of a significantly stronger response to recent experiences among the young than among the old.

We note that a potential alternative explanation for some of the estimated interaction effects is the presence of stronger liquidity constraints among 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 because they are more likely to hit liquidity constraints. These models do not easily predict a more positive reaction to positive shocks, though. To generate the latter prediction, too, these models need to rely on the argument that the young were previously constrained, and that a particularly strong reaction to a positive shock allows the young to adjust to their permanent-income optimum. However, even with this additional argument, liquidity constraints are unlikely to explain our estimates since the identification exploits not only positive shocks at (previously) bad times, but also good shocks at (already) good times. For the latter instances, adjustments to the PIH optimum do not predict a stronger reaction among the young, and liquidity concerns point to the opposite outcome. In fact, young consumers with more positive prior experiences would exhibit a weaker reaction to recent good outcomes, and young consumers with more negative prior experiences would exhibit a stronger reaction to recent good outcomes according to the PIH.[31] Thus, our findings highlight

[31] To show this directly, we estimated a set of regressions that augments the specifications from Table B.18 with triple interactions of age, positive and negative national or local unemployment shocks, and an indicator of above-median unemployment experiences for the respondent's age. The

Table B.18: **Age-Heterogeneity in Reaction to Unemployment Fluctuation**

	(1) $\Delta\ln(C)$	(2) $\Delta\ln(C)$	(3) $\Delta\ln(C)$	(4) $\Delta\ln(C)$	(5) $\Delta\ln(C)$	(6) $\Delta\ln(C)$
Age * $\Delta\ln$(National unemp-down)	-0.023***	-0.023***			-0.021***	-0.021***
	(0.005)	(0.005)			(0.005)	(0.005)
Age * $\Delta\ln$(National unemp-up)	-0.006***	-0.007***			-0.001	-0.000
	(0.002)	(0.002)			(0.002)	(0.003)
Age * $\Delta\ln$(Local unemp-down)			-0.002*	-0.003**	-0.001	-0.002
			(0.001)	(0.001)	(0.001)	(0.001)
Age * $\Delta\ln$(Local unemp-up)			-0.008***	-0.008***	-0.008***	-0.009***
			(0.001)	(0.001)	(0.001)	(0.001)
Local unemployment control	Yes	Yes	Yes	Yes	Yes	Yes
Income control	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	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	Yes	No	Yes	No	Yes
Observations	3,645,362	3,645,362	3,645,362	3,645,362	3,645,362	3,645,362
R-squared	0.010	0.014	0.010	0.014	0.010	0.014

Notes. The dependent variable is the change in log monthly total consumption expenditures, and the main regressors are the interaction terms between age and the change in log national or local unemployment rate, separated into two variables for positive and negative changes (in absolute value), both from time t to $t-1$. Local unemployment controls are the change in log local unemployment rate, also separated into two variables for positive and negative changes. Household characteristics include household size, education, and race. Time fixed effects include year-month fixed effects. The sample period runs monthly from 2004 to 2013. 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.

experience effects as a distinct force in affecting people's consumption behavior.

Appendix C Model

We implement the empirical model of Low, Meghir, and Pistaferri (2010) with a few minor adjustments to our setting. All key equations are retained and, when possible, all parameters are set to the same values. As in Low et al., some parameters are set separately for high- and low-education groups, including the probability of job destruction and job offers.

C.1 Parameters governing the income process and utility maximization

The utility function and lifetime expected utility are defined in equations (4) and (5) in Section IV as $U(c, P) = \frac{\left(c \times e^{\eta P}\right)^{1-\gamma}}{1-\gamma}$ and $U(c_{i,t}, P_{i,t}) + \mathrm{E}_t \left[\sum_{s=t+1}^{L} \beta^{s-t} U(c_{i,s}, P_{i,s})\right]$, respectively. In the simulations, we follow Low et al. and take risk aversion parameter $\gamma = 1.5$ from Attanasio and Weber (1995), use the estimates for η from their Table 2, and set the discount factor $\beta = 1/R$ in the value function.

For the gross quarterly income $w_{i,t}h$, we also follow Low et al. in setting the number of hours worked per quarter to $h = 500$. In the wage process $\ln w_{i,t} = d_t + x'_{i,t}\psi + u_{i,t} + a_{i,j,t_0}$, we recover the parameters α, β_1, and β_2 governing the deterministic component, $d_t + x'_{i,t}\psi = \alpha + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{age}^2$, from the parameters in the Fortran code published alongside Low et al. In the permanent component $u_{i,t} = u_{i,t-1} + \zeta_{i,t}$ where $\zeta_{i,t}$ is i. i. d. normal with mean 0 and variance σ_ζ^2. We use the value of σ_ζ given in Table 1 of Low et al.. The consumer-firm job match component, a_{i,j,t_0}, is drawn from a normal distribution with mean 0 and variance σ_a^2, and we use the value of σ_a given in Table 1 of Low et al..

We obtain the values for the probabilities of job destruction δ, of a job offer when employed $(1-\delta)\lambda^e$, and of a job offer when unemployed λ^n from Table 2 in Low et al. (2010). Note that, while the probability of job destruction is constant across

estimated effects of positive national and local unemployment shocks are weaker (given age) for respondents with worse unemployment experiences, as predicted by the experienced-based learning hypothesis, but not by a standard PIH framework.

time for a given household, the probability of receiving a job offer varies depending on whether or not an agent is employed.

C.2 Budget constraint

The intertemporal budget constraint for a working individual i in period t is given by

$$\begin{aligned} A_{i,t+1} = & R\left[A_{i,t} - c_{i,t}\right] + \left(w_{i,t} h(1-\tau_w) - F_{i,t}\right) P_{i,t} \\ & + \left(B_{i,t} I^{UI}_{i,t}(1 - I^{DI}_{i,t}) + D_{i,t} I^{DI}_{i,t}\right)(1 - P_{i,t}) + T_{i,t} I^{T}_{i,t} \end{aligned}$$

where $A_{i,t}$ is beginning-of-period-t assets, R is the interest factor, τ_w a tax, F the fixed cost of working, P an indicator for whether an individual is working, B are unemployment benefits, D disability benefits, T food stamp benefits, c is consumption, and the I variables are indicators of receiving the associated social insurance.

As in Low et al. (2010), we assume that individuals cannot borrow and thus $A_{i,t} \geq 0 \quad \forall t$. Also as in Low et al. (2010), we set $r = .15$ and define $R = 1 + r$. We use the estimates for F from their Table 2. In Low et al. (2010), τ_w is a variable of interest and solved for, albeit as fixed percentage (not progressive or regressive). As we do not focus on the value of social insurance programs, including the tax revenues to be raised to fund them and their relation with consumption, we normalize $\tau_w = 0$.

During retirement individuals receive social security equal to the value of disability, so the budget constraints simplifies to

$$A_{i,t+1} = R\left[A_{i,t} + D_{i,t} - c_{i,t}\right].$$

C.3 Social Insurance programs

As in Low et al. (2010), we implement three social insurance programs, unemployment insurance, food stamps, and disability insurance.

Unemployment Insurance. Unemployment Insurance is paid only during the quarter following job destruction. Unemployment benefits are given by

$$B_{i,t} = \begin{cases} b w_{i,t-1} h & \text{if } b w_{i,t-1} h < B_{\max}, \\ B_{\max} & \text{if } b w_{i,t-1} h \geq B_{\max}. \end{cases}$$

where b is the replacement ratio, and $B_{\max}$ is the cap on unemployment benefits. We set $b = .75$ as in Low et al. (2010) and $B_{\max}$ to the value used in the associated code.

Food Stamps (Means-Tested Social Insurance). Defining gross income as

$$y_{i,t}^{\text{gross}} = w_{i,t}hP_{i,t} + \left(B_{i,t}I_{i,t}^{UI}(1 - I_{i,t}^{DI}) + D_{i,t}I_{i,t}^{DI}\right)(1 - P_{i,t}),$$

and net income as

$$y = (1 - \tau_w)y^{gross} - d,$$

the amount of food stamps allocated to agent i in period t is

$$T_{i,t} = \begin{cases} \overline{T} - .3 \times y_{i,t} & \text{if}\, y_{i,t} \leq \underline{y} \\ 0 & \text{otherwise,} \end{cases}$$

where $\overline{T}$ is a maximum payment and $\underline{y}$ is a poverty line. One important implication of this definition is that there is no disincentive to hold assets. Adjusting to quarterly values, we set $\overline{T}$ to the maximum food stamp allotment for a couple in the US in 1993, $\underline{y}$ to the maximum food stamp allotment for the US in 1993, and d to the standard deduction for a couple in the US in 1993.

Disability. As in Low et al. (2010), individuals above 50 can apply for disability when they are unemployed and are accepted with a fixed probability of .5. If an application is successful, disability becomes an absorbing state for the remainder of the person's working life. If a person is not accepted, they can only reapply in a future bout of unemployment, after having worked again for at least one year. As a disincentive to applying, the individual must be unemployed in both the period they apply and the period after. We also impose that individuals must have a sufficiently low u and not be working or have a job offer at the time of application. The formula for disability benefits is

$$D_{i,t} = \begin{cases} .9 \times \overline{w}_i & \text{if } \overline{w}_i \leq a_1 \\ .9 \times a_1 + .32 \times (\overline{w}_i - a_1) & \text{if } a_1 < \overline{w}_i \leq a_2 \\ .9 \times a_1 + .32 \times (a_2 - a_1) + .15 \times (\overline{w}_i - a_2) & \text{if } a_2 < \overline{w}_i \leq a_3 \\ .9 \times a_1 + .32 \times (a_2 - a_1) + .15 \times (a_3 - a_2) & \text{if } \overline{w}_i > a_3 \end{cases}$$

where a_1, a_1, and a_3 are fixed thresholds from legislation, and $\overline{w}_i$ is the mean earnings prior to application. Similar to Low et al. (2010), we assume $\overline{w}_i$ can be approximated using the agent's value of $u_{i,t}$ at the time of application.

C.4 Implementation

Appendix-Table C.19 details all parameters referenced above and their sources. As discussed, most values are obtained directly from Low et al. (2010), and some are retrieved from examining the associated Fortran 90 code published with the paper. In cases where we were unable to ascertain values in either source, as is the case for several welfare values, we use actual values from 1993, the year in which the SIPP survey used in Low et al. for hourly wage data begins. This is also the closest year in the SIPP survey to the PSID data, and the values are consistent with the model values.

When we combine the high- and low-education data, we use 70% low- and 30% high-education observations, roughly corresponding to recent US census estimates of those without and with a bachelor's degree.[32]

Like Low et al. (2010), we solve the model numerically. In the last period, all agents consume the entirety of their assets. We then iteratively solve backwards for consumption and other relevant decisions that maximize the agents' value functions. Further details of the model solution can be found in Low et al. (2010).

C.5 Past Experiences and Income

In addition to illustrating the impact of past experiences on consumption, we also apply the model to study the relationship between unemployment experiences and future income. Appendix-Table C.20 replicates Table 4 for EBL consumers using the model accounting for unemployment scarring. Appendix Table C.20 shows the estimation results for predicting future income two, four, six, eight, and ten years ahead, corresponding to the setup in Table 4. As before, we weight past unemployment experiences with either linearly declining weights (λ=1), shown in the top half,

[32] The percent of the US population with at least a bachelor's degree has increased over the last three decades. It was closer to 25% in 2007 and 20% in 1995. We opted for the more recent estimates to err, if anything, on the side of a greater inclusion of high-education individuals.

Table C.19: **Model Parameters Used in Simulations**

Parameter	Low Education	High Education	Source (from Low, Meghir, and Pistaferri (2010))
γ	1.5	1.5	Text
σ_a	0.226	0.229	Table 1
σ_ζ	0.095	0.106	Table 1
$P(\zeta)$	.25	.25	Text
δ	.049	.028	Table 2
λ^e	.67	.72	Table 2
λ^n	.76	.82	Table 2
b	.75	.75	Text
r (yearly)	.015	.015	Text
β	$1/(1+r)$	$1/(1+r)$	Text
F	1088	1213	Table 2
η	-.55	-.62	Table 2
h	500	500	Text
b	.75	.75	Text
UI Cap	3178	3178	Code
P(Disability Acceptance)	.5	.5	Text
a_1	1203	1203	Code
a_2	7260	7260	Code
a_3	16638	16638	Code
α	1.0583	.642	Code
β_1	.0486	.0829	Code
β_2	-0.0004816	-.0007768	Code
Parameter	Low Education	High Education	Source
d	6200/4		Standard couple deduction in 1993[a]
$\underline{y}$	(6970+2460)/4		Actual poverty line in 1993 for couple[b]
$\overline{T}$	203×3		Actual max food stamp allotment for US 1993[c]

[a] See https://web.archive.org/web/20190228193856/https://www.irs.gov/pub/irs-prior/f1040a--1993.pdf.

[b] See https://web.archive.org/web/20190228194017/https://aspe.hhs.gov/prior-hhs-poverty-guidelines-and-federal-register-references.

[c] See https://web.archive.org/web/20190228193653/https://fns-prod.azureedge.net/sites/default/files/Trends1999-2005.pdf. Accessed via https://web.archive.org/web/20190228195514/https://www.fns.usda.gov/snap/trends-food-stamp-program-participation-rates-1999-2005.

and with more weight shifted to recent observations (λ=3), shown in the bottom panel.

The results on unemployment experiences with linearly declining weights show that past experiences do not significantly predict two-years-ahead future income, consistent with the empirical finding. All of the other coefficients in the table suggest a positive relationship between current unemployment experience and future income. The intuition for these results is similar to that for the positive relationship between unemployment experience and consumption for rational consumers: Conditional on current income, unemployment experience positively predicts a higher permanent component of income. If we do not control for income and wealth, unemployment experience and future income are negatively correlated.

Table C.20: **Experience Effects and Future Income: Model**

	Income_{t+2}	Income_{t+4}	Income_{t+6}	Income_{t+8}	Income_{t+10}
Experience , λ=1	-0.005	0.221	0.348	0.404	0.418
	(-0.15)	(6.08)	(11.71)	(16.05)	(18.01)
Experience, λ=3	0.204	0.453	0.554	0.589	0.574
	(4.66)	(10.27)	(14.75)	(17.76)	(17.96)
Income control	Yes	Yes	Yes	Yes	Yes
Wealth control	Yes	Yes	Yes	Yes	Yes
Period (age) fixed effects	Yes	Yes	Yes	Yes	Yes

Notes. The dependent variables are simulated future income in two, four, six, eight, and ten years, respectively, where one year is modeled as 4 periods/quarters. The simulations are for behavioral agents and account for unemployment scarring. Estimations are for $\lambda = 1$ in the top panel and $\lambda = 3$ in the bottom panel. Log simulated income and wealth are controlled for. All estimations include period and education fixed effects and use period-clustered standard errors. Simulations are based on the working periods of 10,000 simulated consumers and thus 1,600,000 observations less 10,000 times each period in the future for which income is taken. t statistics in parentheses.