NBER WORKING PAPER SERIES

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Orazio Attanasio
Kieran P. Larkin
Morten O. Ravn
Mario Padula

Working Paper 27956
http://www.nber.org/papers/w27956

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2020

We are grateful to numerous seminar and conference participants for very helpful comments. Agnes Kovacs and Similan Rujiwattanapong provided expert research assistance. We also acknowledge financial support from the Horizon 2020 ADEMU network. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 27956
October 2020
JEL No. D12,D14,E21,E32

ABSTRACT

US households' consumption and car purchases collapsed during the Great Recession, for reasons that are still poorly understood. In this paper we use the Consumer Expenditure Survey to derive cohort and business cycle decompositions of consumption profiles. When decomposing the car expenditure data into its extensive and intensive margins, we find that the intensive margin contracted sharply in the Great Recession, a finding in stark contrast to conventional wisdom and to the experience of prior recessions. We interpret the evidence through the prism of a very rich life-cycle model where individuals are subject to idiosyncratic uninsurable income shocks, aggregate income shocks, wealth shocks, and credit shocks. We show that, because of their salience and the transaction costs, cars are particularly sensitive to changes in the perception of fu- ture expected income and its variability. We find that on top of a large aggregate income shock, life-cycle income profile shocks and wealth shocks are important determinants of consumption choices during the Great Recession.

Orazio Attanasio
Department of Economics
Yale University
37 Hillhouse Avenue
New Haven, CT 06511
and Institute for Fiscal Studies, FAIR,
BREAD and CEPR
and also NBER
orazio.attanasio@yale.edu

Kieran P. Larkin
Institute for International Economic Studies
Stockholm University
Stockholm SE-106 91
Sweden
kieran.larkin@iies.su.se

Morten O. Ravn
Department of Economics
University College London
London WC1E 6BT
UK
and CEPR
m.ravn@ucl.ac.uk

Mario Padula
Dipartimento di Economia
Ca' Foscari University of Venice
Sestiere Cannaregio, 873
30121 Venezia
Italy
mpadula@unive.it

1 Introduction

Expenditure on durables, and cars in particular, have long been known to exhibit much more variability than other components of private sector consumption. Kydland and Prescott (1982), for instance, report that durables consumption expenditures display a standard deviation more than three times that of output over the business cycle while non-durables consumption expenditures are only two thirds as volatile as output. Some large-ticket items amongst durables are even more volatile. In the US, the variance of (detrended) real motor vehicles expenditure is more than 20 times higher than the volatility of non-durables spending. In an early contribution, Bernanke (1984) tests the permanent income hypothesis (PIH) for car expenditures using household panel data from the Survey of Consumer Finances and finds that high car spending volatility may not be inconsistent with the PIH. Bernanke (1985) instead develops a test of the PIH considering jointly durables and non-durables allowing for convex adjustment costs of the former. He rejects the PIH for aggregate data due to excess volatility. Galí (1993) finds that in 6 OECD countries, not only durables are substantially more volatile than non durable consumption, but are also *excessively smooth*, in that they not react enough to changes of the permanent component of income.[1] In the case of the expenditure on cars, Bar-Ilan and Blinder (1992) also point out that most of the business cycle fluctuations could be explained by the extensive rather than the intensive margin; that is in the number of households buying a car rather than on the amount spent conditionally on buying.

One possible interpretation of these facts is that, as durable consumption (and cars) are usually large and lumpy, involving substantial transaction costs, they might be more salient and informative about news and innovations to permanent income. The fact they react strongly to aggregate shocks indicates that expenditure on durables and cars might be particularly informative about the business cycle and, more generally, about individual expectations about economy-wide conditions. Sales of new motor vehicles tend to lead the business cycle, a feature the former Chair of the Board of Governors Alan Greenspan was well aware of, see Cohen and Greenspan (1990).

Given the saliency of car purchases to expectations of future income, we investigate whether cars expenditure can be used to unpack individual perceptions of economic prospects. For

[1] Galí interprets this evidence as a consequence of possible liquidity constraints or adjustment costs.

such a purpose we develop a sophisticated model of individual behaviour and calibrate its parameters to data observed *before* the Great Recession. We then investigate what combinations of shocks and perceptions can fit the Great Recession data on car purchases. Effectively, we use our model to infer from important and salient choices households make, their implied subjective expectations about future incomes. We put particular emphasis on durable goods adjustments, which we argue to be informative about subjective beliefs. This work complements macroeconomic research aimed at understanding the root causes of the Great Recession and follows in a line of work which has argued that household consumption dynamics can be highly informative of the shocks perceived by households.[2]

We first provide evidence on household consumption spending by analyzing data drawn from the Bureau of Labor Statistics' Consumer Expenditure Survey (CEX). By constructing synthetic cohort panel data, we examine life-cycle and business cycle features of the data. We decompose the CEX average car spending data into an extensive and an intensive margin, which measure, respectively, how many households engage in car transactions and how much households spend on average conditional on buying or selling. During the Great Recession, the extensive margin contracted more than in previous recessions. Moreover, the intensive margin also declined. This latter phenomenon is novel and goes against the perceived wisdom,which, as we mention above, was that the extensive margin is the main source of cyclical variations in car spending. We also find succinct cohort patterns of adjustment with younger and middle-aged households being subject to larger movements in both margins of adjustment than older households when life-cycle patterns are taken into consideration.

We then examine a sophisticated 60-period life-cycle model. Households choose expenditure on non-durables and cars and can save in a liquid asset subject to a sequence of budget and borrowing constraints. Adjustment of the household's car stock is associated with non-convex costs, but cars can also be used as collateral against car loans. Households labor income stream is stochastic while retirees draw certain pension benefits. The household income process is subject to permanent and transitory shocks to the level of income and to its drift reflecting the fact that household income has a strong life-cycle pattern. Income shocks

[2]On the causes of the Great Recession, see Hall (2011), Stock and Watson (2012), Christiano et al (2015), Krueger et al (2016), and Ravn and Sterk (2017). On income and consumption dynamics see Blundell and Preston (1998), Blundell et al. (2008), Guvenen and Smith (2014), Heathcote et al. (2014), Kaplan et al. (2020), and Olivi A. (2019)

may be idiosyncratic, cohort-specific, or aggregate, which allows us to model both the heterogeneity across households in income realizations and business cycle fluctuations deriving from aggregate shocks. Households are also subject to stochastic changes in the premium on car loans and to wealth shock which capture changes in house prices and in equity prices.

The model generates (S, s)-type dynamics of household car stocks, as studied by Attanasio (2000) and, more recently, by Berger and Vavra (2015). The procyclical variation in the extensive margin often observed in the data is consistent with the model and reflects delayed car adjustments of the large share of households who experience adverse conditions during recessions. Intensive margin adjustments, relate only to households who actively adjust their car stock, i.e. households less severely affected by the aggregate contraction or those that are forced to adjust their car stock (e.g. due to a car breakdown). As pointed out by Bertola, Guiso and Pistaferri (2005), the decision at the two margins are driven by different economic factors. The probability of adjustment depends upon the dynamic history of shocks experienced by the household, whereas the size of adjustment is chiefly based on forward looking considerations.

We estimate the model's key structural parameters by indirect inference and then subject households to a sequence of aggregate shocks during the Great Recession, while retaining idiosyncratic shocks as well. We find that the combination of different shocks allow us to reproduce different patterns observed in the data. In particular, our model can account for the size of the consumption adjustments both for non-durables and for cars, for the extensive and intensive car adjustment dynamics, and for the cohort-level adjustments of consumption and savings. First, a large aggregate income shock matters for the large decline in consumption expenditures. However, the unusually large income shocks, by itself, cannot account for the size of the contractions at the extensive and the intensive margins of car purchase: as idiosyncratic shocks are sufficiently large, many households go through the recession relatively unscathed. Second, asset price shocks appears to be an important determinant of household consumption dynamics. While we do not explicitly include housing choices into our model, housing is the main component of household wealth. Therefore booming housing markets are llikely to be an important important explanation for the consumption boom that took place in the US in the late 1990s and the early 2000s. The impact on wealthier household of the housing and equity markets collapses at the onset of the Great Recession helps understanding why consumer durables spending collapsed. Finally, to account fully for the cohort features of the consumption adjustments and savings, we find that it is important to allow for a negative shock to the household life-cycle income profile. This shock does not impact on the level of income (we restrict the actual income decline to match aggregate US income during the Great Recession) but it does impact on future expected income, especially for younger households. Because of this feature, younger households increase their savings as observed in the data.

We also carry out a number of additional policy experiments, analysing the role of fuel prices and uncertainty shocks to the income processes as well as the impact of car purchase subsidies, such as the Cash for Clunkers programme introduced in 2009. We find fuel prices and changes to uncertainty to have minor impacts. As for Cash for Clunkers, its main impact is to bring forward car purchases but once the programme is terminated, its positive impact on expenditures quickly reverts.

Our paper adds to several literatures. We confirm the importance of the combination of wealth and income shocks highlighted by e.g. Mian, et al. (2013). However, in our analysis deteriorating beliefs about future income growth prospects play a key role in explaining the observed patters of data. This emphasis on beliefs echoes Kaplan, et al (2020), who show that such beliefs matter for the house price boom and bust cycle during the Great Recession. The quantitative importance of the wealth channel is also in line Berger et al's (2020) analysis of the impact of income uncertainty in a life-cycle setting.

Our use of consumption choices for making inference about risk extends Guvenen and Smith's (2014) analysis in a number of dimensions. First and foremost, we argue that consumer durables are particularly informative while these authors focus on a composite non-durables and services good. Secondly, we add aggregate shocks on top on the lifecycle dimension. Thirdly, this rich set of shocks goes beyond labor income risk and we show that the model has sharp predictions about their impact. Unlike other studies, such as Berger and Vavra (2015) who examine the role of transaction costs in consumer durables dynamics we focus on both the extensive and intensive margins of car adjustment and the very rich set of shocks that we allow for when conducting inference. The emphasis on the intensive margin enables us to show how income expectations matter for the consumption slump during the Great Recession. In particular, the model is able to capture the novel empirical fact we document of an unusual decline in the intensive margin during this episode. This aspect of our analysis is new to the literature on consumer durables and investment spending. Following the seminal work of Caballero and Engel (1999), the literature has focused on the extensive margin. Our analysis also relates to Harmenberg and Öberg (2019) who consider the impact of persistent income shocks deriving from unemployment in a model with non-convex costs of consumer durables. Our analysis considers a significantly richer setting in terms of asset choices and the source of shocks but a major difference is that we use the model for drawing inference on the shocks rather than understanding the impact of unemployment risk.

The remainder of the paper is organized as follows. In Section 2, we examine CEX data on household consumption. Section 3 presents the life-cycle choice model. We then discuss the parameterization of the model and properties of the policy functions in Section 4. Section 5 contains our analysis of the Great Recession. Finally, Section 6 presents various extensions and the analysis of Cash for Clunkers.

2 Consumption and the Great Recession

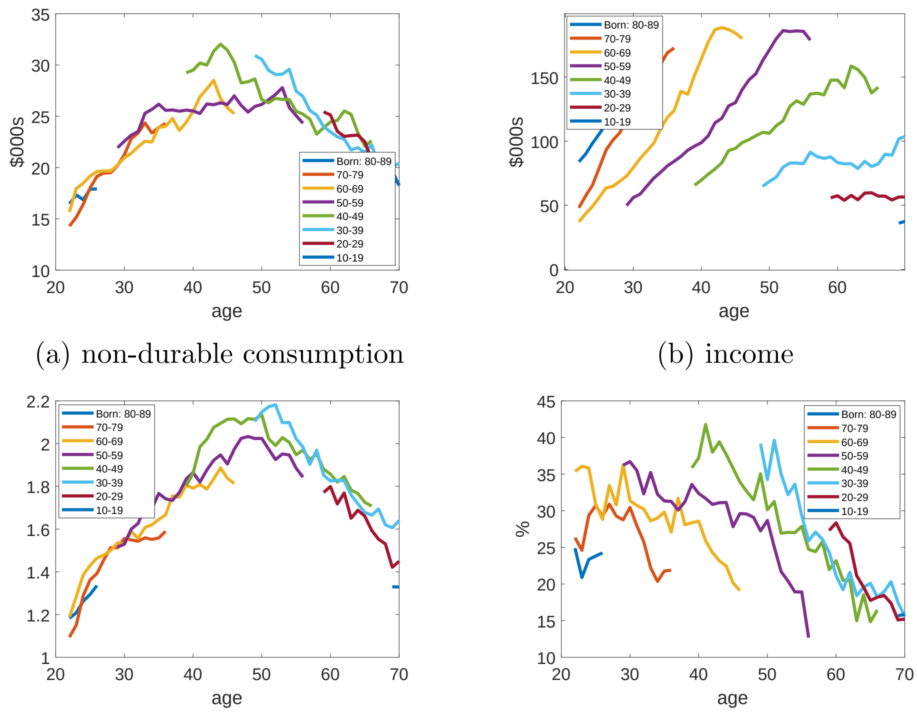
2.1 Data

Data for aggregate variables are from NIPA while household data are obtained from the CEX. The CEX is attractive for our purposes both because of the long sample and because of its detailed information on consumption at the household level.[3] We focus on the CEX sample for households with heads between the age of 25 and 84 years for the 1981-2012 period. Our sample contains around *234,000* household observations, with each household's consumption observed for a maximum of four quarters. Table A.1 in the Appendix contains summary statistics of the data broken into pre and post-Great Recession periods.

2.2 Life-Cycle Dynamics

We first document some salient facts of the life-cycle aspects of the data. An important data obstacle in this dimension is that each household in the CEX is followed only for four consecutive interviews. We therefore adopt a synthetic panel approach by grouping households by the date of birth of the household head, see the appendix for details. Figure 1 illustrates estimates of the life-cycle profiles (using 10 year groupings) of household spending on non-durables and services, total after-tax household income (including financial income apart

[3]The CEX data has been criticized not aggregating up to NIPA statistics. However, the CEX spending categories are very similar to those in NIPA data when controlling for items cand population coverage. Garner, McClelland and Passer (2009) show, as does Figure 3, Panel B that car spending closely mirrors NIPA data when aggregated across households.



(a) non-durable consumption (b) income

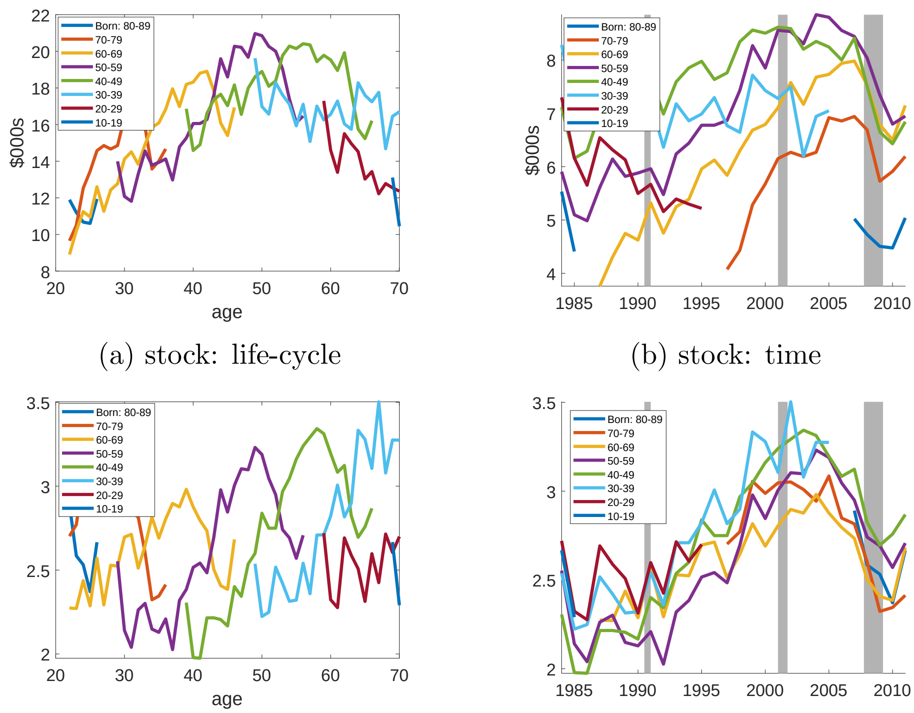
(c) number of cars (d) % hh purchasing

Figure 1: CEX cohorts: non-durable consumption, number of cars and income

from capital gains), the number of cars owned and the percentage of households purchasing a vehicle.[4] The life-cycle pattern of spending on non-durables and the household car stock and services is very clear. Expenditures on non-durables and services (Panel A) and the car stock (Panel C) both rise with age for young households until the household head enter their 40s or early 50s, respectively, then flattens out and start declining gradually for older households. The growth in the number of cars per household is slower for younger households than that in non-durables and services expenditures and the age at which the car stock peaks exceeds the peak age for non-durables spending. Panel B shows the life-cycle profile for income which also increases in the first part of the life cycle and declines in later life but with much clearer cohort effects than for consumption. Finally, Panel D shows the share of households purchasing a car which displays downward trend during the life-cycle especially after the age of 50.

[4]We divide consumption and income by the CPI to convert in 2014 dollars. Figure A.2 shows the profiles for for adult equivalents variables.

Figure 2, Panel A, illustrates the *value* of each cohort's car stock as a function of age which still displays a life-cycle pattern also some scarring effects of business cycles. To see this, Panel B of illustrates the same data but now plotted against calendar time. The long boom in the U.S. economy from the early 1990's recession until the financial crisis increased the value of household car portfolios across cohorts while the leaner aggregate conditions in the mid 1980s saw declines in the value household car stock holdings across households regardless of age. Such scarring effects are even more evident when inspecting the value of the car stock relative to spending on non-durables and services across cohorts, see Panel C. There is no easily visible life-cycle pattern to this measure but, as shown in Panel D, there are very evident common movements over time.



(c) ratio: life-cycle

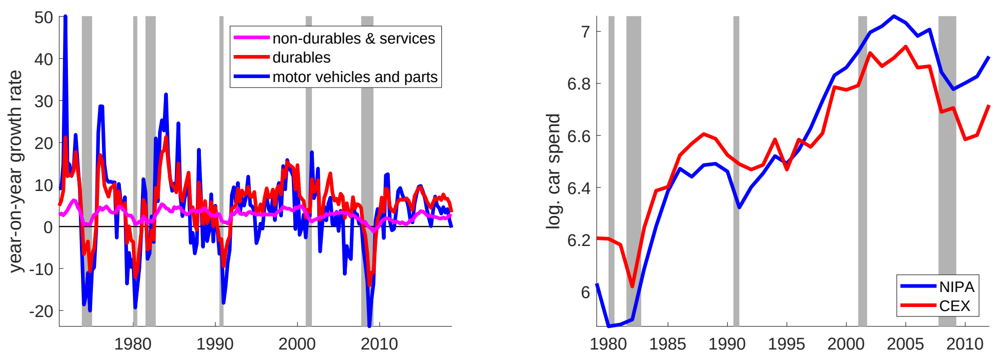
(d) ratio: time

Notes: ratio is the ratio of car stock to non-durables consumption.

Figure 2: CEX cohorts: household car stock over lifecycle and time

2.3 Consumption Adjustments During the Great Recession

Figure 3 shows year-on-year growth rates of NIPA data on aggregate real spending on non-durables and services, consumer durables and on motor vehicles (quarterly data, 1970-2019, shaded areas indicate NBER recessions). Consumption expenditures display notable procyclical business cycle fluctuations. Non-durables and services are relatively smooth while spending on durables, and motor vehicles in particular, is much more volatile having a standard deviation more than seven times higher than consumer non-durables. The impact of the Great Recession on consumption expenditures stands out for a number reasons; spending on non-durables declines during this episode as opposed to slowing down during previous recessions; the decline in spending on motor vehicles is the largest in the sample and, at its maximum in 2008Q4, fell by 24 percent on a year-by-year basis. Panel B of Figure 3 shows that the car spending in the CEX closely replicates the NIPA series. We exploit the CEX data to draw

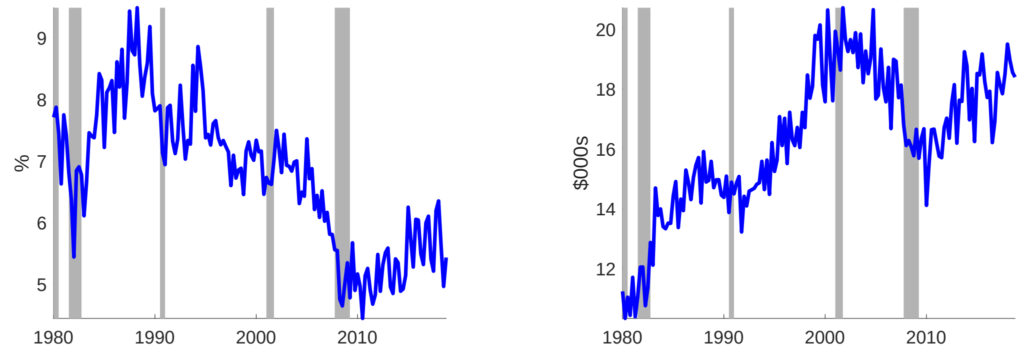


(a) NIPA growth rates

(b) NIPA vs CEX

Figure 3: NIPA car expenditure

out more information about consumption adjustments at the household level. We estimate the extensive margin of car spending by computing the fraction of households in the CEX data who purchase a car per quarter over the sample. In our sample this fraction averages 6.8 percent per quarter and Figure 4, Panel A, illustrates the (seasonally adjusted) estimated time-series. While there is a secular decline in the frequency of car purchases, cyclical variations in the extensive margin of adjustment are evident and particularly so during the Great Recession where this fraction falls abruptly from 6 percent per quarter pre-recession in 2006



(a) % hh purchasing (b) value of purchase

Figure 4: CEX cohorts: extensive and intensive margin, time series

to below 5 percent per quarter in late 2008.[5] Panel B shows the response of the intensive margin, the value of car purchased conditional upon the household buying a car. Over time there is a positive secular trend towards more expensive vehicle purchases, with the trend peaking in about 2005. In contrast to the frequency of car purchases, the intensive margin remained fairly unaffected in previous recessions as argued by Bar-Ilan and Blinder (1992). In the Great Recession instead the intensive margin drops significantly and this holds true both for new and used cars. This intensive margin drop occurs almost coincidentally with the Great Recession and is very persistent. Table 1 reports the outcome of regressing dummy variables for either the probability of purchase or the dollar value of purchases on a dummy variable for NBER recession periods, a dummy for the Great Recession and a quadratic time trend using household level quarterly data. The data covers the period 1979.IV-2012.IV. NBER recessions are associated with a 0.4 percentage point decline in the probability of car adjustment. This is evenly split between new and old purchases. The probability of purchase falls additionally in the Great Recession, although this decline is not statistically significant. In contrast we see that in previous recessions, the average value of cars purchased does not change. However, during the Great Recession the value of the average car purchase fell by almost $1300 dollars and this occurred in both new and old car markets. One explanation could be that these results merely reflect that severity of the Great Recession. To check this, in Table A.2 in

[5]The fall in the frequency of car purchases during recessions occurs for both transactions in the new car market as well as in the second-hand market, see Figure A.4 in the Appendix

Table 1: Car purchasing behavior in NBER recession periods

	% purchase			Value|purchase ($)		
Variable	all	new	old	all	new	old
Recession	-0.43	-0.22	-0.24	219.3	-746.0	879.2
	(0.11)	(0.06)	(0.10)	(205.8)	(344.6)	(175.7)
Great Recession	-0.17	0.09	-0.25	-1319.1	-1980.0	-1425.9
	(0.18)	(0.10)	(0.16)	(364.4)	(606.2)	(312.0)
R^2	0.002	0.001	0.001	0.022	0.058	0.031
N	599,194	599,194	599,194	42,370	12,575	30,242

Notes: Standard errors in parentheses. Data is at quarterly frequency. Variable is regressed on dummy for NBER recession dates and dummy for Great Recession. Additional controls are quarter dummies and a quadratic series for the time period.

the Appendix we replace the NBER recession dummies with the GDP growth rate and the results are largely unchanged. In combination with the results above, we find that the Great Recession stands out for both a large drop in the extensive margin and an atypical contraction in the intensive margin.

2.4 Extensive margin behavior

To understand better the extensive margin variations, we now estimate a probit model for the probability of purchasing a car using individual household data from the CEX. We relate the probability of purchasing a car to the value of the household's stock of cars controlling for household characteristics such as family size, education, age and income. We also experiment with scaling the value of the household's car stock with annual spending on non-durables. In order to evaluate the stability of the correlation structure, we introduce time-fixed effects. The average marginal effects reported in Table 2 show that, consistent with theories of non-convex car adjustment costs, a larger car stock makes car purchases less likely and that higher weekly consumption spending increases the probability of household car investment. The latter is consistent with an income effect and/or non-separabilities between non-durables and durables

Table 2: Probability of Purchasing a Car (Avg. Marginal Effects)

Variable	(1)	(2)	(3)	(4)
Stock ($10,000)	-0.012	-0.008		
	(0.0003)	(0.0014)		
Stock:ndur			-0.010	-0.0068
			(0.0002)	(0.0009)
Log. Income	0.014	0.014	0.011	0.011
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
year F.E	✓		✓	
stock x year		✓		✓
age polynomial	✓	✓	✓	✓
R^2	0.0304	0.0307	0.0369	0.0372
N	458,234	458,234	458,210	458,210

Notes: Probit Estimation of probability of adjustment. Standard errors in parentheses. Stock:ndur is the ratio of the car stock to non-durables consumption. Controls include demographics, education, family composition and whether household head works full time. Full results are presented in Table A.3 in the appendix.

in household preferences.[6] When scaling the value of the household's car stock with annual spending on non-durables, we find a slightly better fit and this specification also delivers a negative impact of the car stock indicating that non-separabilities matter.

Figure 5, illustrates the estimated time-fixed effects which indicates a sharp decline in the time-fixed effect from 2006 suggesting that extensive margin decline during the Great Recession period was unusually large.

3 A Model of Household Behaviour

We formulate a computable life-cycle model of household choices and use it for inference.

[6]We control both for education and for whether the household head holds a full time job which may be important determinants of permanent income. Coefficients for the full set of control variables are presented in Table A.3 in the Appendix. Tables A.4-A.5 in the Appendix replicate the analysis without age or income controls.

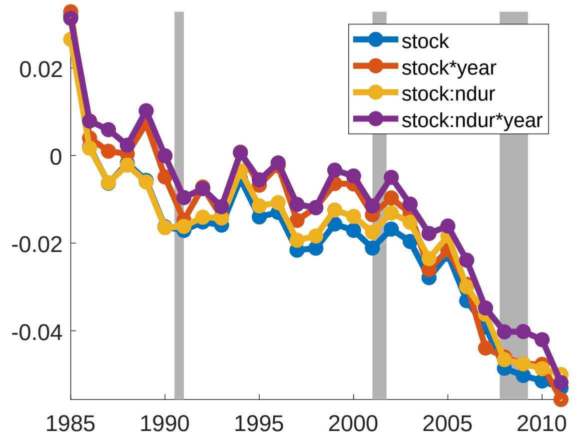


Figure 5: CEX: Probability of purchase, year fixed effects

3.1 Household Problems

Demographics and Preferences: Every period a continuum of mass one of newborn agents enter the economy. Households face age-dependent mortality risk. We let $\pi_a \in [0,1]$ denote the probability that the household survives between age $a-1$ and a. At age $\mathbf{T}$ mortality risk goes to unity, $\pi_{\mathbf{T}} = 0$. The size of each household also varies over the life-cycle but in a deterministic manner. We let γ_a denote the household size of a household of age a. Households work the initial $\mathbf{T}_r - 1$ periods of their life-cycle after which they retire.

Households maximize expected discounted life-time utility. Let $x^a_{j,s}$ denote a variable x for individual $j \in [0,1]$ of age $a < \mathbf{T}$ at date s. Preferences are given as:

$$\mathbb{V}^j_{a,t} = \mathbb{E}_t \sum_{s=t}^{t+\mathbf{T}-a} \beta^{s-t} \pi_a \mathbf{u}^j_{a,s}, \tag{1}$$

$$\mathbf{u}^j_{a,s} = \left\{ \left[\alpha \left(\frac{c^j_{a,s}}{\gamma_a} \right)^{1-1/\mu} + (1-\alpha) \left(\xi \frac{d^j_{a,s+1}}{\gamma_a} \right)^{1-1/\mu} \right]^{(1-\varphi)/(1-1/\mu)} - 1 \right\} / (1-\varphi) \tag{2}$$

$\mathbb{V}^j_{a,t}$ is expected utility, $\mathbb{E}_t$ is the mathematical expectations operator, $\beta < 1$ is the subjective discount factor and $\mathbf{u}^j_{a,s}$ is the flow utility. $c^j_{a,s}$ denotes total household spending on non-durables and services, and $d^j_{a,s+1}$ is the household's stock of cars at the end of period s. ξ converts the stock of cars into its service flow. α is a helps determining the spending shares on the two consumption goods. μ is the elasticity of substitution between consumption of non-durables and the service flow from the stock of cars. φ is the inverse of the intertemporal elasticity of substitution. γ_a converts total household spending into household equivalent utility.

Household Car Dynamics: The law of motion of the household's stock of cars is given as:

$$d^j_{a,s+1} = \left(1 - \delta^j_{a,s}\right) d^j_{a-1,s} + i^j_{a,s} \tag{3}$$

where $i^j_{a,s}$ denotes investment in cars and $\delta^j_{a,s}$ is the depreciation rate. To capture realistic car dynamics, the household depreciation rate can be in one of two states: normal δ^N or breakdown δ^B which have the following properties $\delta^B \in \left(\delta^N, 1\right]$. $\delta^N \in \left(0, \delta^B\right)$. The transition between these two states follows a Markov process. A breakdown occurs with probability τ and is an absorbing state. When the household adjusts the car stock they move deterministically to the normal depreciation state δ^N next period.

We assume that 'actively' adjusting the car stock implies a cost of adjustment, Υ:

$$\Upsilon\left(p_s d^j_{a-1,s}, d^j_{a,s+1}\right) = \begin{cases} 0 & \text{if } d^j_{a,s+1} = (1 - \delta^j_{a,s}\varsigma) d^j_{a-1,s} \\ \psi p_s d^j_{a-1,s} & \text{otherwise} \end{cases} \tag{4}$$

where $p_s > 0$ denotes the price of cars denominated in units of non-durables. $\varsigma \in (0, 1)$ denotes the fraction of depreciation that is maintenance. Households can maintain their car stock, $i^j_{a,s} = \delta^j_{a,s}\varsigma d^j_{a-1,s}$, without incurring any adjustment costs, see e.g. Bachmann, Caballero and Engel (2013), but otherwise car investments induce adjustment costs which are a fraction $\psi > 0$ of the value of their beginning-of-period car stock. The non-convex adjustment cost specification is adopted from Grossman and Laroque (1990) and generates (S, s)-style policy functions for the car stock.[7]An early

Budget and Borrowing Constraints: Household asset portfolios consist of an illiquid asset - cars, and two liquid assets - savings in a financial asset, $b^j_{a,s+1}$, and car loans, $k^j_{a,s+1}$. The financial asset can be purchased or sold each period for price, $q_{a,s}$, which is age specific. Holdings of the asset generate the period coupon $r > 0$.

[7]Attanasio (2000) and Eberly (1994) test and estimate the parameters of $(s.S)$ rules for household automobile purchases. Bertola, Guiso and Pistaferri (2005) and Hassler (2001) have looked at more indirect evidence such as the impact of uncertainty on automobile purchases.

Households cannot issue non-collateralized debt but they have access to collateralized car loans:

$$b^j_{a,s+1} \geq 0 \tag{5}$$
$$k^j_{a,s+1} \leq \eta p_s d^j_{a,s+1} \tag{6}$$

where $\eta > 0$ determines leverage. Thus, households need to provide at least $(1-\eta)\,p_s d^j_{a,s+1} > 0$ as down payment when acquiring a car. The car credit account evolves as:

$$k^j_{a,s+1} = (1 + r^c_s)\,k^j_{a-1,s} + \vartheta^j_{a,s} \tag{7}$$

$r^c_s \geq r$ is the interest rate charged on car loans, $\vartheta^j_{a,s} \in \left(-\,(1 + r^c_s)\,k^j_{a-1,s}, \eta p_s d^j_{a,s+1} - (1 + r^c_s)\,k^j_{a-1,s}\right)$ is the change in household car debt in period s. This incorporates both the repayment of existing car loans and any new car debt issued.

Households maximize their utility subject to (3) – (7) and to a sequence of budget constraints:

$$\begin{aligned} & c^j_{a,s} + \left(i^j_{a,s} - \vartheta^j_{a,s}\right) + \Upsilon\left(p_s d^j_{a-1,s}, d^j_{a,s+1}\right) + q_{a,s} b^j_{a,s+1} \leq \\ & (1 - \chi(a))\, y^j_{a,s} + \chi(a)\, m^j_{a,s} + (1 + r)\, q_{a,s} b^j_{a-1,s} \end{aligned} \tag{8}$$

The left hand side of (8) is total household expenditures while the right hand side is household net-income. $\chi(a)$ is an indicator variable which takes on the value 1 if $a \geq T_r$ and zero otherwise. $y^j_{a,s}$ denotes the households labor income if still participating in the labor market while $m^j_{a,s}$ denotes retirement income. $(1 + r)\, q_{a,s} b^j_{a-1,s}$ is the return that the household receives on its holding of financial assets. We assume that retirement income is a fixed fraction $\varphi \in (0, 1)$ of terminal permanent income, $p^j_{a,s}$, (defined below):

$$m^j_{a,s} = \varphi \exp(p^j_{T_{r-1}, s_j(T_{r-1})}) \tag{9}$$

$s_j\,(T_{r-1})$ is date at which household j reaches retirement age.

3.2 Shocks

We introduce a rich set of shocks which may affect the household. We allow for income shocks, for shocks to borrowing conditions, and for capital gains and losses on financial assets.

Income: The stochastic process for labor earnings, $y^j_{a,s}$, is given as:

$$\log y^j_{a,s} = p^j_{a,s} + u^j_{a,s}, \;\; a < T_r \tag{10}$$

$$p^j_{a,s} = p^j_{a-1,s-1} + g_{a,S} + e^j_{a,s} \tag{11}$$

$$e^j_{a,s} = \upsilon_s + \eta_{a,s} + \varepsilon^j_s \tag{12}$$

$$u^j_{a,s} = \nu_s + \zeta_{a,s} + \epsilon^j_s \tag{13}$$

Log income is the sum of a permanent component, $p^j_{a,s}$, and an idiosyncratic transitory shock, $u^j_{a,s}$. The permanent component is a random walk with drift, $g_{a,S}$, capturing the life-cycle profile, and an innovation, $e^j_{a,s}$. The innovation is the sum of a common income shock, $\upsilon_s \sim N\left(0, \sigma^2_{\upsilon,S}\right)$, a cohort-specific income shock, $\eta_{a,s} \sim N\left(0, \sigma^2_{\eta,S}\right)$, and a idiosyncratic permanent income shock, $\varepsilon^j_{a,s} \sim N\left(0, \sigma^2_{\varepsilon,S}\right)$. The income process is also perturbed by an idiosyncratic transitory shock, $u^j_{a,s}$, which is the sum of a common transitory income shock, $\nu_s \sim N\left(0, \sigma^2_{\nu}\right)$, a cohort-specific transitory income shock, $\zeta_{a,s} \sim N\left(0, \sigma^2_{\zeta}\right)$, and a idiosyncratic transitory income shock, $\epsilon^j_s \sim N\left(0, \sigma^2_{\epsilon}\right)$. We assume that $\sigma^2_{\upsilon,S}$, $\sigma^2_{\eta,S}$, $\sigma^2_{\varepsilon,S}$, and $g_{a,S}$ follow two-state discrete Markov processes $S = 1, 2$.

The household income process in (10) − (12) generalizes commonly used specifications in the literature. First, we allow for aggregate as well as cohort-specific and purely idiosyncratic income shocks. Correlation of shocks across households allows for movements in aggregate income. Cohort specific shocks open up for aggregate income shocks impacting differently on households depending on their age. Secondly, the drift component, $g_{a,S}$ is allowed to vary stochastically over time between a normal growth state and a low growth state. This changes the perceived life-cycle profile for different cohorts. Third, we allow for shocks to conditional income uncertainty through changes in the variances of υ_s, $\eta_{a,s}$ and $\varepsilon^j_{a,s}$ which may matter due to non-convex adjustment costs and the general non-linear nature of the model.

Car loan rate: The car loan borrowing rate follows the stochastic process:

$$\log\left(r^c_s - r\right) = \frac{\log\left(\overline{r}^c - r\right)}{1-\rho_r} + \rho_r \log\left(r^c_{s-1} - r\right) + \varepsilon^r_s \tag{14}$$

where $\varepsilon^r_s \sim N\left(0, \sigma^2_{\theta}\right)$. ρ_r is persistence of the log car loan interest rate and its long-run mean is $\overline{r}^c$.

Wealth: Mian, et al. (2013) emphasize the importance of household wealth shocks as important for consumption adjustments during the Great Recession. We introduce these through stochastic capital gains and losses on financial assets. We assume that $q_{a,s}$, which impacts wealth for household's with positive net financial assets, follows a random walk:

$$\log q_{a,s} = \log q_{a,s-1} + \varepsilon^q_{a,s} \tag{15}$$

where $\varepsilon^q_{a,s} \sim N\left(0, \sigma^2_{q,a}\right)$.

Finally, we assume that new households entering the economy with initial income and asset portfolios (consisting of cars, car loans and risk-free assets) which are drawn from log normal distributions.

3.3 Household Dynamic Programming Problems

Consider the dynamic programming problem for a household of age a. Such a household chooses the vector $h^j_{a,s} = \left(c^j_{a,s}, d^j_{a,s+1}, i^j_{a,s}, \vartheta^j_{a,s}, b^j_{a,s+1}, k^j_{a,s+1}\right)$ given the relevant state variables $s^j_a = \left(d^j_{a-1,s} b^j_{a-1,s}, k^j_{a-1,s}, \delta^j_{a,s}, a, p^j_{a,s}, u^j_{a,s}, m^j_{a,s}, x_s\right)$ where $x_s = \left(g_{a,s}, \sigma^2_{\upsilon,s}, \sigma^2_{\varepsilon,s}, r^c_s, q_{a,s}\right)$ are exogenous aggregate variables.

We remove time, age, and individual indicators. The household choices will be determined by the outer envelope of two value functions:

$$\mathbb{W}(s) = \max\left(\mathbb{W}^p(s), \mathbb{W}^{np}(s)\right) \tag{16}$$

where $\mathbb{W}^p(s)$ is the value of actively adjusting the household car stock (i.e. purchasing or selling) and $\mathbb{W}^{np}(s)$ is the value of non-adjusting (maintenance). Bellman's equation for an adjusting household is given as:

$$\mathbb{W}^p(s) = \max_h u_a(c, d') + \beta\pi(a)\,\mathbb{E}\left(\mathbb{W}(s')\right) \tag{17}$$

subject to the constraints in equations (3) - (15), and imposing $\delta' = \delta^N$ such that households who adjust their car stock avoid breakdown risk in the first period thereafter.

The value of non-adjusting is:

$$\mathbb{W}^{np}(s) = \max_{h^{np}} u_a(c, d') + \beta\pi(a)\,\mathbb{E}\left(\mathbb{W}(s')\right) \tag{18}$$

subject to (3) - (15), imposing that car investment equals required maintenance, $d' = (1-\delta\varphi)d$.

Having solved the household choice problems, we define aggregate variables as:

$$z_s = \frac{\sum_{a=1}^{a^{\max}} \lambda_a \int_{s_a} z^j_a(s_a)\, d\mu_a(s_a)}{\sum_{a=1}^{a^{\max}} \lambda_a} \tag{19}$$

where $\mu_a(s_a)$ denotes the distribution of cohort a agents over the states.

3.4 Parametrization and Policy Functions

We solve the model numerically by value function iterations assuming discrete but very fine grids for cash on hand, the riskless asset and cars (see Appendix A.2 for details). We parametrize the model using both calibration and estimation (indirect inference) using information only for the Pre-Great Recession period.

3.5 III.1 Calibrated parameters

The calibrated parameters and their values are reported in Table 3. A model period is a calendar year. Households enter the economy at age 25, work for 40 years and live for a maximum of 60 years. All households face mortality risk, we calibrate $(\pi_{25}, .., \pi_{84})$ to match the population averages in the 2009 Lifetable of the United States. These probabilities imply a life expectancy of 50 years at age 25.

The annual real return on the risk free asset is 4 percent. Based on the estimates of Attanasio and Weber (1995) and Eichenbaum, Hansen and Singleton (1986), we set the elasticity of intertemporal substitution, $1/\varphi$, equal to 2/3. The premium on car loans over the risk free rate is 1.78 percent annually. This estimate is consistent with the difference between the assumed risk free rate and the average real interest rate on auto loans issued by Auto Finance Companies and commercial banks (5.78 percent adjusted for CPI inflation) in the 1970-2006 sample. The parameters of the stochastic process for the car loan interest premium are derived by fitting an autoregressive process to the Auto Finance Company lending rate premium using monthly data from 1970 to 2006. This gives us estimates of $\rho_r = 0.500$ and $\sigma_r^2 = 0.297^2$.

The variance of the idiosyncratic income risk is calibrated using the estimates of Blundell, Pistaferri and Preston (2008) and Gourinchas and Parker (2002). We set $\sigma_u^2 = 0.246^2$ and $\sigma_\varepsilon^2 = 0.140^2$ so that amongst the idiosyncratic income risk, transitory shocks dominate. We assume the transitory aggregate income shocks are related to variation in unemployment type states. Therefore, we calibrate it to the share of households reporting zero annual income in the Current Population Survey. This gives a variance of $\sigma_\nu^2 = 0.008^2$.[8]

[8] For simplicity in household's expectations we abstract from the correlation between the aggregate permanent and transitory shocks. However, in the simulation we impose a correlation of 0.44 between these two aggregate shocks. As the idiosyncratic components of both permanent and transitory shocks is much greater than the aggregate ones, from the household's perspective, this restriction in quantitatively unimportant.

Table 3: Externally calibrated parameters

	Parameter	Value
$a_{\max}$	maximum lifespan (life starts at age 25)	60 years
T_r	retirement age	40 years
π_a	survival probability	match 2009 Life Table
$1/\varphi$	intertemporal elasticity of substitution	2/3
r	annual real return on savings	4 percent
r^k	annual car loan interest rate	5.78 percent
κ	pension replacement rate	66.8 percent
τ	probability of car breakdown	0.15
σ_u^2	variance of transitory idiosyncratic income shock	0.246^2
σ_ε^2	variance of persistent idiosyncratic income shock	0.140^2
σ_ν^2	variance of transitory aggregate income shock	0.01^2
$\rho_{\nu,\upsilon}^2$	correlation of aggregate income shocks	0.44
$\sigma_{Y^{25}}^2$	cross-sectional variance of initial log. income	0.582^2
$\bar{b}_{25}$	mean initial assets	0.086
$\sigma_{b_{25}}^2$	cross-sectional variance of initial assets	1.036^2
$\bar{d}_{25}$	mean initial log. car	-1.39
$\sigma_{d_{25}}^2$	cross-sectional variance of initial log. car	1.04^2
P_{adj24}	share of HHs allowed to adjust car in period 0	70.5
g_a	life-cycle income factor	matched to CEX
γ_a	household equivalent size	matched to CEX
$\rho_{r^k}^2$	persistence of car loan spread	0.500
$\sigma_{r^k}^2$	variance of car loan spread	0.297^2
σ_{house}^2	variance of house price shocks	0.031^2
σ_{stock}^2	variance of stock price shocks	0.133^2
$\sigma_{house,stock}$	covariance of asset and stock price shocks	-0.0002^2
s_a	life-cycle portfolio weightings	matched to 2004 SCF
g_a^{post}	life-cycle growth shock	0.581
ρ_{fuel}	persistence of fuel process	0.909
σ_{fuel}^2	variance of fuel process shocks	0.099^2

We initially assume that the drift term in the life-cycle income process is constant over time, i.e. $g_{a,s} = g_a$. We calibrate g_a so that it implies life-cycle income profiles consistent with a polynomial approximation of average income over the life-cycle that we estimate in the

CEX data (controlling for demography, education, cohort and year effects).[9]

Our calibration matches assets up with a portfolio of equity and housing assuming age specific portfolio weights for housing, ω_a^H, and equity, ω_a^E. Prices in the housing and stock market follow a random walk in logarithms:

$$\begin{aligned}
\log q_s^H &= \log q_{s-1}^H + \varepsilon_{q,s}^H \\
\log q_s^E &= \log q_{s-1}^E + \varepsilon_{q,s}^E \\
\begin{pmatrix} \varepsilon_{q,s}^H \\ \varepsilon_{q,s}^E \end{pmatrix} &\sim N\begin{pmatrix} \mu_q^H & \sigma_{q,H}^2 & \sigma_{q,HE} \\ \mu_q^E & \sigma_{q,HE} & \sigma_{q,E}^2 \end{pmatrix}
\end{aligned}$$

We set the means to $\mu_q^H = -0.5\sigma_{q,H}^2$ and $\mu_q^E = -0.5\sigma_{q,E}^2$ such that the price indices do not have a drift. It follows that

$$\begin{aligned}
\varepsilon_{a,s}^q &= \omega_a^H \varepsilon_{q,s}^H + \omega_a^E \varepsilon_{q,s}^E \\
\sigma_{q,a}^2 &= (\omega_a^H)^2 \sigma_{q,H}^2 + (\omega_a^E)^2 \sigma_{q,E}^2 + 2\omega_a^H \omega_a^E \sigma_{q,HE}
\end{aligned}$$

We estimate the mean share of household's asset in housing, ω_a^H, and stocks, ω_a^E, over the life-cycle from the 2004 Survey of Consumer Finance.[10] We then estimate the variance of innovations to the (linearly detrended) log of the house price index produced by the Federal Housing Finance Association. For the 1975-2007 sample, this gives us an estimate of $\sigma_{q,H}^2 = 0.031^2$. We estimate the variance of innovations to the log of the stock price, using the S&P500 for the period 1960-2007. This gives us a value of $\sigma_{q,E}^2 = 0.133^2$. Finally, the covariance of the shocks is $\sigma_{q,HE} = -0.0002$.

We calibrate initial income and assets of newborn households by matching data from the CEX and from the Survey of Consumer Finances (SCF). Initial income is log normally distributed with mean one and variance $\sigma_{Y_0}^2 = 0.582^2$. This variance matches the cross-sectional variance of (log) income residuals of households aged 24-26 in the CEX. The distribution of initial assets is also assumed to be normal with a mean $\bar{b}_0 = 0.086$ and variance $\sigma_{b_0}^2 = 1.036^2$. These values match the mean and variance observed in the 2007 sample of the SCF for households at age 24 re-scaled by income of households aged 24-26. We assume that the logarithm of households' stock of cars at birth at birth is given by a normal distribution with mean

[9] In particular, we regress the family earnings on an age polynomial controlling for cohort, race and education. We include time dummies for imputed family income in 2004 and 2005.

[10] Figure A6. in the Appendix shows these profiles.

$\overline{d}_0 = -1.39$ and variance $\sigma_d^2 = 1.040^2$, values that match the average value of cars per household at age 24 (re-scaled by income as well) from the CEX. Finally, to avoid excessive car purchases in the first period of life, 70 percent of the households entering the economy can optimally adjust their car stocks conditional upon their initial asset draw.[11]

The retirement replacement rate, φ, is set such that in the absence of shocks the household would receive 60 percent of their average income in the last five years of working life, see Bernheim, Skinner and Weinberg (2001). This gives a value of $\varphi = 0.668$. Finally, we assume that the probability of a car breakdown is set to $\tau = 0.15$.

3.6 Estimated parameters

We estimate the remaining parameters by indirect inference targeting a number of household and aggregate statistics. We initially assume that the aggregate shocks impact equally on all cohorts, i.e. that $\sigma_\eta^2 = 0$ and $\sigma_\zeta^2 = 0$. The estimated parameters then consist of the vector $\left(\alpha, \xi, \mu, \varrho, \psi, \delta^N, \delta^B, \sigma_\upsilon^2, \beta\right)$.

Model moments are computed over simulations of the model for 2,000 periods with 2,000 households per cohort (and using the first cohort to burn in) and we minimize a quadratic form in deviations of the model moments (averaged over panels of cohorts) from the empirical targets using an identity matrix as the weighting matrix. The targets that we use for estimation of the structural parameters all refer to the pre-Great Recession period. In this way, we parametrize the model, including agents' expectations, so that they refer to 'normal' circumstances. The first subset of targets refer to household specific moments derived from the CEX. We target the average share of households who purchase a car at the annual frequency (19.1 percent on average in the CEX data); the average spending on cars per year relative to non-durables spending, 9.89 percent in the data; the mean spending on cars relative to their car stock for households that purchase a car, 83.3 percent in the CEX. We also target the growth in the household spending non-durables spending from age 25 to peak, 41.9 percent on average, and the share of households below the age of 45 years who do not have a car loan, 55.5 percent according to the SCF. Finally, we target the standard deviation of aggregate real car purchases computed in the CEX data (2.69 percent). The second set of moments that we include are aggregate moments computed from annual NIPA data for the

[11] We impose that no household breaks its collateral constraint at the initial asset allocation.

Table 4: Model moments

Moment	Source	Data	Model
Targeted Moments			
Percentage of households purchasing a car	CEX	19.1	18.1
Ratio of car spending to non-durables spending	CEX	0.099	0.098
Ratio of car purchases to car stock | purchase	CEX	0.833	0.756
Growth in non-durables from age 25 to peak	CEX	41.9	43.8
Percentage of households under 45 without car loan	SCF	55.5	49.4
Std dev. of aggregate non-durables	NIPA	0.77	0.86
Std dev. of aggregate car expenditure	NIPA	5.91	5.18
Std dev. of aggregate car intensive margin	CEX	2.69	2.31
Correlation of aggregate non-durables and car spending	NIPA	0.72	0.78
Non-targeted Moments			
Age at peak of non-durables spending	CEX	45	54
Age at peak of car stock	CEX	53	55
Growth of car stock from age 25 to peak	CEX	60.5	71.4
Cross sectional standard deviation of value of car stock	CEX	94.7	94.8

sample period 1970-2006.[12] We target the standard deviation of real non-durable consumption goods expenditure (0.77 percent), the standard deviation of real car expenditure (5.91 percent), and the cross-correlation of these two time series (72.1percent). The targets are summarized in Table 4 along with their model equivalents while Table 5 contains the estimates of the structural parameters. We find an estimate α of 82.7 percent and an elasticity of substitution between non-durables and cars slightly larger than one, $\mu = 1.14$. The normal car depreciation rate, δ^N, is estimated to be 14.6 percent per year, while the breakdown value is estimated as $\delta^B = 20.7$. This gives an average depreciation rate that is close to the value of earlier estimates such as Attanasio (2000). The estimate of the proportion of depreciation that correspond to maintenance, ς, is 81.7 percent. In combination these two estimates imply that a passive strategy of simply carrying out maintenance induce a net depreciation rate of cars of 11.9 percent per year. Combining these parameters with the fact that 19.1 percent of households adjust their car stock every year, implies that households (without a breakdown)

[12]We detrend the three time-series (which are measured in constant prices) with the Hodrick-Prescott filter using a smoothing parameter of 6.25 (Ravn and Uhlig, 2002).

Table 5: Estimated Parameters

	Parameter	Base	Income	Skew	Fuel
α	weight on non-durables in utility function	0.827	0.814	0.814	0.775
μ	elasticity of substitution	1.145	1.258	1.404	1.088
ξ	service flow from durables	0.724	0.719	0.728	0.685
ψ	car adjustment cost parameter	0.130	0.148	0.122	0.136
ς	car maintenance cost parameter	0.817	0.773	0.777	0.782
δ^N	normal car depreciation rate	0.146	0.155	0.165	0.149
δ^B	break down car depreciation rate	0.207	0.225	0.213	0.212
σ_v^2	variance of aggregate permanent income shock	0.020^2	0.023^2	0.009^2	0.021^2
β	subjective discount factor	0.944	0.944	0.921	0.946
α_{fuel}	weight of cars in sub-utility function				0.905
μ_{fuel}	fuel elasticity of substitution				0.738

Notes: Fuel demand is modeled as a nested CES utility function, where the car service flow is a CES over the car stock and period fuel consumption.

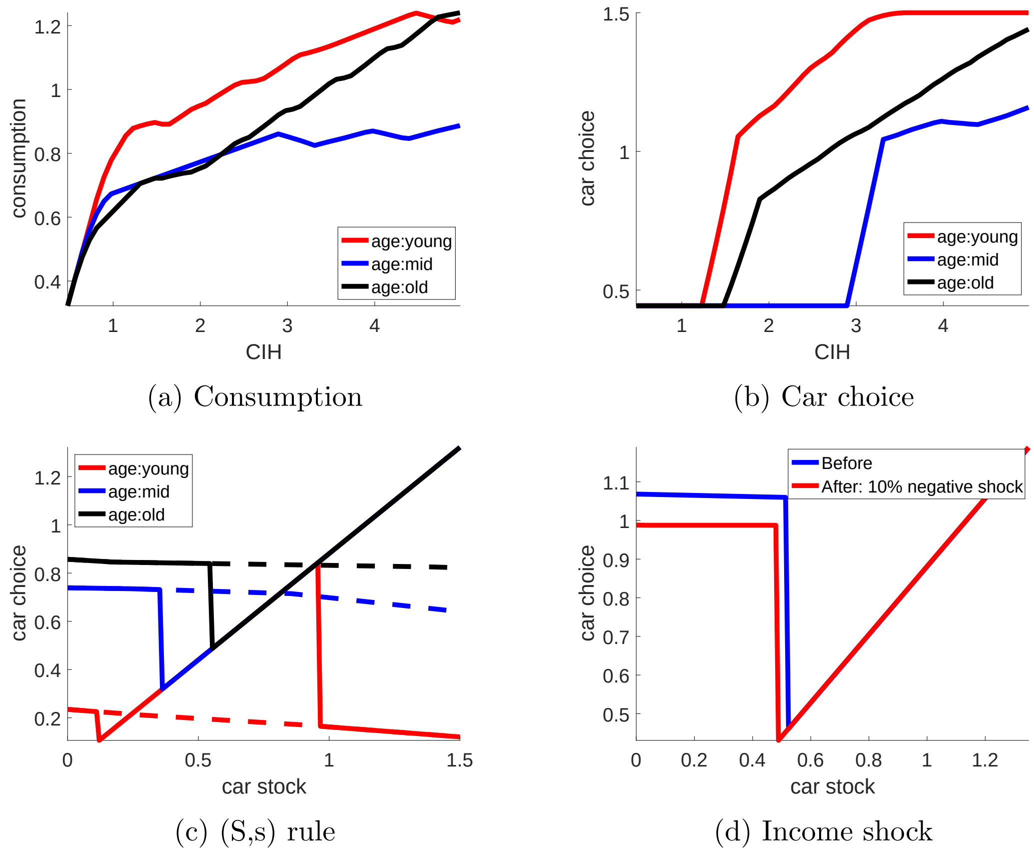
let their car stock depreciate on average 51.5 percent before adjustment.

The transactions cost, ψ, is estimated as 13 percent of the car value. We then calibrate η which enters the collateral constraint when purchasing a car so that we rule out default (due to inability to pay) by setting it equal to $\eta = (1 - \delta - \psi) / (1 + r^c)$ which delivers a value of 68.4 percent. Finally, the volatility of non-durables consumption implies that $\sigma_v^2 = 0.02^2$.

The model does an excellent job at matching the targets (see Table 4). Many moments are matched to within a few percent deviations from the target and the matches are particularly close for the mean of the extensive margin and the ratio of spending on cars relative to non-durables. We also report the match of the model to the data for a few non-targeted moments, the ages at which household spending on non-durables and cars peak, the growth of the household car stock from age 25 to peak, and the cross-sectional variances real spending on non-durables and on cars. The model matches each of these non-targeted moments closely.

3.7 Policy functions

Figure 6, Panel A, shows the policy function for consumption expenditures plotted against cash on hand for a young, middle-aged, and older household. Non-linearities are most evi-



(a) Consumption

(b) Car choice

(c) (S,s) rule

(d) Income shock

Figure 6: Model policies

dent for younger households due to binding borrowing constraints induced by expectations of future income growth. Panel B illustrates car spending plotted against cash on hand. These policy functions illustrate the lumpiness of investment in cars: Poor households choose not to adjust their car stock because of the non-convex adjustment costs and because of the need to generate sufficient savings to provide for the down payment. Therefore, as cash in hand rises it eventually reaches a threshold value at which households invest positively in cars but the size of the car that they choose depends on their asset position.

Panel C illustrates a households' current choice of the value of their car stock plotted against their beginning of period car stock. The policy function brings out in a very clear fashion the (S, s) properties of car adjustments; There are upper and lower bounds on the household's car stock and whenever the car stock is outside this zone, it is adjusted to d^*; Inside the zone, the car stock declines gradually over time as the household pays for maintenance costs only. The adjustment point is higher for older and middle-aged households because they have higher household consumption equivalence requirements. However, since younger households find themselves on the part of the life-cycle where income is expected to rise, the optimal adjustment point will be increasing over time and the policy function for these households displays significant asymmetry insofar as households tolerate much more deviation of the actual car stock from its target on the upside than on the downside.

Panel D shows the policy function for an agent who has experienced a 10 percent drop in income. This triggers a downward revision in the no-adjustment zone of the policy function as well as in d^*. Consequently, in recessions where many households experience negative income shocks, the extensive margin contracts as households delay adjusting their car stock. Moreover, high idiosyncratic income variance implies that those who purchase cars during recessions tend to be households that, despite the economy-wide contraction, are doing well. Thus, in 'normal' recessions, the drop in durables spending derives from the extensive margin while the intensive margin tend not to adjust much as in 'normal' recessions but not the Great Recession.

4 The Great Recession

We now use the model to examine the sources of the Great Recession with the aim of drawing inference on the shocks and beliefs about these that triggered this large contraction in the U.S. economy.

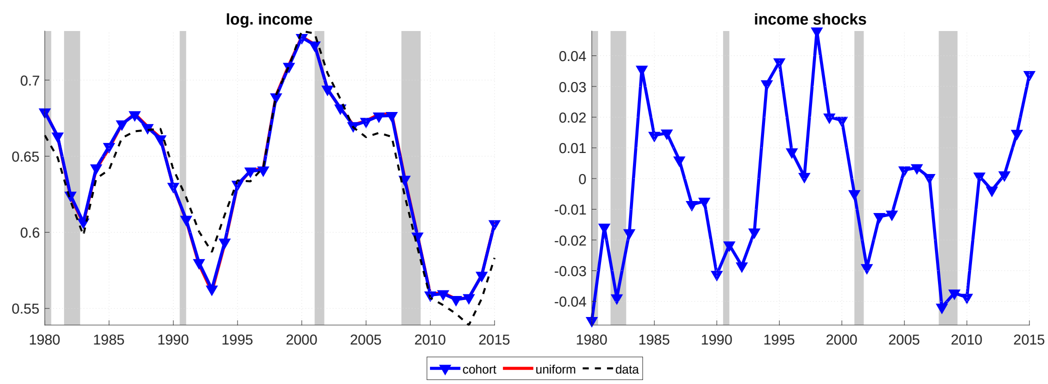
4.1 Method

We simulate the model in response to idiosyncratic and aggregate shocks under alternative assumptions about their nature. We then inspect the consumption responses during the Great Recession in each case constraining ourselves by drawing idiosyncratic shocks from their asymptotic distributions and aggregate shocks that match in size those observed in the data.

The rich wealth distribution in the model and the presence of non-convex adjustment costs imply that the model has path dependence. We address this issue by simulating the Great Recession from an initial condition that takes into account the conditions leading up to this recession in terms of aggregate income and the credit market situation. We first feed in a long series of the aggregate shocks pre-Great Recession and then simulate the model from 2007 to 2015 feeding in either one or more aggregate shocks. We simulate a panel of 120,000 households and compute aggregate variables by cross-sectional aggregation while cohort specific variables are found by aggregating at the cohort level. We repeat this exercise 100 times.

4.2 Aggregate Income Shocks

Perhaps the most obvious explanation for the dramatic consumption adjustments during the Great Recession is that the aggregate income shocks were very large relative to what agents could reasonably have expected on the basis of past data. Figure 7, Panel A shows log detrended aggregate real income per capita from 1980 (estimated from the CPS by cross-sectional aggregation). The innovations to aggregate income are combinations of permanent and transitory shocks. The permanent innovations are measured as changes in (detrended) average log income $\widehat{\upsilon}_{it} = \frac{1}{N}\sum_i \log y_{it} - \frac{1}{N}\sum_i \log y_{it-1}$, while the transitory shocks are measured as deviations from trend in the share of households with zero income $\widehat{\nu}_{it} = \widehat{\Pr}(y_{it} = 0)$.[13] Panel B illustrates the combined innovations to the aggregate real income series, the first difference of log income.



Notes: Estimated from Current Population Survey

Figure 7: Income shocks

The 2008 permanent income shock is around 1.5 standard deviations in magnitude, with

[13]The CPS income series is deflated by the GDP deflator. We use CPS income series from 1964, while we use the BLS wage and income series prior to this. For most of the period this series move together closely.

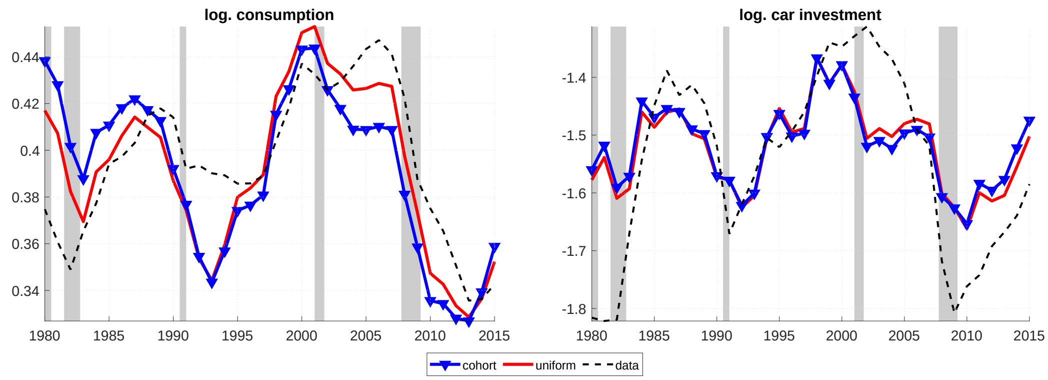
similar sized shocks realized in 2009 and 2010. Our first experiment thus considers this source of aggregate shocks in isolation. We expose all households in the economy to the aggregate income shocks, $(\widehat{\upsilon}_{1946:2015}, \widehat{\nu}_{1964:2015})$, in addition to idiosyncratic shocks, $\left(u^{j}_{1920:2015}, \varepsilon^{j}_{1920:2015}\right)$ which we draw from their respective asymptotic distributions.

Figure 8, Panel A reports the resulting time-series for the log of aggregate consumption expenditures plotted along with the detrended cross-sectionally aggregated log consumption estimate from the BLS and CEX (both in real per capita terms). The model provides a perhaps surprisingly precise account of consumption pre-Great Recession although it cannot fully account for the pre-Great Recession consumption boom and exaggerates the consequences of the early 1990s recession. The large income shocks observed in the Great Recession do not, however, generate consumption responses consistent with the empirical evidence: While the drop in overall consumption expenditures implied by the model is qualitatively similar to the data, in the NIPA data consumption expenditures drop approximately 10.5 log points from 2006 to 2015 but only 7.6 log points in the model.

More importantly, the responses of total car investment (Panel B) and its extensive and intensive margins (Figure 9, Panels A and B respectively) are entirely inconsistent with the data. The decline in car investment over the Great Recession implied by the model, 18 log points between 2005 and 2010, is only a half of what is observed in the data (35 log point).[14] This far smaller decline in car investment reflects both a more modest contraction of the extensive margin (1.8 percentage point as opposed to 5 percentage points in the data) and in the intensive margin (12.3 log point compared to the 17.8 percent decline in the data, during the same period). The reason for this finding is that, although the size of the aggregate income drop during the Great Recession was large, it is still moderate relative to the variance of idiosyncratic income risk. Therefore, there will always be households that do well in a recession. Such households dominate amongst those that adjust car stocks and have no reason to reduce the size of their cars.

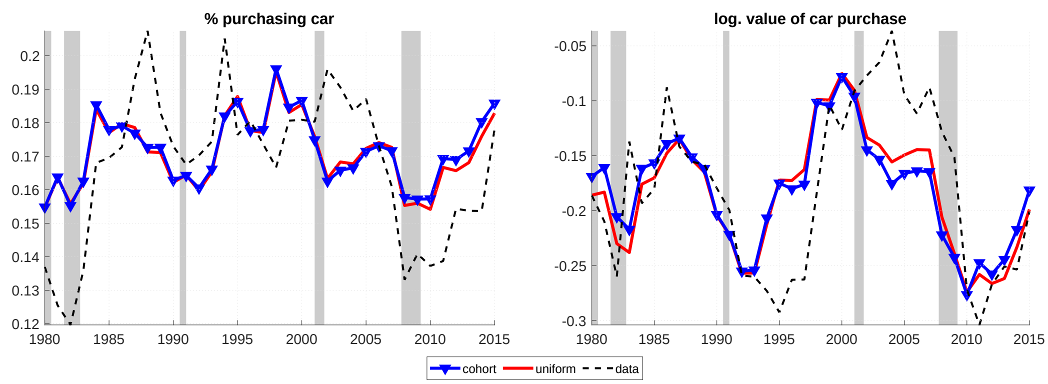
Cohort consumption responses: Figure 10 presents the percentage deviations from a predicted life-cycle trend for three working age cohorts: young (aged 25-34 in 2007), middle (aged 35-44 in 2007) and older (aged 45-55 in 2007). In the CEX, the consumption growth

[14] In the NIPA the decline is 25 percent in the CEX (where our definition excludes maintenance) the decline is 43 percent.



Notes: Data from NIPA

Figure 8: Uniform versus cohort income shocks: consumption and car expenditure



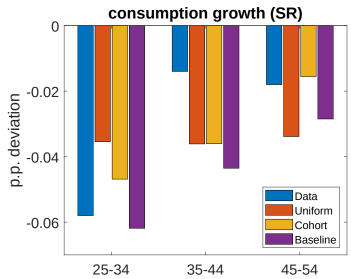
Notes: Data from CEX

Figure 9: Uniform versus cohort income shocks: extensive and intensive margin

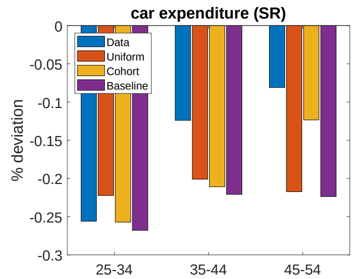
and car expenditures of the youngest cohort declined much more than the other two cohorts.[15] This was primarily driven by a very large extensive margin response. The oldest cohort's car expenditure fell the least. On the intensive margin it is the middle cohort the responds most. These consumption adjustments contrast with the model where the consumption growth rates are very similar across cohorts when we assume a uniform aggregate income shock and no other aggregate shocks. Although financial portfolios and expected future income paths differ across cohort, the common shock implies common (and counterfactual) consumption adjustments.

[15]The methodolody is described in the appendix. For consumption growth we take advantage of the short panel dimension of the CEX and compare the log change of non-durables consumption of a household in the last quarter they are interviewed to the first quarter: $\log C_{int:4} - \log C_{int:1}$.

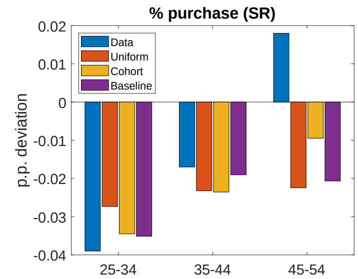
Finally, we look at savings where for each cohort we show the proportion of households with higher income (including returns on financial assets) than consumption expenditures. In the CEX, middle and older cohorts reduced net savings but younger households *increased* their savings. The model instead implies a fairly uniform savings decline across cohorts.



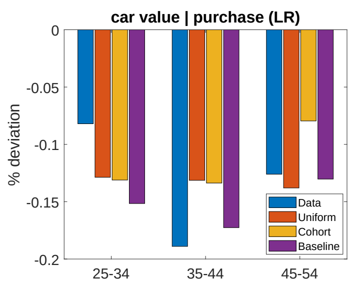
(a) Consumption growth



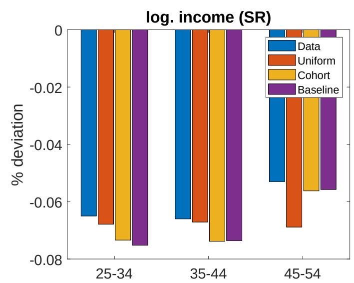
(b) Car expenditure



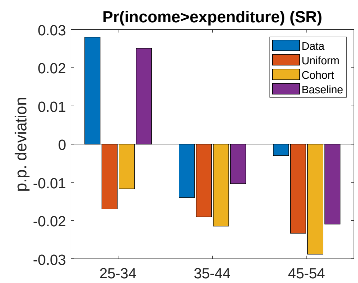
(c) Extensive margin



(d) Intensive margin



(e) Income



(f) Net saving position

Figure 10: Cohort response: model comparison

4.3 Cohort Specific Shocks

We now examine the importance of cohort-specific income shocks during the Great Recession. We feed in cohort specific income shocks, $\{\widehat{\eta}_{a,s}, \widehat{\zeta}_{a,s}\}$, under the restriction that these induce exactly the same path of aggregate income shock as in Section 4.2. To estimate $\widehat{\eta}_{a,s}$ we first remove aggregate time and life-cycle trends from log income; we then divide the CPS households into age-year groups defined by the age of the household head; for each group we compute fluctuations in income over time which are aggregated up to decennial cohorts by averaging over the shocks of the age-year groups in a given year. We use deviations from the life-cycle trend in the age 25 households to define an initial income shock for each year for each birth year cohort. The transitory shocks, $\widehat{\zeta}_{a,s}$, are estimated similarly, full details are provided in the Appendix. The cohort income shocks as measured in the CPS imply a similar size decline in income for the young and medium aged cohorts and a smaller decline for the old cohort (see Figure 10).

Figures 8 and 9 report the implications of this model for the aggregate variables (shown in blue). The cohort specific shocks increase the extent to which the model undershoots the consumption boom in the pre-Great Recession period. As far as aggregate car investment is concerned, there is hardly any impact of allowing for cohort specific income shocks. Considering the extensive and intensive margins, we see the extensive margin is unchanged, while the intensive margin decline is slightly reduced, but less so than consumption.

While introducing cohort specific shocks fails to improve the aggregate performance of the model, its ability to account for the cohort level adjustment of car expenditures *does* improve. In particular, this version of the model is now consistent with older households cutting their car investment less during the Great Recession than the younger cohorts and with the 25-34 year old cohort adjusting the extensive margin more than other cohorts (Figure 10). Nonetheless, the model still under-predicts the decline in consumption growth and the increase in net savings observed for the young cohort; and it fails to account for the fact that the middle cohort adjusts the intensive car purchase margin more than other cohorts.

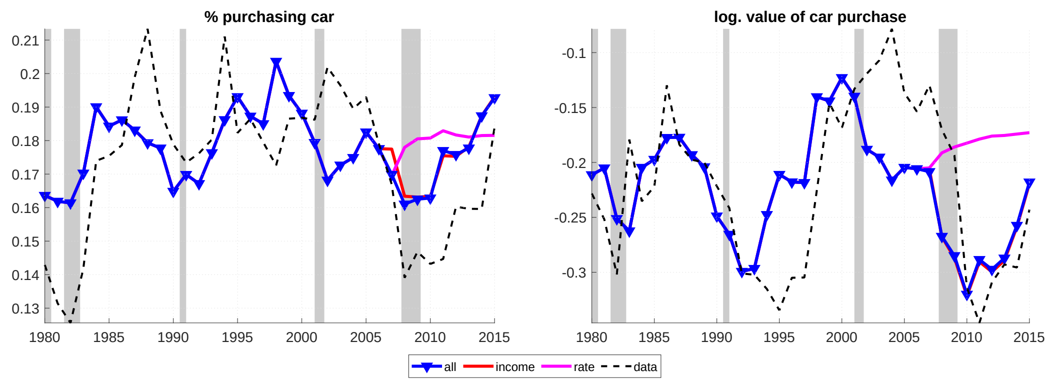
4.4 Cost of Car Finance

During the financial crisis the spread of interest paid on car loans above the risk free rate jumped from 50 percent below trend in 2006 to more than 50 above trend in 2010 (see Figure A.9 in the Appendix). This surge in the cost of car finance might be an important factor behind the unusual car purchase dynamics during the Great Recession. We therefore now allow for stochastic shocks to the car loan premium. We calculate the sequence of shocks to the interest rate premium using the autoregressive specification in (14):

$$\widehat{\varepsilon}_s^r = \log\left(r_s^c - r\right) - \rho_r \log\left(r_{s-1}^c - r\right) - \frac{\log\left(\overline{r}^c - r\right)}{1 - \rho_r}$$

imposing that $\rho_r = 0.50$ as estimated earlier. This delivers the sequence of interest rate shocks reported in Figure A.9 Panel B including the very large positive shock at the onset of the recession.

Figure 11 shows how the surge in the car loan premium impact on the extensive and intensive margins of car purchases. We show both the impact of the financial shock in isolation, the impact of the cohort income shock in isolation and the two aggregate shocks in combination from 2007 onwards. In isolation, the increase in the car loan premium actually leads to an increase in the intensive margin because only richer households choose to adjust car stocks when car finance becomes more expensive. A minor fraction of the reduction in the extensive margin during 2007 and 2008 appears to derive from the car premium shock but its impact is dwarfed by the income shock. Car debt is concentrated on very young households and on households very close to the end of the life-cycle (who short-sell their cars), households that have low wealth and account for only a small share of spending. Hence, the contribution of this source of shocks is marginal.



Notes: Data from CEX

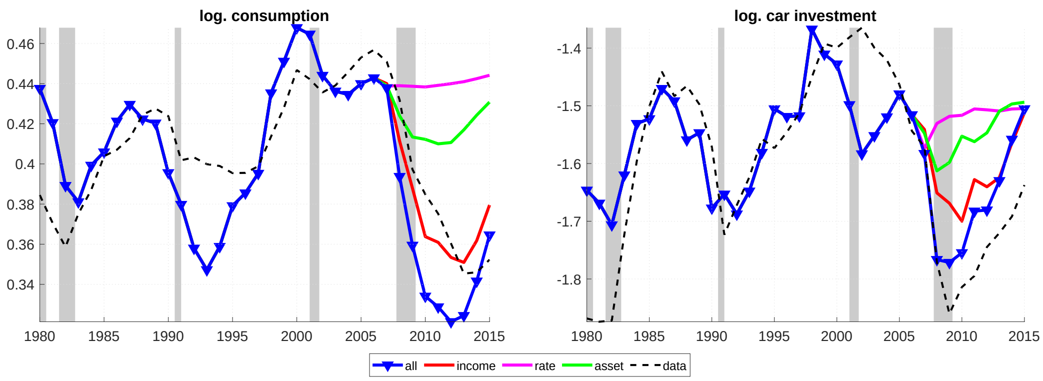
Figure 11: Interest rate spread shock: extensive and intensive margin

4.5 Wealth Shocks

Mian et al. (2013), argue that the bust of the housing market at the onset of financial crisis had a large impact on consumption. Berger et al (2018) show that incomplete markets models such as ours can potentially generate large marginal propensities to consume out changes in wealth induced by real estate price changes. Thus, we now introduce shocks to the aggregate house and stock price which impact on the wealth of households with positive net asset positions. We estimate the sequence of shocks as the innovations to the log of the house price index produced by the Federal Housing Finance Association and innovations to the log of the stock price, using the S&P500 for the period 1960-2007 assuming both follow a random walk.[16]

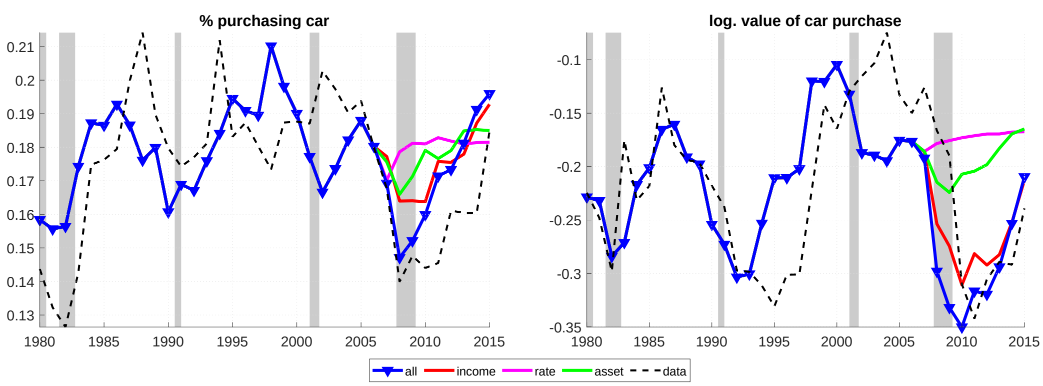
[16]We remove linear trends from the log house price index and from the log stock price index.

As above we introduce asset price changes on top of income shocks and changes in the car loan premium. The effect of these respective shocks on the household's wealth depends on their age specific portfolio shares. Figure A.11, Panel A, in the Appendix shows that both shocks are important, with the stock price raising the average (asset-weighted) price in the late 1990s boom, while house prices played a significant role in the lead up to the Great Recession.



Notes: Data from NIPA

Figure 12: Asset price shock: consumption response



Notes: Data from CEX

Figure 13: Asset price shock: extensive and intensive margin

When we add the boom-bust asset price cycle, the model matches the consumption spending boom from the mid-1990s to 2006, see Figure 12, Panel A. Furthermore, during the Great

Recession, the combined effects of income and asset price shocks imply a peak-to-trough decline in consumption expenditures very similar to what is observed in the data. In isolation, the decline in aggregate income dominates that of housing wealth but the latter occurs in a very persistent manner and accounts for an increasing share of the consumption decline as the crisis moved forward in time. Thus, in line with Kaplan, Mitman and Violante (2020), we find that housing prices matter for consumption dynamics.

Introducing wealth shocks also has important consequences for consumer durables dynamics. The combined impact of lower incomes and falling house prices imply that aggregate spending on cars in the model falls by around 25 log points from 2006 to 2010, a decline which is not quite as large as in the data but much larger than in the absence of wealth shocks. Furthermore, the introduction of the wealth shock allows us to match almost perfectly the peak-to-trough decline in the extensive margin, see Figure 13, and the intensive margin now contracts by more albeit less than in the data.

The asset price shock matters for our analysis because it impacts on wealthy households who are "consumption intensive" and account for a large fraction of total consumption. A household that is simultaneously hit by a negative income shock and a decline in their wealth will have a strong incentive to reduce their car stock size while the size of the asset price shock induces an incentive to delay car adjustment for households with positive net wealth even if they should be lucky enough not to experience a drop in income.

4.6 Long-Run Income Risk

The Great Recession induced a severe deterioration in the labor market prospects of U.S. households which in combination with the slow recovery, raised concerns about secular stagnation, e.g. Summers (2014). Such expectations of persistently low growth of the aggregate economy may also have spilled over to households and impacted on their consumption choices beyond the direct effects of lower income.

So far we have assumed $g_{a,s} = g_a$ (constant life-cycle income profiles) but we now want to allow for shocks. We assume that changes in the life-cycle income profile are rare but persistent so that they can be thought of as introducing long-run household income risk similar in nature to the long-run risk shocks studied by Bansal and Yaron (2004) in the asset pricing literature. One can therefore think of the combination of the two permanent income shocks, $e^j_{a,s}$ and $g_{a,s}$, as determining household beliefs in a similar fashion to the house price beliefs examined by Kaplan, Mitman and Violante (2020).

The hypothesis that we are pursuing is that life-cycle income profile expectations may have flattened as a result of the Great Recession. Figure A.12 illustrates the life-cycle income profiles estimated using CEX income data for the 1989-2006 sample and for the 2009-2012 sample. These estimates do seem consistent with the idea that g_a declined post recession, see also Kong, Ravikumar and Vandenbroucke (2018).

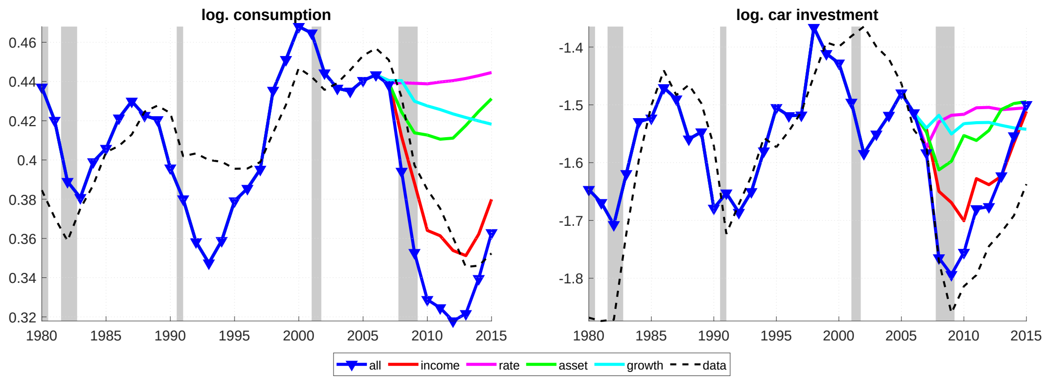
Assume that g_a follows a two-state discrete Markov chain with values:

$$g(a)_{low} = \begin{cases} \gamma g(a)_{high} & \text{if } \; g(a)_{high} > 0 \\ g(a)_{high} & \text{o.w} \end{cases},$$

where g_a is a polynomial approximation to the estimates of the life-cycle profiles, see Appendix A.3 for details.[17] We find $\gamma = 0.58$ indicating a very dramatic decline in the life-cycle income growth profiles. As is evident from Figure A.14, this shock have potentially large impacts on especially younger households up to the age of 40 or so. We then simulate the model assuming that the economy starts with $g(a)_{high}$ and switches to $g(a)_{low}$ in 2007 where it remains for the remainder of the simulation. We assume that the high growth state is an absorbing state with households placing zero probability on the prospect of a low growth economy. The low income growth state has expected duration of 40 years, such that households expect the state to last for the duration of their working life. The income shocks that hit the economy from 2007 onwards are then mixes of the cohort-specific levels shock, $\eta_{a,s}$, and the growth rate shock, $g_{a,s}$, constrained so that aggregate income changes by exactly the same amount as in the data.

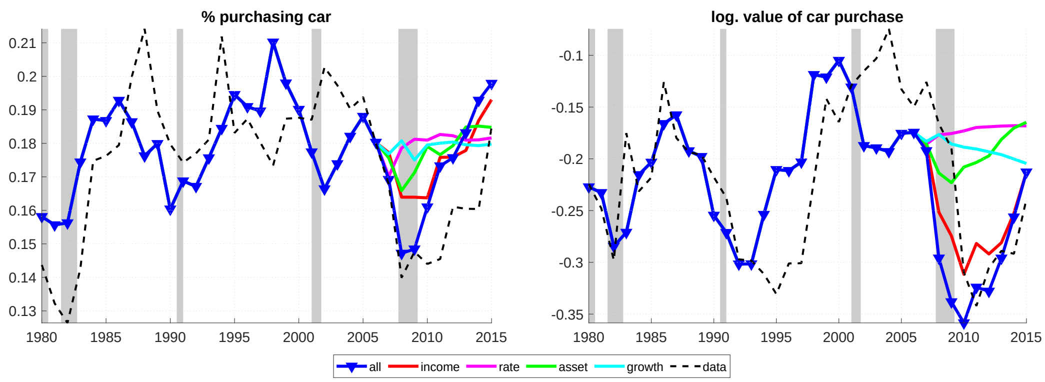
Figure 14 illustrates the results. The long-run income risk shock contributes significantly to explaining the consumption dynamics. In particular, income shocks and wealth shocks now not only explain most of the decline in total non-durable consumption expenditures but also helps model account for almost all of the decline in spending on cars from 2007. When we assume the growth shock hits in 2009, car investment fall further to its lowest point, matching the data. Turning to the extensive and intensive margins we see the growth shock primarily operates on the extensive margin, generating an additional decline in purchases in 2009 (Figure 15, Panel B). This implication comes from the long-run risk shock's impact on

[17] We restrict the fall in the growth rate to households on the growing section of the lifecycle profile.



Notes: Data from NIPA

Figure 14: Growth rate shock: consumption and car expenditure



Notes: Data from CEX

Figure 15: Growth rate shock: extensive and intensive margin

younger households such as those in their 30s who account for a large fraction of car purchases and whose expected life-time incomes are particularly sensitive to the perceived flattening of the life-cycle income profile.

The growth rate shock is important for explaining the cohort pattern of car spending adjustments during the Great Recession, see Figure 10. We see that the allowing for asset price, interest rate and income level and growth shocks, produces cohort level consumption changes that match the data very well, closer than those implied by the model with cohort income shocks, and much better than the model with uniform income shocks. Moreover, the model now also generates the U-shaped response across cohorts on the intensive margin, with the middle cohort reducing the value of purchases most strongly. Importantly, the model now also matches that savings increase for the young cohort, whereas the middle and older cohorts see savings fall. The reason behind that is a shallower life-cycle income profile induces the young cohort to save more.

5 Extensions

This section of the paper discusses a number of extensions to the model. For simplicity and computational expediency, the extensions are solved in the version of the model with only income shocks.

5.1 Fuel price

Fuel prices moved dramatically during the Great Recession. Such movements might have impacted on car choices. To examine this, we introduce car utilization into the model. Utilizing cars at a higher rate is assumed to involve higher consumption of fuel. Let the fuel input be denoted by $f^j_{a,t}$, and its stochastic price by $q_{F,t}$. Car services are now assumed to be a nested CES aggregator of the car stock, $d^j_{a,t+1}$, and fuel used, $f^j_{a,t}$.

$$\mathbf{u}^j_{a,t} = \left\{ \left[\alpha \left(\frac{c^j_{a,t}}{\gamma_a} \right)^{1-1/\mu} + (1-\alpha) \left(\xi \frac{\mathbf{D}^j_{a,t}}{\gamma_a} \right)^{1-1/\mu} \right]^{(1-\varphi)/(1-1/\mu)} - 1 \right\} / (1-\varphi) \quad (20)$$

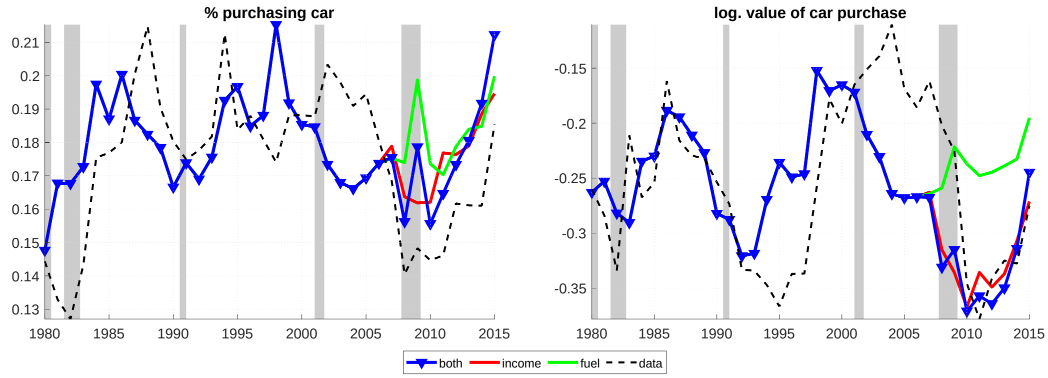
$$\mathbf{D}^j_{a,t} = \left[\alpha^F \left(d^j_{a,t+1} \right)^{1-1/\mu^F} + \left(1-\alpha^F\right) \left(f^j_{a,t} \right)^{1-1/\mu^F} \right]^{1/\left(1-1/\mu^F\right)} \quad (21)$$

and the budget constraint and fuel price process are given as:

$$\begin{aligned} & c^j_{a,t} + \left(i^j_{a,t} - \vartheta^j_{a,t} \right) + \Upsilon \left(p_t d^j_{a-1,t}, d^j_{a,t+1} \right) + b^j_{a,t+1} \leq \\ & (1-\chi(a))\, y^j_{a,t} + \chi(a)\, m^j_{a,t} + (1+r)\, b^j_{a-1,t} - \xi \left(k^j_{a-1,t} \right) - q_{F,t} \cdot f^j_{a,t} \end{aligned} \quad (22)$$

$$\log q_{F,t} = \rho^F \log q_{F,t} + \varepsilon^F_t$$

where $\varepsilon^F_t \sim N\left(0, \sigma^2_{\varepsilon,F}\right)$. The fuel process is calibrated externally using the CPI price index for gasoline deflated by the all goods and services index. After linearly detrending over the time period 1967-2007, we get a persistence parameter of $\rho^F = 0.907$ and a variance of $\sigma^2_{\varepsilon,F} = 0.092^2$. Relative to the baseline model there are two additional parameters to estimate, the share of cars in car service production, α^F, and the car service production elasticity of substitution, μ^F. We estimate these parameters by targeting two additional moments, the ratio of fuel expenditure to car expenditure (0.606 in the CEX data) and the correlation between (detrended) car expenditure and the fuel price, which is -0.308. The rest of the parameters are reestimated using the moments used previously. The full set of estimated parameters is presented in Table 5. Figure A.17 in the Appendix shows the substantial



Notes: Data from CEX

Figure 16: Fuel price shock: extensive and intensive margin

increase in the cost of fuel between 2001 and 2007. The cost of fuel continued to rise following the onset of the Great Recession, before collapsing precipitously in the face of a decline in demand for oil. We then feed the estimated car fuel shocks into the model and examine the car expenditure dynamics. We find, however, that the paths of the extensive and intensive margins of car purchases during the Great Recession are insensitive to fuel shocks relative to the income shocks (Figure 16). The reason for this is that most of the production of car services comes from the car stock, and this is a slow moving variable. Thus, while higher fuel prices depress car demand, quantitatively this aspect matters little.

5.2 Higher moment shocks

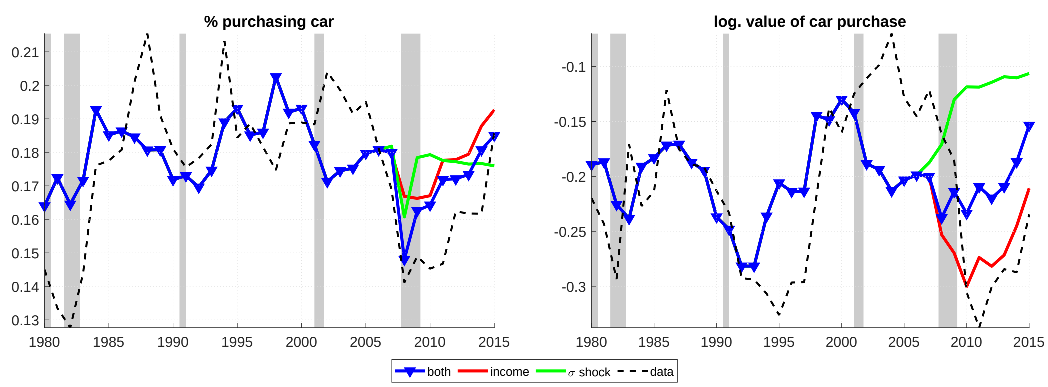
An influential literature has highlighted that uncertainty increased significantly during the Great Recession and that this can have important implications for firm and household choices.[18] We now explore the importance of this for our analyses.

[18] See: Storesletten, Telmer, & Yaron (2004); Justiniano & Primiceri (2008); Bloom (2009); Bloom et al (2018), Bayer et al (2019), Fernandez-Villaverde et al (2011).

5.2.1 Uncertainty

We first introduce uncertainty shocks assuming that the variances of the shocks to the permanent income process are state dependent with $\upsilon_t \sim N\left(0, \sigma^2_{\upsilon,S}\right)$, $\eta_{a,t} \sim N\left(0, \sigma^2_{\eta,S}\right)$, $\varepsilon^j_{a,t} \sim N\left(0, \sigma^2_{\varepsilon,S}\right)$. We assume a two state Markov process for the variances so that S moves between a high and low uncertainty regime with transition probability $P_u(S, S')$. We adopt the probabilities for the Markov chain over the uncertainty regime from Bloom et al. (2018) transformed to an annual frequency. The variance of the shocks in the low uncertainty regime is the same as in the baseline model. In the high uncertainty regime the variance of the aggregate and cohort shocks increases by a factor of 1.6, also following Bloom et al. (2018). For the idiosyncratic shocks we consider a two standard deviation increase and use the estimate of Bayer et al. (2019) who find a one standard deviation increase in income uncertainty raises the variance of income shocks by 54 percent. This gives a scaling factor of 1.44. The full list of parameters can be found in Table A.6.

We assume that prior to the Great Recession the economy was in the low uncertainty state. Then in 2008 with the onset of the recession the economy switches to the high uncertainty regime and remains there for the rest of the simulation. The aggregate shocks are those estimated from the data so these are unchanged, but the idiosyncratic persistent shocks are now drawn from the higher variance distribution.



Notes: Data from CEX

Figure 17: Uncertainty shock: extensive and intensive margin

The response of the probability of car purchase can be seen in Figure 17, Panel A. The increase in uncertainty substantially reduces the share of households purchasing cars, relative to the model with income shocks. The effect of uncertainty on increasing the size of the (S, s) region has previously been highlighted by Eberly (1994). Most of this effect occurs in the first period of the shock, but there is some persistence in the reduction in household adjusting their car stock. However, once one allows for higher uncertainty, it becomes even more important to allow for wealth shocks and long-run risk. In particular when uncertainty rises, those who chose to adjust their car are wealthier and faced with favorable income shocks and therefore the the intensive margin response moves even less when uncertainty increases contrary to the data.

5.2.2 Negative Skewness

An alternative formulation involving higher order moment that has been discussed in the literature is negative skewness. Guvenen et al. (2014) argue that countercyclical left skewness of income shocks better captures the US data than countercyclical variance.[19] We follow the Guvenen, Ozkan & Song (2014) and specify the income shocks with a mixture of normals with state varying parameters. Each period idiosyncratic permanent shocks can be drawn from either a high variance or (a close to degenerate) low variance distribution:

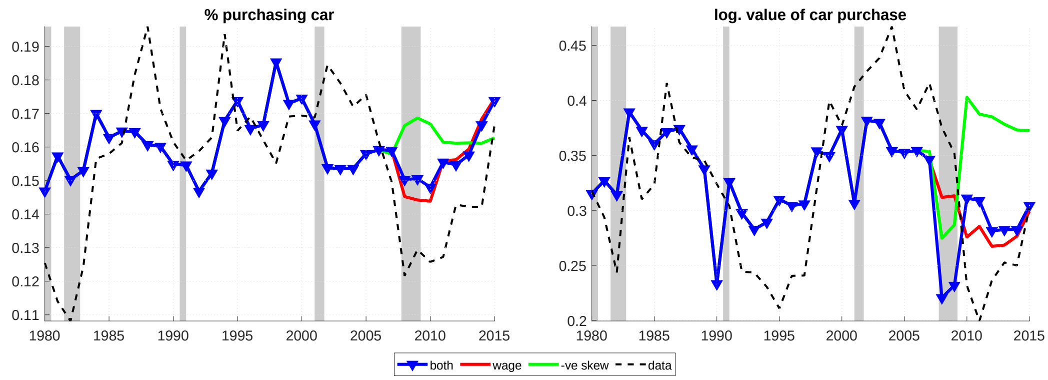
$$\varepsilon_{t,a,S}^{j} \sim \begin{cases} N\left(\mu_{\varepsilon,1}^{S}, \sigma_{\varepsilon,1}^{2}\right) & \text{with probability } p_{\varepsilon} \\ N\left(\mu_{\varepsilon,2}^{S}, \sigma_{\varepsilon,2}^{2}\right) & \text{with probability } 1 - p_{\varepsilon} \end{cases}$$

The state S is a Markov process which moves between boom and recession with probability $P_N(S, S')$. The means of the two normals differ in boom and recession. The differing means of these distributions generate the skewness of the shocks. We use the parameter values from Guvenen et al. (2014), and estimate an annual transition matrix for NBER recession years. The full list of parameters can be found in Table A.6.[20] As in Guvenen et al. (2014), skewness falls by around 15 points on Kelly's measure of skewness during a recession

We simulate the Great Recession experiment using the same income shocks, but with the economy moving to the recessionary negative skewness regime at NBER recession dates so that skewness of income returns to normal in 2010. As can be seen from Figure 18, Panel

[19] There is an obvious relation between negative skewness shocks and the growth shock we investigated in the baseline model. However, as negative skewness shocks affect all ages they have a less clear lifecycle dimension.

[20] We add an additional moment to target the standard deviation of income in the baseline model. As idiosyncratic shocks now effectively contain an aggregate component, the model requires smaller aggregate income shocks $\sigma_v^2 = 0.009^2$.



Notes: Data from CEX

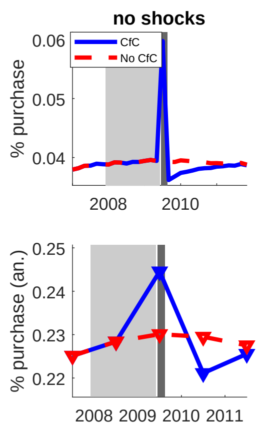
Figure 18: Negative skewness shock: extensive and intensive margin

B the negative skewness has a dramatic effect on the value of cars purchased, significantly reducing the value during the period of the recession. However, given the temporary nature of the shock this variable rebound strongly once the recession passes.[21] The skewness shocks also result in large falls in the value of car purchases in the previous recessions. This is not consistent with the data shown in Section 2.3. The effect on the share of agents adjusting in more muted, with negative skewness reducing the fall in agents purchasing cars (Figure 18, Panel A).

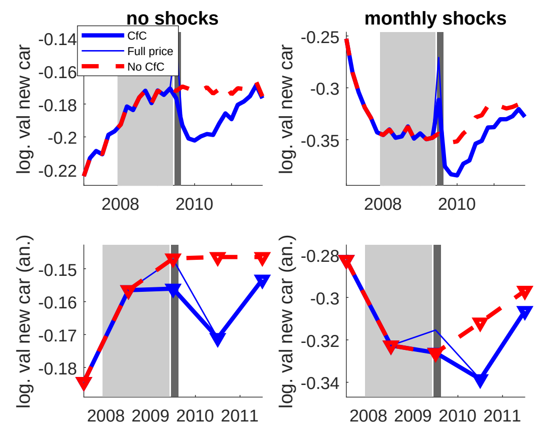
5.3 Cash for Clunkers

The Obama administration enacted in 2009 a programme to support the automotive sector during the Great Recession, the Car Allowance Rebate System or Cash for Clunkers program. Under this stimulus policy, the government provided $3 billion of subsidies worth $3,500 to $4,500 per household purchasing new cars and trading in an old vehicle fulfilling certain age and environmental criteria. In empirical analyses, Mian & Sufi (2010), Hoekstra et al (2017), Green et al (2018) find this program significantly stimulated car purchases while subsidies were available but mainly through altering the timing of purchases rather than by spurring additional purchases; that the policy design implied a decline in the value of car purchases; and that household liquidity constraints interacted with policy's effectiveness.

[21] If instead the period of negative skewness was assumed to last for the rest of the simulation period the negative affect on the intensive margin would persist.



(a) % hh purchase



(b) value|purchase

Notes: Top row shows the results of the monthly model, the bottom row is the results of the monthly model aggregated on a household basis to yearly averages. The dashed red line is without the policy intervention. The solid thick blue line is with the policy, calculated on a post subsidy household expenditure basis. The thin blue line is with the policy and includes the value of the subsidy. *No shocks* is a model without aggregate shocks, *monthly shocks* is the aggregate shocks from the data averaged across the year.

Figure 19: Cash for clunkers: extensive and intensive margin

It is interesting to introduce Cash for Clunkers matters in the life-cycle model to examine its impact on choices. The short duration of the program, which lasted from July 1, 2009 to August 24, 2009, makes our annual model unsuitable for analysis so we instead simulate a bi-monthly parametrization.[22] The policy itself is modelled as a two state Markov process, where switching to the policy is a zero probability event, but the household understands the policy is a time limited state. During the Cash for Clunkers regime, households that receive the subsidy and adjust their stock such that a purchase that changes the stock by $d^j_{a,t+1} - \left(1 - \delta^j_{a,t}\right) d^j_{a-1,t}$ costs the household: $(1 - \varpi)d^j_{a,t+1} - \left(1 - \delta^j_{a,t}\right) d^j_{a-1,t}$ with $\varpi \in (0, 1)$.[23]

We calibrate the policy such that the expected duration of the state is two periods, as initially the program was scheduled to end in November. The size of the subsidy, ϖ, is

[22]Unsurprisingly, when simualted in the baseline annual model, we see a large increase in the probability of purchase and a fall in the value of purchases in 2009. The monthly model is however, exceedingly computationally intensive.

[23]To capture the policy incentive to purchase a lower value vehicle, the household is only eligible for the subsidy if $d^j_{a,t+1}/p^j_{a,t} < \overline{D}$. Congestion effects are modelled assuming only a fraction of households, π, are transitioned to the policy state.

Table 6: Bi-monthly Cash for Clunkers Calibration

Parameter	Value	Source
Parameters		
Percentage of households eligible for Cash for Clunkers	12.0	
Discount on car stock (ϖ)	0.036	
Probability of Cash for Clunkers continuing	0.5	Duration: July-Nov
Targets		
Policy cost as a share of 2008 car expenditure	1.0	\$3bn prog. cost
Effective discount on a new car purchase	10.0	max discount:max price
Decline in value of purchase of eligible households	6.8	Hoekstra et al (2017)

chosen to target a 10 percent subsidy on the value of a purchase, in line with the data. The car size threshold, $\overline{D}$, is set so that eligible households make car purchases that are 6.8 percent lower than similar control households during a one year window. This matches the quasi-experimental results of Hoekstra et al (2017).[24] The eligibility fraction is chosen to match the total size of the government subsidy relative to total car expenditure in 2008. Total expenditures on new and used cars in 2008 were \$287.9 billion, which gives a target of approximately one percent. Table 6 summarizes the parametrization.

We simulate the bi-monthly model with the Cash for Clunkers policy taking place in July 2009 for one period. As can be seen from Figure 19, Panel A the policy results in a substantial increase in car purchases of around 2 percentage points during July 2009 and a fall in the value of cars purchased (Panel B), with the latter a model target. Consistent with the empirical studies cited above, the increase in cars purchased then depresses future car purchases. As such a significant fraction of the purchases can be classified as a change in timing rather than additional purchases. It is also interesting to observe that the fall in the value of purchases occurs mostly after the policy rather than during the policy period itself. The reasoning is that the "average purchase" are preempted, so it only the more constrained households making purchases in the period that follows and these tend to be of lower value.

In the bottom row of Figure 19 we re-aggregate the monthly data into annual variables.

[24] In Hoekstra et al (2017), Table 3 reports an average fall in spending of \$1,900 and an average purchase price of \$28,160.

At the annual frequency the effects of the Cash for Clunkers program are fairly modest with a small increase in share of household adjusting and small decline in the value of cars purchased relative to the decline due to aggregate shocks.[25]

6 Conclusion

We have provided new empirical facts about household consumption adjustments during the Great Recession and confronted these facts with a sophisticated life-cycle model with the aim at drawing inference on household perceptions of the shocks that affected them during this business cycle episode. Expenditures on cars, a large ticket consumer durable, fell dramatically during the Great Recession and that this decline derived from both an unusually large contraction in the extensive margin and from a unique decline in the intensive margin. We also documented that the Great Recession impacted differentially on cohorts with younger cohorts reducing their consumption the most while intensive margin reduction on car purchases derives mainly from 35-44 year old households.

We find that wealth shocks are important on top of the large aggregate income shock are required to account for the car purchase dynamics during the Great Recession because otherwise the intensive margin does not move much. Moreover, to account for the cohort level adjustments, we argue that negative expectations about future income growth are required. The latter may indicate that negative expectations were an important determinant of the severity of this business cycle episode.

Our analysis has considered a consumer choice problem. It would be interesting to introduce equilibrium features into the modeling so that one could ask about the sources of the large declines in wealth and income. It would also be interesting to consider housing more explicitly in the model and to allow for long-term housing finance. Similarly, we do not explicitly model the sources of very persistent income changes and it would be interesting to consider these in more detail by, for example, introducing search and matching features in the labor market as these may interact with portfolio choices. We leave these and other extensions for future work.

[25] Figure A.18 presents the results for total car expenditure and the aggregate car stock. Table A.7 reports the additional car expenditure of the programme under alternative policy designs.

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A Online Appendix: additional material

Not for publication

A.1 Data description

A.1.1 Consumer Expenditure Survey

Our core CEX extract covers 1981 to 2012. For the aggregate level series, we use quarterly expenditure by a household (summing across monthly reported expenditures) and calculate the average expenditure in each quarter. For aggregate moments we use all households in the survey and apply a seasonal adjustment. For lifecycle cohorts we take an average across households quarterly spending in a given cohort-year cell. We assign the cohort the median age of the group and multiply by 4 to get the average quarterly expenditure. For household level micro moments we aggregate expenditure to the household level and assign the relevant year. For model targets we use the sample of households aged 25-84, consistent with our model calibration.

Except for the value of car purchases, we adjust for households with missing quarters by a simple 4 divided by # of quarterly observations present weighting. For the value of car purchases we weight missing quarters with an age-year specific probability of purchase to avoid inflating infrequent purchases. Non durables expenditure and income are deflated by the CPI. For car expenditure we deflate by the new or used car CPI except in the aggregate figures where we use the all item CPI.

The value of car purchases is the value of new and used car purchases. In aggregate statistics we include the value of trade in credit.[1] A household is recorded as purchasing a vehicle if they report a positive purchase value. The value of a household's stock of cars comes from an average of CEX imputed values using dummies for the car model. Our definition of non-durables includes: food in and out, alcohol and tobacco, fuel, education, clothing, insurance payments, transport costs, childcare, medical and hospital bills, entertainment, and donations. For estimation of the lifecycle profile we use the log of the sum of head and spouse/partner labor earnings. We drop observations earning less the $10,000 or where the household head works less than an average of 20 hours a week to avoid conflating the wage profile with

[1] This is excluded when comparing the model to the data as the definition is more applicable.

households that exit the labor market.

A.1.2 National Income and Product Account

From the Bureau of Economic Affairs National Income and Product Accounts (NIPA) we use wages and salary, compensation of employees (Table: 2.1, line: 3) for the income shocks pre-1964. Aggregate consumption is Non-durable goods (Table: 2.3.5, line: 8) and Services (Table: 2.3.5, line: 13). Car expenditure is Motor vehicles and parts (line: 2.3.5, line: 4). All variables are deflated by the the Personal consumption expenditures deflator (Table: 1.1.4, line: 2) and divided by the mid-year population (Table 2.1, line: 40). The savings rate is Personal saving (Table 2.1, line 34) divided by Disposable personal income (Table 2.1, line 27).

A.1.3 Current Population Survey

For the income measure from 1964 onwards we use the Current Population Survey Annual Social and Economic Supplement (CPS ASEC). Our measure of income is income from wages for all household members. In the ASEC, income reported in the March survey is for the previous year. We set income to zero if households report no income, but report being unemployed. The wage is deflated by the personal consumption expenditures deflator.

A.1.4 Other

Rate spread: To calculate the spread we combine the New Car Average Finance Rate at Auto Finance Companies (1971-2010) and the Finance Rate on Consumer Installment Loans at Commercial Banks, New Autos 48 Month Loan (1972-2015) both from Federal Reserve Board's G.19 Consumer Credit tables.

To calculate the total loan rate on cars we subtract inflation and weight the series according to Attanasio, Goldberg, and Kyriazidou (2008) which puts 41 percent on auto finance and 59 percent on bank finance. The car loan rate is the average value over 1970-2006.

To estimate the spread process and shocks we take subtract the 1-yr treasury rate from both series and combine with the weighting above. From 2011 we put 100 percent weighting on bank loans, adjusting the level to match the series up to 2011. We then estimate an AR(1) process for the detrended log of this series.

Asset price: We use the 2004 Survey of Consumer Finance to estimate the housing and stock share of net wealth. Housing is primary residence and other real estate. Stock holdings includes corporate stock, mutual funds and other business equity.

For the house price index we use the US Federal Housing Finance Agency's All-Transactions House Price Index (1975-2015). For the stock price we use the S&P500 Adjusted Close Price (1960-2015). Both variables are deflated with the CPI. We detrend the log series and assume both prices follow a random walk.

Car loans: Aggregate car loans is Motor Vehicle Loans Owned and Securitized, Outstanding from Federal Reserve Board's G.19 Consumer Credit tables.

Fuel price: The fuel price is the Price index for Gasoline (All Types), deflated by the CPI. BLS Consumer Price Index tables (1967-2015). We then estimate an AR(1) process for the detrended log of this series.

A.2 Solution method

For ease of exposition and with no loss of generalisation we condense the decision whether to adjust or not into the choice of d'. Further, given the positive interest rate spread $r_k > 0$ it is not optimal for a household to hold both savings and a car loan. Therefore, we can consider a single asset k, with a kink in the interest rate schedule, and shocks to the return that are only present when $k > 0$.

A.2.1 Redefine variables in terms of permanent assets and income

$$
\begin{aligned}
V_a(k, d, r_k, q, P, U, G_{a,j}) = &\max_{c,d',k'} u(c, d') + \beta \mathbf{E} V_{a+1}(k', d', r'_k, q', P', U', G_{a+1,j'}) \\
&s.t. \\
c + qk' \cdot \mathbb{1}[k' \geq 0] + k' \cdot \mathbb{1}[k' < 0] + d' =&(1+r)qk \cdot \mathbb{1}[k \geq 0] + (1 + r + r^k)k \cdot \mathbb{1}[k < 0] + \\
&(1-\delta)d - \Psi d \cdot \mathbb{1}[\text{adj}] + Y \\
k' \geq& -\eta d' \\
Y =& PU \\
P =& G_{a,j} P_{-1} V \\
q =& q_{-1} W
\end{aligned}
$$

Given the restriction $q > 0$ we can define[2]:

$$\mathbf{k}' = \begin{cases} qk' & if\ k' \geq 0 \\ k' & if\ k' < 0 \end{cases}$$

And therefore if $k' > 0$:

$$\begin{aligned} qk = & \frac{q}{q_{-1}}\mathbf{k} \\ & W\mathbf{k} \end{aligned}$$

We can rewrite the problem, removing the asset price q as a state variable:

$$\begin{aligned} V_a(\mathbf{k}, d, r_k, P, U, G_{a,j}) = & \max_{c,d',\mathbf{k}'} u(c, d') + \beta \mathbf{E} V_{a+1}(\mathbf{k}', d', r_k', P', U', G_{a+1,j'}) \\ & s.t. \\ c + \mathbf{k}' + d' = & (1+r)W\mathbf{k} \cdot \mathbb{1}[\mathbf{k} \geq 0] + (1 + r + r^k)\mathbf{k} \cdot \mathbb{1}[\mathbf{k} < 0] + \\ & (1-\delta)d - \Psi d \cdot \mathbb{1}[\text{adj}] + Y \\ \mathbf{k}' \geq & -\eta d' \\ Y = & PU \\ P = & G_{a,j} P_{-1} V \end{aligned}$$

Now redefine assets in terms of the maximum collateral constraint, $b' = \mathbf{k'} + \eta d'$:

$$\begin{aligned} V_a(b, d, r_k, P, U, G_{a,j}) = & \max_{c,d',b'} u(c, d') + \beta \mathbf{E} V_{a+1}(b', d', r_k', P', U', G_{a+1,j'}) \\ & s.t. \\ c + b' + (1-\eta)d' = & (1+r)W(b - \eta d) \cdot \mathbb{1}[(b \geq \eta d)] + (1 + r + r^k)(b - \eta d) \cdot \mathbb{1}[(b < \eta d)] + \\ & (1-\delta)d - \Psi d \cdot \mathbb{1}[\text{adj}] + Y \\ b' \geq & 0 \\ Y = & PU \\ P = & G_{a,j} P_{-1} V \end{aligned}$$

[2]If the interest rate premia is not impose for $k < 0$ we cannot make this simplification as $\mathbf{k} > 0$ does not guarantee $k > 0$

Define variable in current permanent income: $\tilde{c} = c/P$ and yesterday's permanent income: $\hat{b} = b/P_{-1}$ and $\hat{d} = d/P_{-1}$. Divide through by permanent income, following

$$\begin{aligned}
\left(\frac{1}{P}\right)^{1-\rho} V_a(\tilde{b}, \tilde{d}, r_k, U, G_{a,j}) =& \max_{\tilde{c},\hat{d}',\hat{b}'} u(\tilde{c}, \hat{d}') + \beta \mathbf{E} \left(\frac{1}{P}\right)^{1-\rho} V_{a+1}(\tilde{b}', \tilde{d}', r_k', U', G_{a+1,j'}) \\
& s.t. \\
\tilde{c} + \hat{b}' + (1-\eta)\hat{d}' =& (1+r)W(\tilde{b} - \eta\tilde{d}) \cdot \mathbb{1}[(\tilde{b} \geq \eta\tilde{d})] + (1+r+r^k)(\tilde{b} - \eta\tilde{d}) \cdot \mathbb{1}[(\tilde{b} < \eta\tilde{d})] + \\
& (1-\delta)\tilde{d} - \Psi\tilde{d} \cdot \mathbb{1}[\text{adj}] + U \\
\tilde{b}' \geq & 0 \\
\tilde{b}' =& \frac{P}{P'}\hat{b}', \ \ \tilde{d}' = \frac{P}{P'}\hat{d}'
\end{aligned}$$

Let $\tilde{V}_a(\cdot) = \left(\frac{1}{P}\right)^{1-\rho} V_a(\cdot)$. Then as $P/P' = G_{a+1,j'}V'$:

$$\begin{aligned}
\tilde{V}_a(\tilde{b}, \tilde{d}, r_k, U, G_{a,j})) =& \max_{\tilde{c},\hat{d}',\hat{b}'} u(\tilde{c}, \hat{d}') + \beta \mathbf{E} \left(G_{a+1,j'}V'\right)^{1-\rho} \tilde{V}_{a+1}(\tilde{b}', \tilde{d}', r_k', U', G_{a+1,j'}) \\
& s.t. \\
\tilde{c} + \hat{b}' + (1-\eta)\hat{d}' =& (1+r)W(\tilde{b} - \eta\tilde{d}) \cdot \mathbb{1}[(\tilde{b} \geq \eta\tilde{d})] + (1+r+r^k)(\tilde{b} - \eta\tilde{d}) \cdot \mathbb{1}[(\tilde{b} < \eta\tilde{d})] + \\
& (1-\delta)\tilde{d} - \Psi\tilde{d} \cdot \mathbb{1}[\text{adj}] + U \\
\tilde{b}' \geq & 0 \\
\tilde{b}' =& \frac{\hat{b}'}{G_{a+1,j'}V'}, \ \ \tilde{d}' = \frac{\hat{d}'}{G_{a+1,j'}V'}
\end{aligned}$$

Finally, rewrite problem in terms of cash in hand, $\tilde{x}$:

$$\begin{aligned}
\tilde{V}_a(\tilde{x}, \tilde{d}, r_k, G_{a,j}) =& \max_{\tilde{c},\hat{d}',\hat{b}'} u(\tilde{c}, \hat{d}') + \beta \mathbf{E} \left(G_{a+1,j'}V'\right)^{1-\rho} \tilde{V}_{a+1}(\tilde{x}', \tilde{d}', r_k', U', G_{a+1,j'}) \\
& s.t. \\
\tilde{c} + \hat{b}' + (1-\eta)\hat{d}' =& x - \Psi\tilde{d} \cdot \mathbb{1}[\text{adj}] \\
\tilde{b}' \geq & 0 \\
\tilde{d}' =& \frac{\hat{d}'}{G_{a+1,j'}V'} \\
\tilde{x}' =& \begin{cases} (1+r)W(\hat{b}' - \eta\hat{d}')/(G_{a+1,j'}V') + (1-\delta)\hat{d}'/(G_{a+1,j'}V') + U & if\ \hat{b}' \geq \eta\hat{d}' \\ (1+r+r^k)(\hat{b}' - \eta\hat{d}')/(G_{a+1,j'}V') + (1-\delta)\hat{d}'/(G_{a+1,j'}V') + U & if\ \hat{b}' < \eta\hat{d}' \end{cases}
\end{aligned}$$

A.2.2 Computation

The model is solved by Value Function Iteration. We use 200 grid points for cash in hand, x, 200 grid points for assets a', 150 grid points for cars, d and 5 grid points for the interest rate spread, r_k. Expectations are taken over future shocks, using 7 grid points for permanent income, V, 5 grid points for transitory shocks U and 5 grid points for the asset price shock, W. As the model is partial equilibrium, the household does not need to distinguish between aggregate and idiosyncractic shocks to permanent income, V.

We then simulate a panel of households with 2,000 household born age 25 each period, for 4,000 periods to calculate the aggregate properties of the economy. We also simulate the lifecycle of a panel of households without aggregate shocks to uncover the lifecycle properties. Finally, we feed in a series of shocks estimated from the data to income $\{Y_t\}_{t=1946}^{2015}$, the interest rate spread $\{r^c\}_{t=1972}^{2015}$, the asset price $\{q_t\}_{t=1976}^{2015}$ and deterministic growth rate of economy to replicate the behaviour of the economy in the period 1980-2015

A.3 Estimating growth profile

A.3.1 Growth rate measurement

The primary measure is Financial Income Before Tax. We drop household who have income below \$10,000 or work less the 20 hours a week. For the estimation of the growth rate annual household income aggregated to year,t. age, a cell: Y_t^a. Then for each year age income growth is calculated:

$$dY_t^a = Y_t^a - Y_{t-1}^{a-1}$$

For each age the average of these growth rates across years was calculated for the pre-recession (1990-2005) and post-recession (2010-2012) period.

$$d\hat{Y}^{a,\mathbf{pre}} = \frac{1}{T^{pre}} \sum_{t=1990}^{2006} dY_t^a$$
$$d\hat{Y}^{a,\mathbf{post}} = \frac{1}{T^{post}} \sum_{t=2010}^{2012} dY_t^a$$

Having calculated the average growth rate at each age in the pre- and post- recession period we fit a polynomial $f(a)$ across all ages to smooth the pattern:

$$d\hat{Y}^{a,\mathbf{x}} = g^{\mathbf{x}}(a) + \epsilon_a \tag{1}$$

The implied lifecycle can be calculated by cumulating the estimated growth rate polynomials $\hat{g}^{\mathbf{pre}}(a)$ and $\hat{g}^{\mathbf{post}}(a)$.

A.3.2 Lifecycle measurement

Lifecycle estimation is directly estimating the lifecycle by regression of income on age polynomial and controls, using household level data. The pre-recession period is 1989-2005 and the post recession period is 2009-12. Controls are included for demography, education (e), cohort (j) and year. The estimation equation is:

$$y_{it} = \alpha_0 + f(a) + \sum_j^M \gamma^j + \sum_e^E \beta^e + \alpha_1 race_i t + \phi t + \epsilon_{it} \tag{2}$$

Having estimated the lifecycle polynomials $\hat{f}^{\mathbf{pre}}(a)$ and $\hat{f}^{\mathbf{post}}(a)$ the implied growth rate is then computed, $\hat{g}_{LC}^{\mathbf{pre}}(a)$ and $\hat{g}_{LC}^{\mathbf{post}}(a)$.

A.4 Growth rate shock calibration

Given model specification:

$$G^{post} = min\big\{(G^{pre})^{\gamma}, G\big\} \tag{3}$$

and growth rate polynomials, we estimate $\hat{\gamma}$ to find model that fits decline: $\hat{g}^{\mathbf{pre}}(a)$ to $\hat{g}^{\mathbf{post}}(a)$. We estimate $\hat{\gamma}$ for both the growth rate estimated series and implied growth from the lifecycle estimated series and take the average of these two measures.

A.5 Growth rate shock calibration

Given model specification:

$$G^{post} = min\{(G^{pre})^{\gamma}, G\} \tag{4}$$

and growth rate polynomials, we estimate $\hat{\gamma}$ to find model that fits decline: $\hat{g}^{\mathbf{pre}}(a)$ to $\hat{g}^{\mathbf{post}}(a)$. We estimate $\hat{\gamma}$ for both the growth rate estimated series and implied growth from the lifecycle estimated series and take the average of these two measures.

A.6 Estimating cohort shocks

Our income measure of choice is household income from wages. We use a sample in the CPS of households aged 25-64, for the years 1963-2015. We generate shocks for 10 year cohorts, such that a household is a member of cohort s if born in the 10 year period $19s3$ to $19(s+1)2$.

We use two measures to uncover aggregate permanent income shocks and aggregate "transitory" shocks.[3] Let $y_{it} = log(Y_{it})$ be the log of household income and $p_{it} = \mathbf{1}[Y_{it} \leq 0]$ and indicator variable for household income being zero (or below).

A.6.1 Permanent shocks

We first remove a trend from log income, using the period 1975-2007. To find the permanent income component we regress the detrended income data, $\hat{y_{it}}$, on a lifecycle age polynomial, cohort (s) dummies, and demographic controls using data for $\leq$ 2007:

$$\hat{y}_{it} = \alpha + f(age_{it}) + \sum_{s} \gamma^{s} + \beta X_{it} + \xi_{it}$$

We then construct a "year of birth" synthetic cohort, j, such that year of birth earnings is:

$$\bar{y}_{jt} = \gamma^{s} + \frac{1}{N_t^j} \sum_{i \in j} \xi_{it}$$

[3]Note: Our definition of aggregate transitory shocks differs somewhat from that typically used in the literature. We are seeking to capture the share of households with zero income, which increased during the Great Recession. These observations would typically be excluded from standard wage estimation.

The initial income of each household during the simulation is then:

$$\hat{\bar{y}}_{j,t=j+25} = \bar{y}_{j,t=j+25} - \frac{1}{N^{J^{25}}} \sum_{j \in J^{25}} \bar{y}_{j,t=j+25}$$

where we normalise such that the average initial income is zero.

We then use $\bar{y}_{jt}$ as the year of birth permanent income. Given the random walk in permanent income a shock for a year of birth cohort is:

$$\eta_{jt} = \bar{y}_{jt} - \bar{y}_{jt-1} \ \forall t$$

Finally, we the average over these year of birth cohort shocks to find the cohort shocks that we feed into the model.

$$\hat{\eta}_{st} = \frac{1}{N_t^s} \sum_{j \in s} \eta_{jt}$$

A.6.2 Transitory shocks

For the transitory shocks we subtract a trend and then construct "year of birth synthetic cohorts", this is the share of a year of birth cohort with zero income.

$$\bar{p}_{jt} = \frac{1}{N_t^j} \sum_{i \in j} \hat{p}_{it}$$

We regress share of cohorts with zero income, $\bar{p}$, on a lifecycle age polynomial, and cohort (s) dummies using data for ≤ 2007:

$$\bar{p}_{jt} = \alpha + f(age_{jt}) + \sum_{s} \gamma^s + \nu_{it}$$

The aggregate transitory shock for the year of birth cohort is ν_{it}. We the average over these year of birth cohort shocks to find the cohort shocks that we feed into the model.

$$\hat{\nu}_{st} = \frac{1}{N_t^s} \sum_{j \in s} \nu_{jt}$$

A.7 Estimating cohort responses

To estimate the deviations in the consumption response of households during the Great Recession, we regress the log of a consumption variable, x_{it}, on a lifecycle age polynomial, cohort (s) dummies, and linear trend, using data for ≤ 2007:[4]

$$x_{it} = \alpha + f(age_{it}) + \sum_{s} \gamma^{s} + \phi t + \epsilon_{it}$$

For each household we can now predict consumption in each year during the Great Recession, in the absence of the crisis as:

$$\hat{x}_{it} = \hat{\alpha} + \hat{f}(age_{it}) + \sum_{s} \hat{\gamma}^{s} + \hat{\phi} t$$

We divide the sample up into three cohorts j based on their age in 2007: $j = 1$ if $25 \leq age_{2007} < 34$, $j = 2$ if $35 \leq age_{2007} < 44$ and $j = 3$ if $45 \leq age_{2007} < 54$. We measure average consumption for a cohort in year t as:

$$X_{jt} = \frac{1}{N_t^j} \sum_{i \in j} x_{it}$$

Actual consumption growth for year t in the recession is, growth relative to the 2007 baseline year[5]:

$$\Delta X_{jt} = X_{jt} - X_{j,2007}$$

While predicted consumption growth is the analogue:

$$\Delta \hat{X}_{jt} = \hat{X}_{jt} - \hat{X}_{j,2007}$$

[4]Where it makes more sense we use the level of a variable rather than logs and calculate percentage deviations: $\Delta X_{jt} = (X_{jt} - X_{j,2007})/X_{j,2007}$. We do this for *car expenditure* and the *value conditional on purchase*.

[5]For the value of car purchase conditional on adjustment we use a baseline year of 2006-07, to increase the available observations. We also use a longer impact period (2008-12)

Again to reduce measurement error, we also tend to focus on the average value of consumption during the recession. i.e.:

$$\Delta \hat{X}_{j,08:09} = \frac{1}{2} \sum_{t=2008}^{2009} \hat{X}_{jt} - \hat{X}_{j,2007}$$

The reported consumption deviation is then measured as:

$$\Omega_x^j = \Delta X_{j,08:09} - \Delta \hat{X}_{j,08:09}$$

We undertake the same operation on model generated data. The measures are comparable as we are controlling for cohort specific level effects and and trend growth in the data.

A.7.1 Cohort time period definitions

Our base line is the average 2008-09, relative to the level in 2007, using the same time period in the data and model. However, for a few variables we make an adjustment. In particular we choose a longer time period for the value of purchases as this is measured less precisely due to fewer observations. For net saving (Pr(income>expenditure)) we move the effect one period onwards in the model to capture the full effect of the growth shock.

- **Consumption growth:** pre: 2007, impact period: 2008-09
- **Car expenditure:** pre: 2007, impact period: 2008-09
- **% purchase:** pre: 2007, impact period: 2008-09
- **Car value:** pre: 2006-07, impact period: 2008-12
- **log income:** pre: 2007, impact period: 2008-09
- **Pr(income>expenditure):**
  - *data:*- pre: 2007, impact period: 2008-09;
  - *model:*- pre: 2008, impact period: 2009-10

B Online Appendix: additional tables

	1981-2007		2007-12	
	25-64	65-84	25-64	65-84
Non durables	33,677.4	27,543.9	33,554.7	30,631.6
Car expenditure	3,528.2	1,835.1	3,361.3	2,088.6
Car purchase | adj	16,897.7	17,868.0	21,949.3	22,403.7
New car purchases | adj	27,601.6	25,889.0	36,253.3	32,318.6
Old car purchases | adj	11,137.5	11,262.0	15,385.3	14,065.2
% car purchase	0.209	0.103	0.153	0.093
% new car purchase	0.068	0.045	0.045	0.041
% old car purchase	0.149	0.060	0.113	0.054
Car stock	16,005.6	12,591.1	15,510.6	13,701.7
Number of cars	1.159	1.012	0.886	0.881
Age of cars	7.946	8.424	8.688	9.328
Employed	0.899	0.233	0.877	0.278
Hours worked	39.1	7.2	37.6	9.1
Family income (before tax)	71,866.3	40,025.6	75,401.6	46,492.4
Family income (after tax)	66,316.3	37,938.6	72,328.3	45,199.4
Family labor earnings	60,262.6	6,665.1	62,597.8	10,245.8
Head labor earning	48,816.3	5,477.1	49,926.2	8,316.3
Age	41.9	72.6	44.1	72.3

Notes: All variables are in 2014 prices and deflated by the CPI.

Table A.1: Consumer Expenditure Survey Summary Statistics

	% purchase			Value|purchase ($)		
Variable	all	new	old	all	new	old
GDP growth	0.020	0.020	0.002	49.5	116.0	-24.0
	(0.013)	(0.007)	(0.011)	(23.5)	(39.5)	(20.0)
Great Recession	-0.500	-0.035	-0.469	-909.7	-2222.4	-687.2
	(0.156)	(0.087)	(0.133)	(321.9)	(534.7)	(275.9)
R^2	0.002	0.001	0.001	0.022	0.058	0.031
N	599,194	599,194	599,194	42,370	12,575	30,242

Notes: Standard errors in parentheses. Data is at quarterly frequency. Variable is regressed on annualized quarterly GDP growth and dummy for Great Recession. Additional controls are quarter dummies and a quadratic series for the time period.

Table A.2: Car purchasing behavior in recessions

Variable	(1)	(2)	(3)	(4)
Stock ($10,000)	-0.012	-0.008		
	(0.0003)	(0.0014)		
Stock:ndur			-0.010	-0.0068
			(0.0002)	(0.0009)
Black	-0.028	-0.028	-0.029	-0.029
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Education	-0.005	-0.0054	-0.007	-0.007
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Sex	-0.027	-0.027	-0.026	-0.026
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Family size	0.013	0.0126	0.011	0.011
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Full time	0.004	0.004	0.005	0.005
	(0.0011)	(0.0011)	(0.0011)	(0.0010)
Weeksp.	0.0002	0.0002	0.0002	0.0002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	-0.018	-0.018	-0.013	-0.013
	(0.0024)	(0.0024)	(0.002)	(0.002)
Log. Income	0.014	0.014	0.011	0.011
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
year F.E	✓		✓	
stock x year		✓		✓
age polynomial	✓	✓	✓	✓
R^2	0.0304	0.0307	0.0369	0.0372
N	458,234	458,234	458,210	458,210

Notes: Probit Estimation of probability of adjustment. Standard errors in parentheses. Stock:ndur is the ratio of the car stock to non-durables consumption. Age polynomial specification is quartic, only first term is shown

Table A.3: Probability of Purchasing a Car (Avg. Marginal Effects)

Variable	(1)	(2)	(3)	(4)
Stock ($10,000)	-0.010	-0.008		
	(0.0003)	(0.0014)		
Stock:ndur			-0.0093	-0.0068
			(0.0002)	(0.0009)
Black	-0.031	-0.031	-0.031	-0.031
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Education	-0.002	-0.0025	-0.004	-0.004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Sex	-0.031	-0.031	-0.030	-0.030
	(0.0011)	(0.0011)	(0.0010)	(0.0011)
Family size	0.014	0.014	0.012	0.012
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Full time	0.009	0.009	.009	.009
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Weeksp.	0.0003	0.0003	0.0003	0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age				
Log. Income				
year F.E	✓		✓	
stock x year		✓		✓
age polynomial				
R^2	0.0256	0.0258	0.0331	0.0334
N	500,018	500,018	499,984	499,984

Notes: Probit Estimation of probability of adjustment. Standard errors in parentheses. Stock:ndur is the ratio of the car stock to non-durables consumption.

Table A.4: Probability of Purchasing a Car (Avg. Marginal Effects)

Variable	(1)	(2)	(3)	(4)
Stock ($10,000)	-0.010	-0.007		
	(0.0003)	(0.0013)		
Stock:ndur			-0.009	-0.0065
			(0.0002)	(0.0009)
Black	-0.031	-0.030	-0.031	-0.031
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Education	-0.003	-0.0025	-0.004	-0.004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Sex	-0.032	-0.032	-0.031	-0.031
	(0.0011)	(0.0010)	(0.0012)	(0.0011)
Family size	0.014	0.0138	0.012	0.012
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Full time	0.009	0.009	.009	.009
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Weeksp.	0.0003	0.0003	0.0003	0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	-0.012	-0.012	-0.008	-0.008
	(0.0023)	(0.0027)	(0.002)	(0.002)
Log. Income				
year F.E	✓		✓	
stock x year		✓		✓
age polynomial	✓	✓	✓	✓
R^2	0.0266	0.0269	0.0343	0.0345
N	500,018	500,018	499,984	499,984

Notes: Probit Estimation of probability of adjustment. Standard errors in parentheses. Stock:ndur is the ratio of the car stock to non-durables consumption. Age polynomial specification is quartic, only first term is shown

Table A.5: Probability of Purchasing a Car (Avg. Marginal Effects)

Parameter	Value	Source
Uncertainty		
Variance of aggregate shock in high uncertainty state	0.032^2	Bloom et al (2018)
Variance of idio. shock in high uncertainty state	0.202^2	Bayer et al (2019)
Probability of transition to high uncertainty state	0.10	Bloom et al (2018)
Persistence of high uncertainty state	0.79	Bloom et al (2018)
Negative Skew		
Variance of transitory idio. income shock (σ_u^2)	0.186^2	Gueven et al (2014)
Variance of persistent idio. income shock (1) ($\sigma_{\varepsilon,1}^2$)	0.325^2	Gueven et al (2014)
Variance of persistent idio. income shock (2) ($\sigma_{\varepsilon,2}^2$)	0.001^2	Gueven et al (2014)
Mean of persistent idio .income shock (1,boom) ($\mu_{\varepsilon,1}^B$)	0.119	Gueven et al (2014)
Mean of persistent idio .income shock (2,boom) ($\mu_{\varepsilon,2}^B$)	-0.026	Gueven et al (2014)
Mean of persistent idio .income shock (1,recess) ($\mu_{\varepsilon,1}^R$)	-0.102	Gueven et al (2014)
Mean of persistent idio .income shock (2,recess) ($\mu_{\varepsilon,2}^R$)	0.094	Gueven et al (2014)
Probability of persistent idio. state 1	0.49	Gueven et al (2014)
Probability of transition to recession state	0.17	NBER
Persistence of recession state	0.33	NBER

Table A.6: Income parameters for higher order moment models

	% Additional car expenditure			Cost
Variable	July 09-Aug 09	July 09-June 10	July 09-Dec 11	(% Inv. 2008)
Cash for Clunkers	70.3	4.6	-0.2	1.0
No car threshold, same cost	72.6	6.6	0.7	1.0
No car threshold, same share	157.1	14.0	1.4	2.1

Notes: Variable of interest is total car expenditure relative to counterfactual with no Cash for Clunkers policy. No threshold, removes the maximum stock size threshold from eligibility for the discount. Same cost rescales the share of eligibile households to deliver the same program cost, same share retains the same eligibility share as in the calibrated policy.

Table A.7: Cash for Clunker policy experiment

C Online Appendix: additional figures

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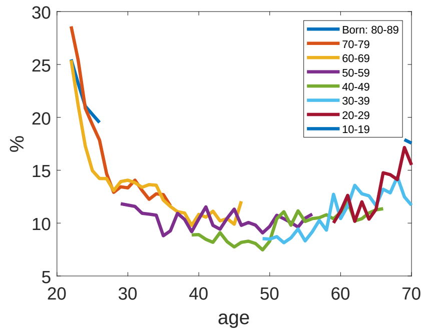
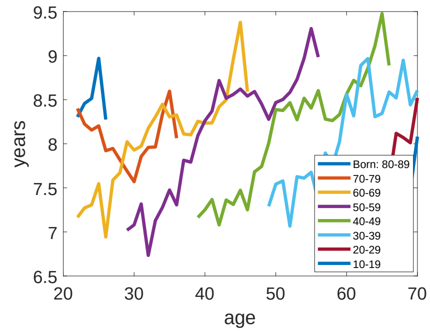
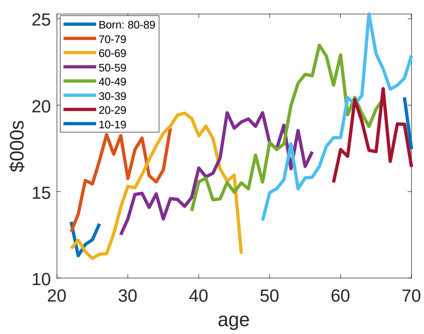


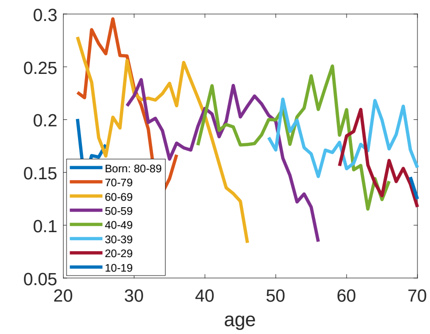
(a) % no car



(b) average car age

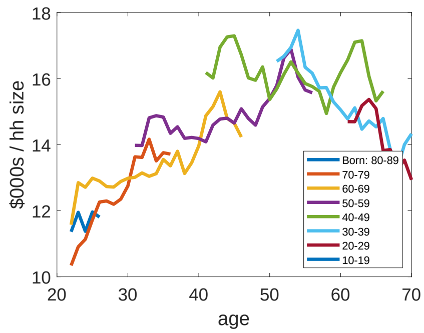


(c) value of purchase

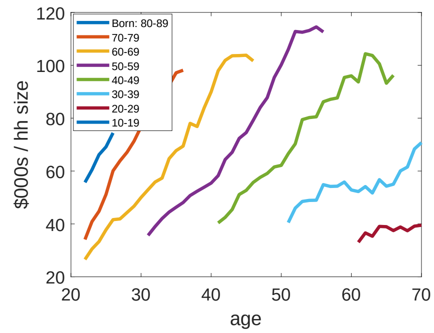


(d) car spend:non durables

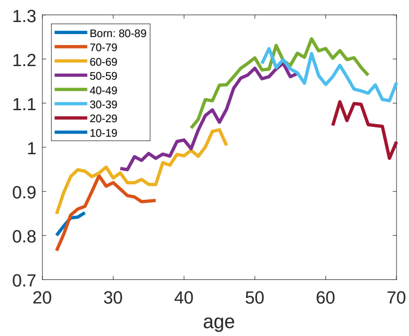
Figure A.1: CEX cohorts: No car, car age and value of purchase



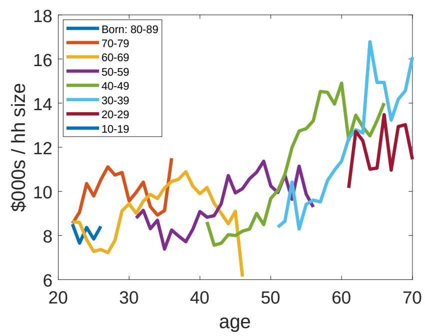
(a) non-durable consumption



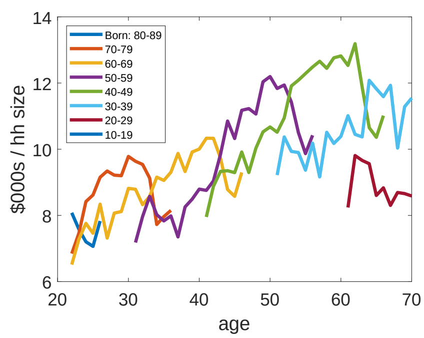
(b) income



(c) number of cars



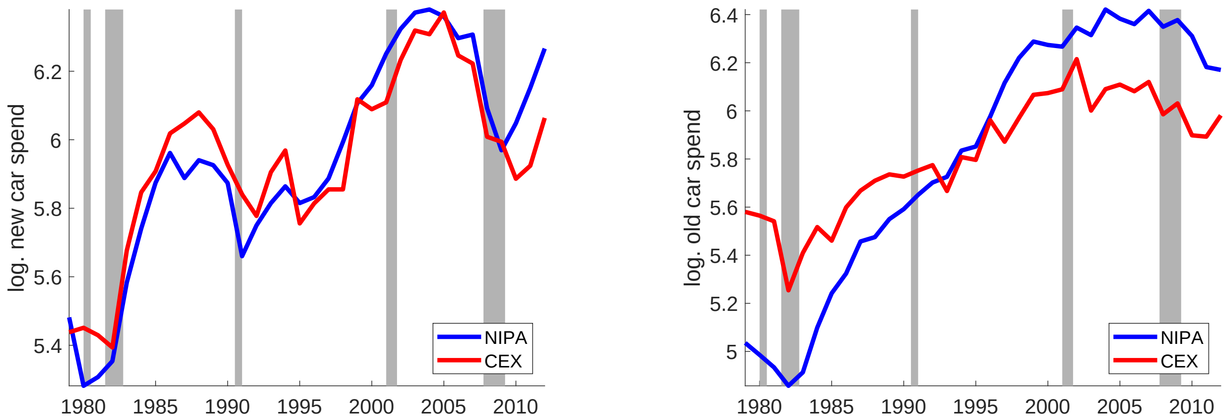
(d) value of purchase



(e) stock

Notes: Each variable is divided by the OECD equivalent scale, which assigns 1 to the first adult, 0.5 to each additional adult and 0.3 to children aged 18 and under.

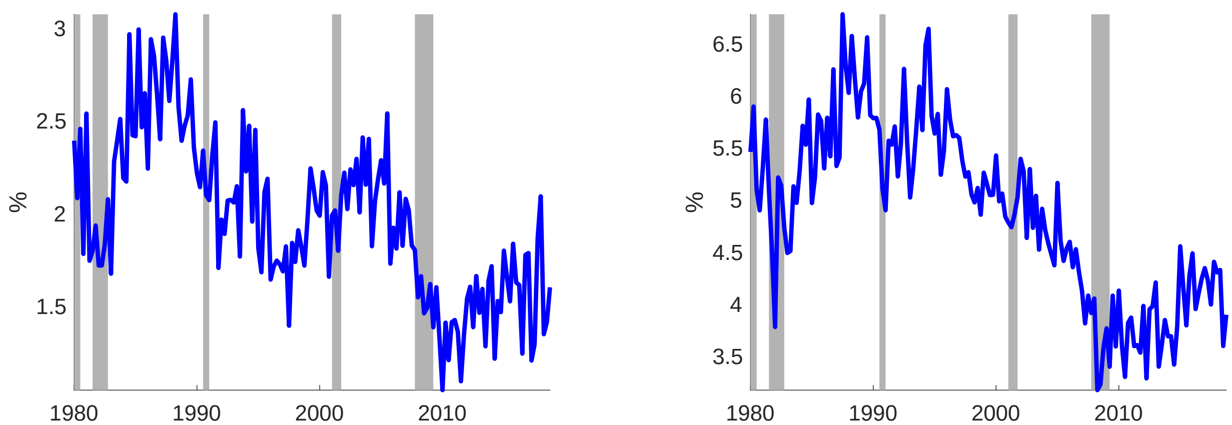
Figure A.2: CEX cohorts: household equivalent measures



(a) new cars

(b) old cars

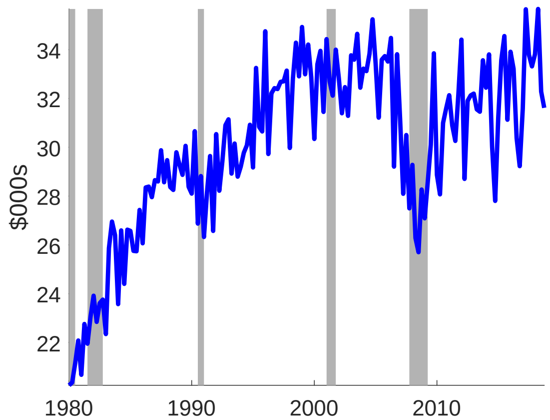
Figure A.3: Comparing NIPA to CEX: new and old cars



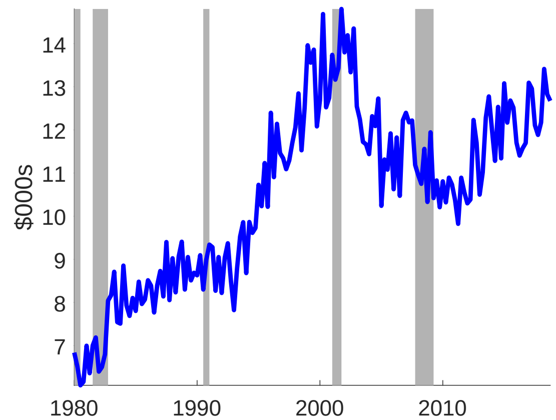
(a) new

(b) used

Figure A.4: Extensive margin time series: % hh purchasing, new and used

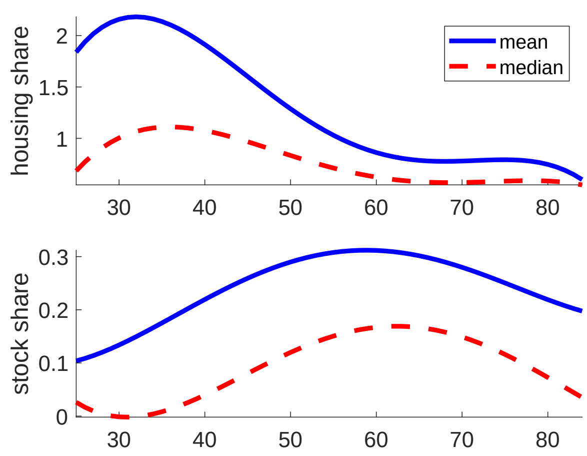


(a) new



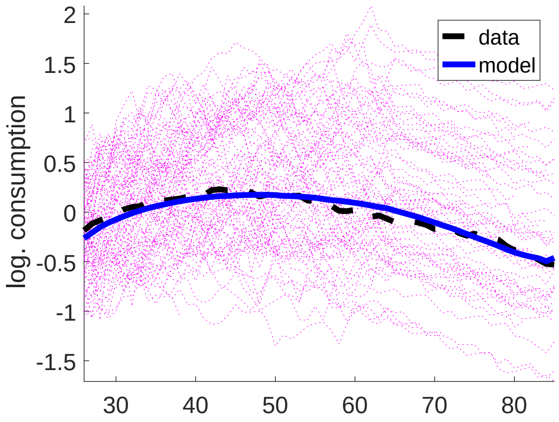
(b) used

Figure A.5: Intensive margin time series: value of purchase, new and used

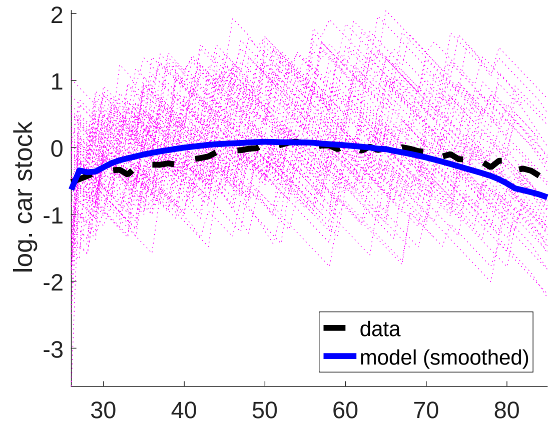


Notes: Estimated from 2004 Survey of Consumer Finance

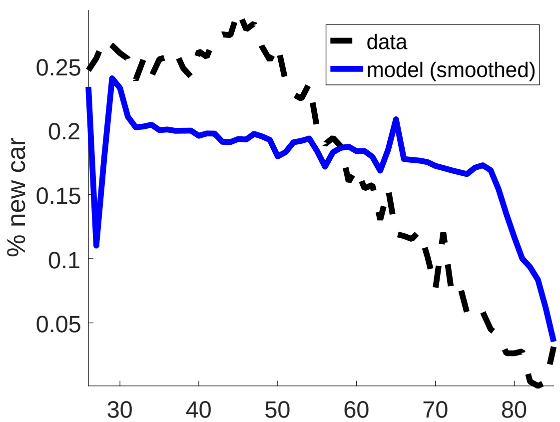
Figure A.6: Lifecycle portfolio shares



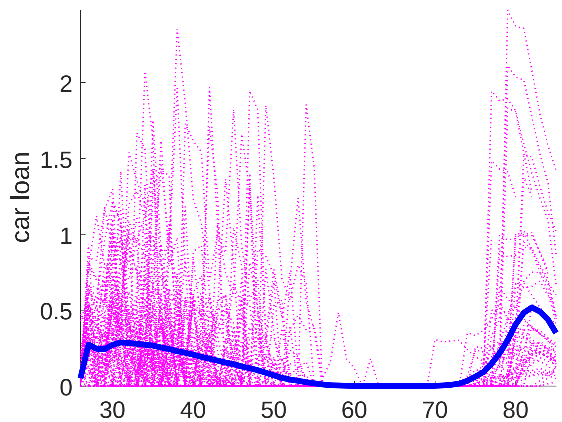
(a) Consumption



(b) Car stock

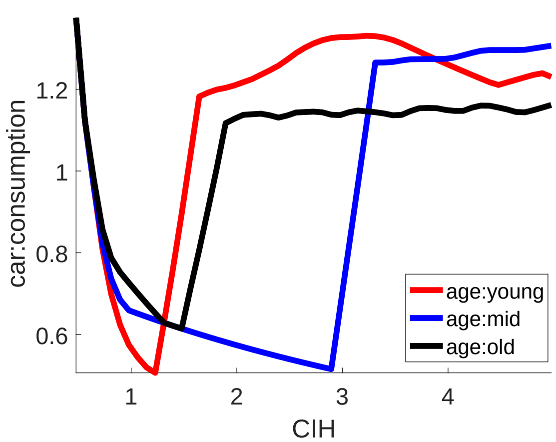


(c) % new car

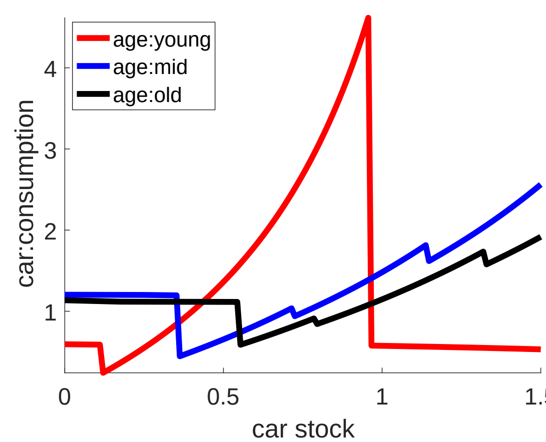


(d) Car loan

Figure A.7: Model life-cycle fit

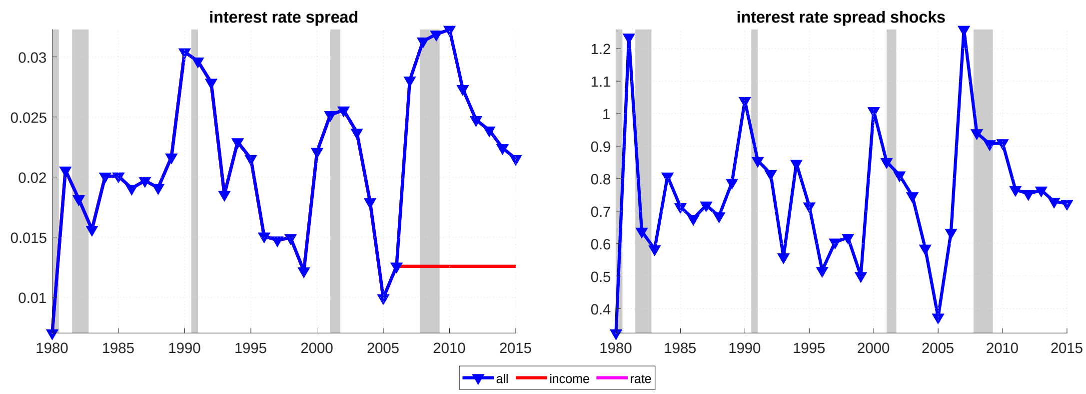


(a) Cash of hand



(b) Car stock

Figure A.8: Model policies: optimal stock:consumption ratio

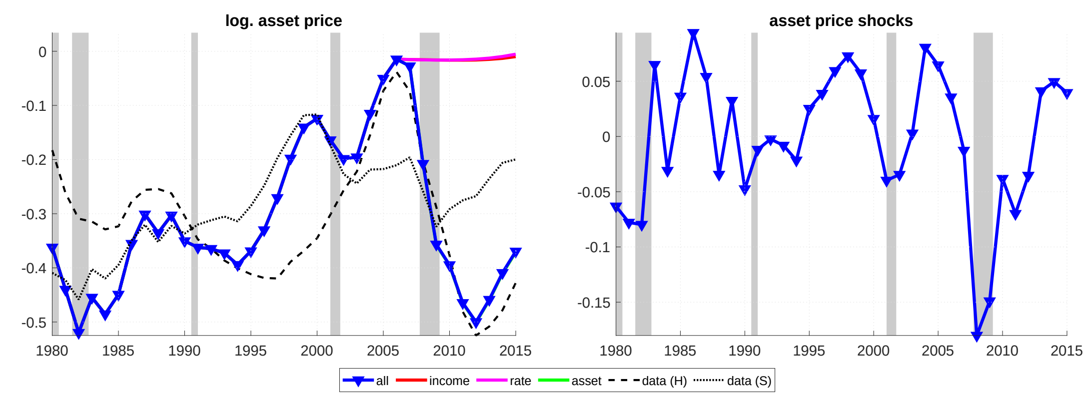


Notes: Estimated from FRB G19 Consumer Credit

Figure A.9: Interest rate spread shock

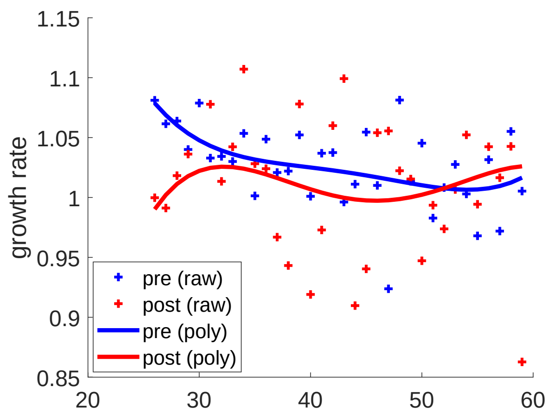
Notes: Data from NIPA

Figure A.10: Interest rate spread shock: consumption and car expenditure

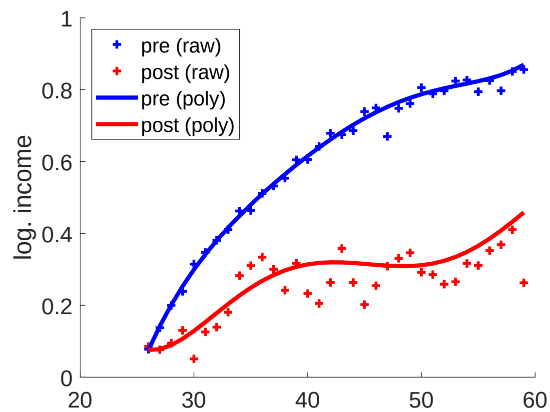


Notes: Data (H): House price data series [FHFA All-Transactions House Price Index], Data (S): Stock price data series [S&P 500]

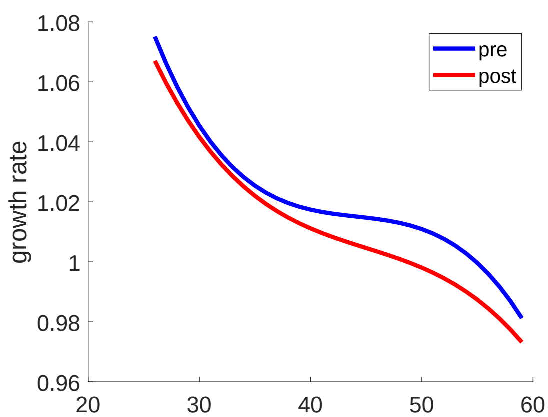
Figure A.11: Asset price shock



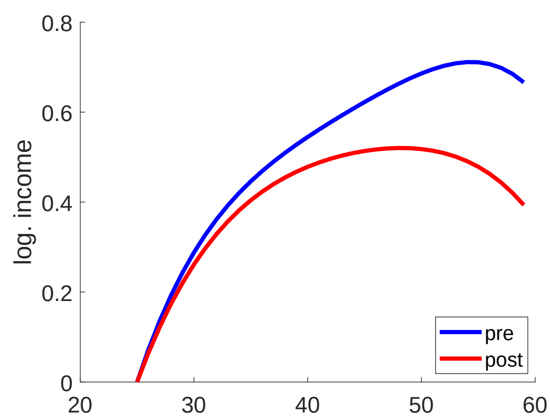
(a) Estimated fall in growth rate



(b) Implied life-cycle

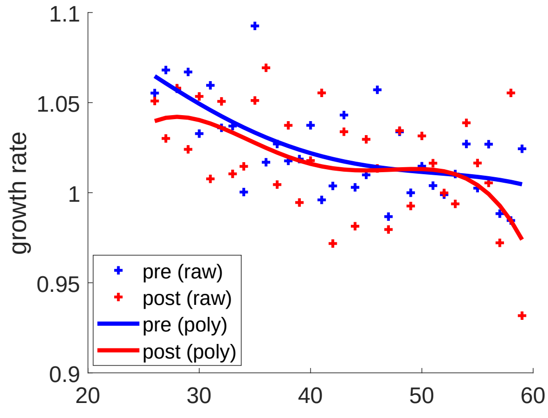


(c) Implied growth rate

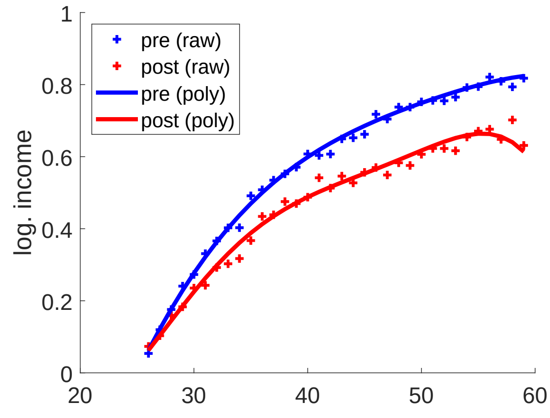


(d) Estimated fall in life-cycle

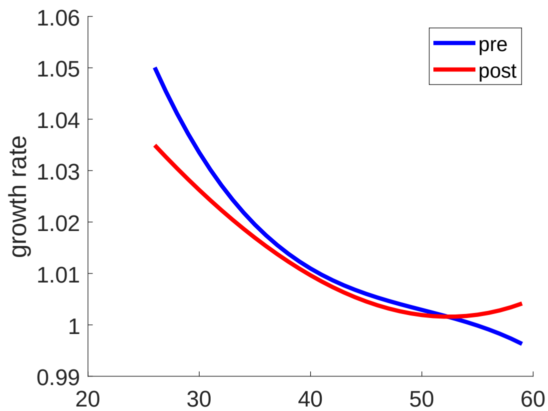
Figure A.12: Evidence supporting decline in life-cycle growth rate (CEX)



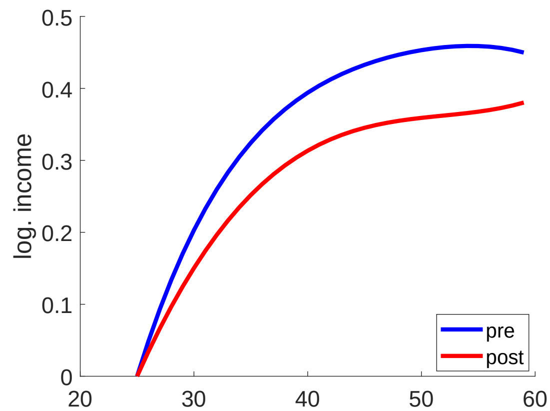
(a) Estimated fall in growth rate



(b) Implied life-cycle



(c) Implied growth rate



(d) Estimated fall in life-cycle

Figure A.13: Evidence supporting decline in life-cycle growth rate (CPS)

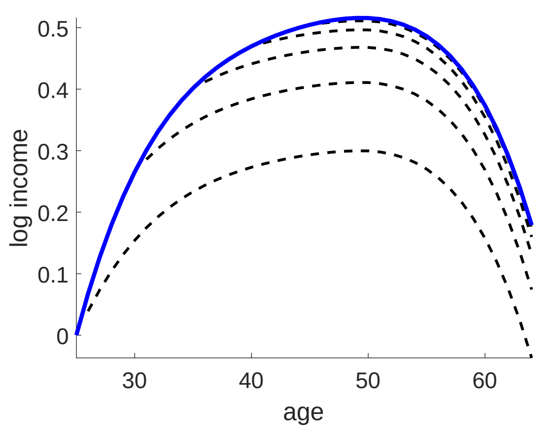
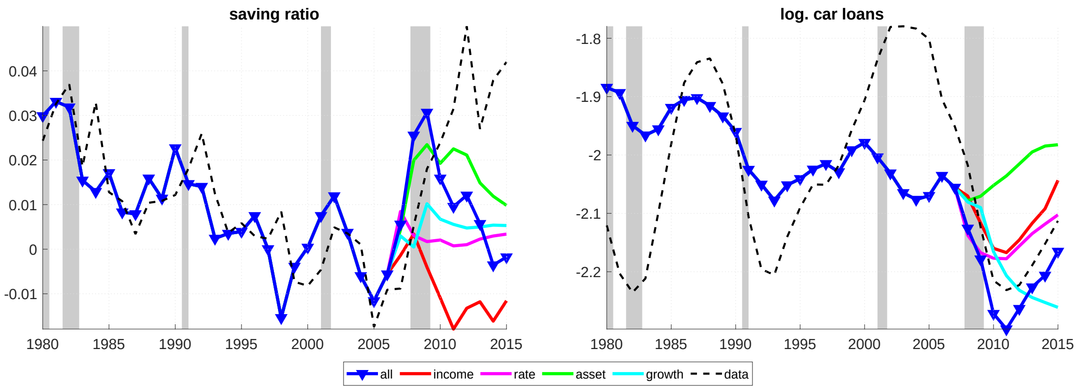


Figure A.14: Growth rate shock: example paths



Notes: Data for savings ratio from NIPA, data for car loans from FRB G19 Consumer Credit

Figure A.15: Growth rate shock: saving and car loans

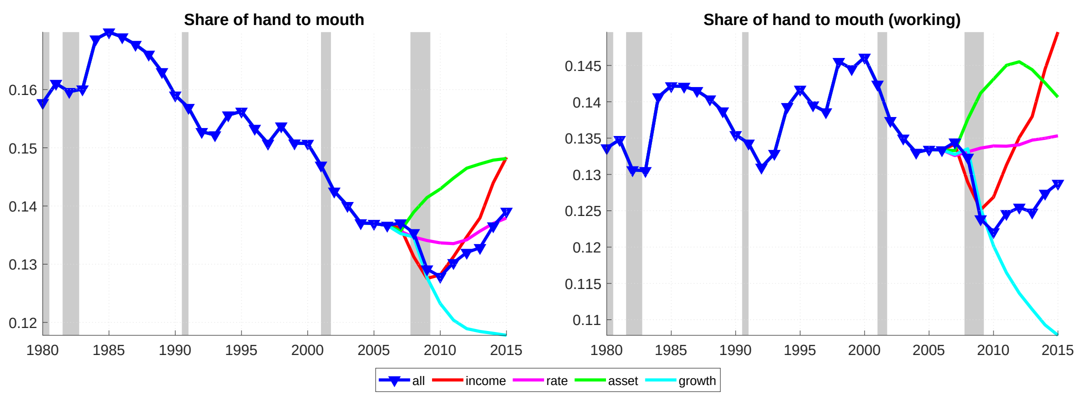
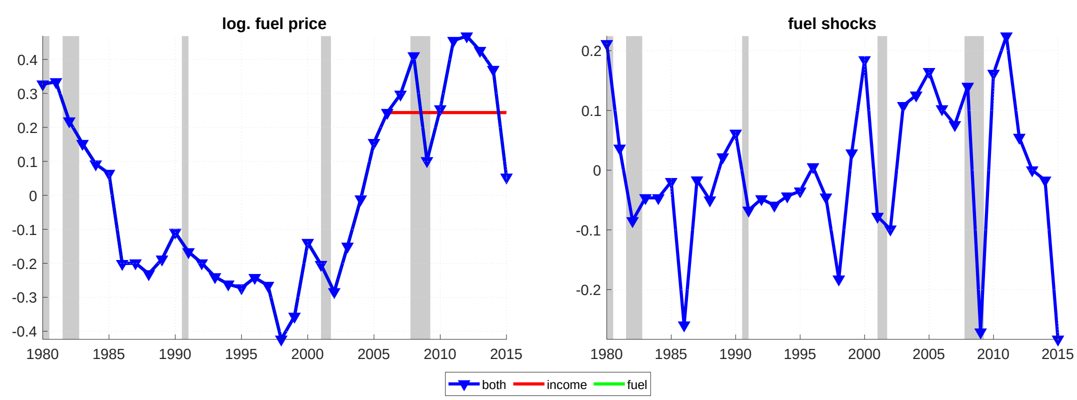
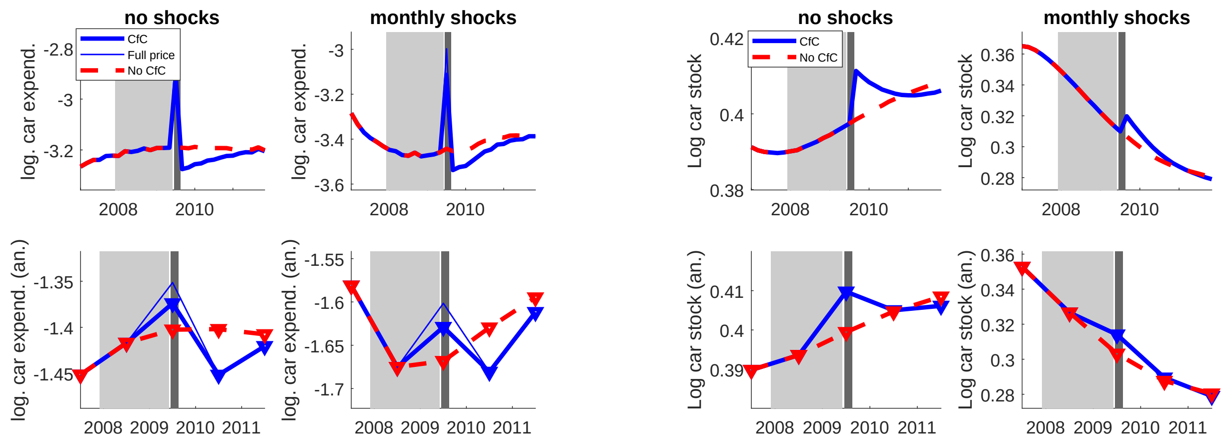


Figure A.16: Growth rate shock: hand to mouth



Notes: Estimated from BLS Consumer Price Indicies, Gasoline price index

Figure A.17: Fuel price shock



(a) car expenditure (b) car stock

Notes: Top row shows the results of the monthly model, the bottom row is the results of the monthly model aggregated on a household basis to yearly averages. The dashed red line is without the policy intervention. The solid thick blue line is with the policy, calculated on a post subsidy household expenditure basis. The thin blue line is with the policy and includes the value of the subsidy. *No shocks* is a model without aggregate shocks, *monthly shocks* is the aggregate shocks from the data averaged across the year.

Figure A.18: Cash for clunkers: car expenditure and stock