

Consumption Dynamics under Time-varying Unemployment Risk*

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Abstract

We study the response of households' demand for durable goods to fluctuations in unemployment risk. Using survey data, we document that household durable expenditures react strongly to unemployment risk, while the effect on nondurable expenditures is indistinguishable from zero. A buffer-stock savings model that includes adjustment frictions for durable goods reproduces this pattern. Using the model, we find that the inclusion of adjustment frictions significantly increases aggregate durable expenditure volatility and produces state-dependent dynamics in response to countercyclical risk fluctuations.

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1 Introduction

With the advent of heterogeneous-agent models for business cycle analysis, a recent literature has emphasized the role of precautionary savings as a key driver of fluctuations in consumption demand: in recessions, idiosyncratic income risk increases (Storesletten et al., 2004, Guvenen et al., 2014), which induces households to reduce nondurable consumption and build a larger buffer stock of liquid assets (McKay, 2016, Challe and Ragot, 2016). Such demand amplification may increase overall business cycle volatility (Ravn and Sterk, 2013, Den Haan et al., 2015) and warrant more aggressive countercyclical fiscal and monetary policy as a response (McKay and Reis, 2016, Kekre, 2016, Berger et al., 2016).

However, the empirical evidence on micro-level consumption behavior in response to income-risk shocks is scarce and, as a consequence, quantitative-theoretic models have rarely been evaluated against such evidence. In this paper, we present new micro-level evidence on the consumption behavior in response to risk shocks, introduce a consumption-savings model which is consistent with this evidence, and analyze its implications for aggregate consumption dynamics and macroeconomic stabilization policy. A distinctive feature of our analysis is that it separates between nondurable and durable goods, in contrast to much of the previous literature studying the aggregate effects of fluctuations in income risk.¹ This distinction is a priori motivated by the empirical observation that durable consumption is adjusted in a lumpy manner, suggesting the presence of non-convex adjustment costs, which may generate “wait-and-see” effects in response to temporarily increased income risk (Bernanke, 1983, Dixit and Pindyck, 1994, Hassler, 1996). Our findings suggest that taking such adjustment costs into account is indeed very important: we find that 1) in the data, the demand response to fluctuations in idiosyncratic unemployment risk is weak for nondurable goods but strong for durables, 2) that this pattern is predicted by an incomplete-markets model in which household face non-convex adjustment frictions and 3) that such adjustment frictions substantially alter aggregate consumption dynamics in response to countercyclical risk fluctuations.

Our analysis starts by documenting expenditure patterns at the micro level. We use the Italian Survey of Household Income and Wealth, a large representative panel survey asking households about nondurable and durable consumption expenditures, income, and asset holdings. We estimate time and household-specific probabilities of transitioning to unemployment and exploit the panel dimension of the data to construct household-level fluctuations in unemployment risk.² We document that durable expenditures react strongly to fluctuations in unemployment risk, with a semi-elasticity around 3, while the semi-elasticity for nondurable

¹Two exceptions are Carroll and Dunn (1997) and Druedahl (2015), both of which investigate the response of durable goods demand to risk shocks using models with incomplete insurance.

²Benito (2006) similarly uses panel data to estimate expenditure responses to unemployment risk. To the best of our knowledge, previous micro-level studies on the relation between expenditures and income risk have only used cross-sectional variation, see Carroll et al. (2003) for nondurable expenditures and Eberly (1994), Foote et al. (2000) and Bertola et al. (2005) for durable expenditures. Without time variation, the effect of level differences in income risk from growth differences in income risk cannot be separated. For durable expenditures, this distinction is particularly important, as the theory predicts that the “wait-and-see” motive to decrease expenditures only arise in response to temporary increases but not to permanent level differences in income risk.

expenditures is small and statistically indistinguishable from 0.

To relate the microeconomic estimates to aggregate consumption dynamics and to perform counterfactual policy experiments, we propose a model of household consumption and saving decisions. Our model extends a standard buffer-stock savings model to include frictions in the adjustment of durable goods, similar to the frameworks of [Grossman and Laroque \(1990\)](#) and [Berger and Vavra \(2014\)](#). The frictions make it costly for households to frequently adjust their stock of durable goods. Households optimally employ an (S,s)-type decision rule where they purchase new durable goods only if their stock falls below a lower threshold in relation to their current income and liquid wealth. When households experience a temporary increase in unemployment risk, the adjustment threshold shifts downwards because 1) with higher unemployment risk, the desired level of consumption in the near future is more uncertain and because 2) this uncertainty will be resolved when the increase in unemployment risk reverts — a “wait-and-see” effect.

We estimate income and unemployment processes from the survey data. Taking these processes as given, we calibrate preference and technology parameters to match unconditional sample moments of the distribution of wealth and durable purchases. We test the quantitative performance of the model by running the same micro-level regressions on model-generated data as on the survey data. Although not targeted in the calibration, the responses of durable and nondurable goods to fluctuations in unemployment risk are close to the empirical estimates.

Having evaluated the model performance at the micro level, we study its macroeconomic implications. We compute, in partial equilibrium, the aggregate impulse-response functions to an increase in the job-separation rate that mimics the Italian experience during the recent Eurozone crisis.³ Compared to the response in a standard model without adjustment frictions the demand response of durable goods to the aggregate job-separation rate shock is amplified by roughly 40 percent. We decompose the total response into an *ex-ante risk channel*, capturing the expenditure response due to the increase in perceived unemployment risk, and an *ex-post income channel*, capturing the expenditure response due to the income losses from the more frequent realizations of unemployment spells. Compared to the response in the frictionless model, the ex-post income channel in the model with adjustment frictions is approximately 30 percent weaker. The amplified total response in the model with adjustment frictions is explained by the ex-ante risk channel, which is approximately 200 percent stronger.

Moreover, with adjustment frictions, the consumption dynamics are state dependent.⁴ We evaluate the responsiveness of aggregate expenditures on durable goods to transitory income shocks, i.e., the “marginal propensity to spend”, as well as to changes in the real interest rate, two key statistics in the transmis-

³We discuss general equilibrium considerations in the concluding remarks.

⁴State dependence in durable expenditure dynamics has also been analyzed recently in [Berger and Vavra \(2014\)](#). Whereas they focus on the dynamics in response to first-moment income shocks, we analyze the dynamics in response to a job-separation shock, which, as we show, primarily affects durable consumption via raising ex ante income risk.

sion of monetary and fiscal transfer policies to consumption.⁵ When unemployment risk increases and the adjustment threshold shifts downwards, more households are further away from the margin of making an adjustment. The demand response to an additional marginal incentive to invest thus falls. Upon entering the recession, the aggregate marginal propensity to spend on durable goods falls by 30 percent and the aggregate responsiveness of durable expenditures to the real interest rate falls by 40 percent. In sum, the presence of adjustment frictions both amplifies the shortfall in demand for durable goods to an increase in perceived unemployment risk and simultaneously decreases the capability of monetary and fiscal transfer policies to compensate this shortfall.

Our analysis proceeds as follows. In Section 2, we estimate semi-elasticities of expenditures to unemployment risk growth using the survey data. In Section 3, we describe the model setup, parametric assumptions and the calibration procedure. In Section 4, we characterize and discuss the decision rules that households employ in the model. In Section 5, we test the model by repeating the regressions from Section 2 on model-generated data. In Section 6, we study the macroeconomic implications. Section 7 concludes the paper.

2 Evidence from survey data

In this section, we document expenditure patterns, for both nondurable and durable goods, using the Italian Household Survey of Income and Wealth (SHIW). In particular, we estimate the responses of durable and nondurable expenditure to fluctuations in unemployment risk.

2.1 Data description

The SHIW is administered by the Bank of Italy and surveys a representative sample of Italian households since the 1960s.⁶ The survey has grown in scope and sample size over time; in recent years approximately 8,000 households are interviewed in each wave. About half of the sample has been interviewed in previous surveys, with gradual replacement over time. To be able to include all relevant variables with consistent definitions, we will use data starting with the 1998 wave; since then the survey has been conducted biennially.

The data contain information on households' consumption expenditures, with separate questions for purchases and sales of *Motor vehicles* and *Furniture, household appliances and similar items*. The survey also asks households to estimate their current wealth of possessed items in these categories. In addition, the

⁵The response of expenditures to changes in the real interest rate is the standard transmission channel of monetary policy to consumption in new Keynesian models (see, e.g., [Erceg and Levin \(2006\)](#) for a workhorse representative-agent model with durable goods). The marginal propensity to spend directly identifies the consumption response to fiscal transfers in partial equilibrium. In addition, the marginal propensity to spend captures the consumption response to the additional indirect income effects that monetary policy may generate in general equilibrium, as recently emphasized in [Kaplan et al. \(2016\)](#).

⁶The SHIW data have previously been used for documenting expenditure patterns in, e.g., [Bertola et al. \(2005\)](#), [Jappelli and Pistaferri \(2014\)](#) and [Auclert \(2015\)](#).

survey contains detailed information on income, wealth decomposed into several categories, and a rich set of household characteristics.

Information regarding state variables, such as wealth and several characteristics (such as age), refers to that state at the end of the year. Information regarding flow variables, such as consumption expenditures and income, refers to the sum of the flow over the year. A detailed description of all variables used, more information on survey design and data quality and a comparison to other survey data sets are located in Appendix A.

2.2 Sample selection

The raw data from the survey waves from 1998-2014 have 71,173 household observations. To estimate the effect of future unemployment risk on current expenditure growth, we require that households are surveyed in three consecutive waves which leaves us with 19,825 observations.

Consumption expenditure is measured at the household level. For variables measured at the individual level, such as unemployment risk, we focus on the household head. We define the household head as the individual in the household with the highest income, both from labor and financial earnings. We require that the household head is aged 25-60, currently employed, and part of the labor force (employed or unemployed) in the next wave, bringing down the sample to 5,960 observations.

To ensure that an unemployment spell is a meaningful income loss for the household, we restrict the sample to households where the household head has labor earnings that are at least 40 percent of the total household income, leaving us with 4,574 observations. In Appendix B, we check whether our results are robust to changing this cutoff value.

2.3 Econometric framework

We seek to identify the expenditure response to fluctuations in unemployment risk, both in terms of durable and nondurable goods. Since durable purchases are lumpy and since the wait-and-see effect operates on the extensive margin, we will estimate a probit model of the probability of a durable purchase on the growth of unemployment risk. Let DP_{it} be an indicator variable that takes the value of 1 if a durable good has been purchased in year t , denote the probability of being unemployed in year $t + 2$ by $Urisk_{it}$ and define the Δ -operator by $\Delta X_t = X_t - X_{t-2}$ for any variable X (recall that the SHIW surveys households at a biennial frequency). We estimate

$$P(DP_{it} = 1) = \Phi(\beta\Delta Urisk_{it} + \beta_x \mathbf{X}_{it}), \tag{1}$$

where $\Phi()$ is a cumulative normal distribution, and \mathbf{X}_{it} is a collection of relevant covariates.

For nondurables, expenditures are always positive, and we can estimate the effect of unemployment risk growth on log expenditure growth Δc_t in a standard OLS specification:

$$\Delta c_t = \alpha_0 + \alpha \Delta U_{\text{risk}_{it}} + \alpha_x \mathbf{X}_{it} + \epsilon_t. \quad (2)$$

The collection of covariates \mathbf{X}_{it} can be separated into two: $\mathbf{X}_{it} = [\mathbf{X}_{1it}, \mathbf{X}_{2it}]$. The collection \mathbf{X}_{1it} contains variables that we would expect to influence the household purchase decision of durable and nondurable consumption goods within a buffer-stock model featuring adjustment frictions for durable goods. \mathbf{X}_{1it} includes log income growth $\Delta \log Y_t$, quartile bins of the household's stock of wealth in durable goods D_{it} (excluding net purchases in year t), as well as net financial and total net assets FA_{it-2} , A_{it-2} . All stock variables are normalized by the previous period income Y_{it-2} . We condition on financial and total wealth measured in year $t - 2$ to ensure that they are predetermined to the consumption decisions made in year t . \mathbf{X}_{1it} also includes the previous period level of log income $\log Y_{t-2}$, since the level and growth of income are likely to be correlated.

The second collection \mathbf{X}_{2it} contains control variables that are part of the identification strategy, discussed in the next subsection.

2.4 Identification of unemployment risk

To retrieve a measure of unemployment risk, we condition the probability of being unemployed in year $t + 2$ on characteristics observed at time t . Specifically, the baseline strategy is to estimate a probit model for each year in the sample,

$$P(U_{it+2} = 1) = \Phi(\beta_t \mathbf{Z}_{it}), \quad (3)$$

where U_{it+2} is an indicator that takes the value of 1 if the household head is unemployed in year $t + 2$ and 0 otherwise, and \mathbf{Z}_{it} is a vector of covariates.

The covariates in \mathbf{Z}_{it} are chosen to partition the labor market into fairly narrow categories, which are subject to idiosyncratic shocks and/or common shocks with category-specific treatment intensity. The variables in \mathbf{Z}_{it} are occupation, industry of employment, superregion of residence (north, center and south/islands), region of residence (the 20 administrative regions of Italy), bins of population size of the town area in which the household resides, education level, five-year age bins, sex, marital status and household size. Basic job characteristics, such as industry or region, are plausible sources of idiosyncratic demand shocks. In addition, basic household characteristics, such as age and household size, are plausible determinants of selection into unemployment.

We do not directly regress the employment status on \mathbf{Z}_{it} . Instead, we retrieve factors \mathbf{F}_t from the

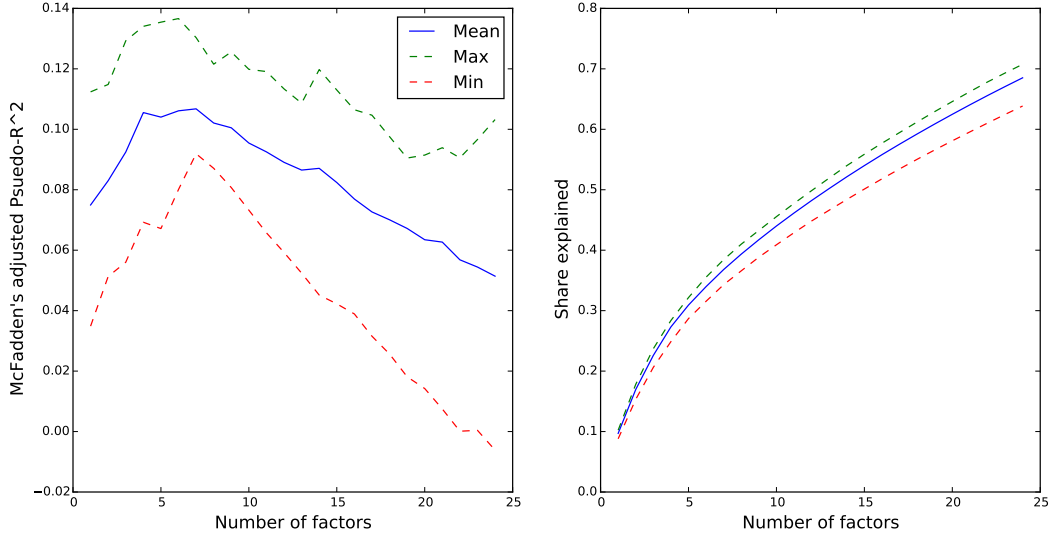


Figure 1: To the left: The mean, min and max of the explanatory power when estimating (4) for each year in the sample, as a function of the number of factors used. To the right: The mean, min and max of the share of the variation in the underlying covariates that is explained by the factors for each year in the sample, as a function of the number of factors used.

covariates \mathbf{Z}_{it} and use the associated factor projections \mathbf{f}_{it} for the estimation of unemployment risk:

$$P(U_{it+2} = 1) = \Phi(\beta_t \mathbf{f}_{it}). \quad (4)$$

The motivation for this approach is that the yearly samples contain 381 observations on average, while the total number of categories formed by the set \mathbf{Z}_{it} is 88. If we directly regress employment status on \mathbf{Z}_{it} , we will likely overfit the data. By regressing on the factor projections, we reduce the dimensionality while simultaneously keeping as much of the variation in the underlying independent variables as possible.

We retrieve the factors by multiple correspondence analysis, which is analogous to principal component analysis but adapted to suit categorical variables (Greenacre, 2007). In the choice of the number of factors used, there is a tension between how much of the variation in the underlying covariates the factors explain and explanatory power when using the factors for estimating (4). Figure 1 shows how McFadden’s adjusted R^2 from estimating (4) and the share of the variation in the underlying covariates that the factors explain vary with the number of factors used. As a baseline, we choose the number of factors that maximizes the mean of McFadden’s adjusted R^2 from the regressions, which gives us 6 factors. However, the marginal contribution of adding additional factors to the explained variation in the underlying covariates is still substantial at this level. As a robustness check, we therefore re-estimate our model using up to 12 factors as well.

Since we retrieve the factors for each year separately, the factor loadings are year specific. However, the first factor almost always loads heavily on sex, marital status and household size variables. The second factor almost always loads heavily on education, industry and occupation variables. For some years, both the first and second factor also load heavily on the 1-digit superregion indicators. The third factor almost exclusively loads heavily on the 1-digit superregion and 2-digit region indicators.

Having estimated individual-specific unemployment risk for all years in the sample, we recover the growth of unemployment risk by taking the first difference:

$$\Delta\text{Urisk}_{it} = P(\text{U}_{it+2} = 1|\mathbf{f}_{it}) - P(\text{U}_{it} = 1|\mathbf{f}_{it-2}). \quad (5)$$

Descriptive statistics of the distribution of Urisk_{it} and ΔUrisk_{it} are shown in Table 1.

The variation in ΔUrisk_{it} derives from two sources. First, household characteristics may change between any two waves in the sample. For example, which age bin the household head belongs to will mechanically change for some households in the sample. More importantly, the same set of covariates can predict a different unemployment rate in year t than in year $t - 2$, creating variation in ΔUrisk_{it} while holding the household characteristics constant. For example, if there is a regional-industry specific adverse demand shock in year t that raises the unemployment rate in that region-industry in year $t + 2$, households belonging to that region and industry will experience a higher unemployment risk in year t than they did in year $t - 2$.

Can ΔUrisk_{it} be treated as exogenous in (1) and (2)? The variation in Urisk_{it} derives from the variation in region of residence, occupation and industry of employment and basic household characteristics. These variables are most likely pre-determined to household consumption decisions made in year t . In addition, the effect of constant household unobservable characteristics, such as preferences, are filtered out by first-differencing Urisk_{it} .

Still, there are a number of potential threats to identification. At the microeconomic level, an increase in ΔUrisk_{it} could affect the consumption decision through a tightened credit constraint, as financial institutions are likely to be less inclined to lend to a household with worse employment prospects. To control for this indirect feedback mechanism, \mathbf{X}_{2it} also includes a dummy variable that indicates whether the household has faced a binding credit constraint. The dummy variable takes the value of 1 if the household has been denied or discouraged from applying for credit in year t .⁷ Second, it is likely that the level and growth of unemployment risk are correlated. Therefore, \mathbf{X}_{2it} includes the same variables used to predict Urisk_{it} .⁸

At the macroeconomic level, if a significant share of ΔUrisk_{it} arises from aggregate business cycle shocks, ΔUrisk_{it} may be correlated with changes in prices, in particular the interest rate and the relative price of

⁷We define a household to be discouraged when the interviewee has answered that someone in the household has thought about applying for credit, but later changed his/her mind in anticipation that the application would be denied.

⁸This is not strictly true. The regions and superregions are perfectly collinear, and therefore we only include the regions in \mathbf{X}_{2it} .

durables, which have a separate effect on consumption decisions. To control for such general equilibrium feedback, our set of control variables \mathbf{X}_{2it} includes time fixed effects. Local variation in the relative price for durables is more difficult to control for as time-region fixed effects would absorb a significant amount of the variation in ΔUrisk_{it} . However, an adverse shock that disproportionately reduces the demand for durables should lead to a decline in their relative price. Our estimates for the effect of unemployment risk on the expenditure on durables (nondurables) should in that case be interpreted as lower (upper) bounds of the true partial equilibrium effects. Another potential concern is that the variation in unemployment risk stems for local wealth shocks (e.g. house price shocks), which also have a separate effect on consumption decisions. This concern, however, is mitigated by the inclusion of total net wealth in the set of basic controls \mathbf{X}_{1it} .

2.5 Measurement

We consider two types of durable goods: *Motor vehicles* and *Furniture, household appliances and similar items*, hereafter referred to as *Furniture*. We define a purchase in any of these two categories in year t as net expenditures that exceed one half of the sample mean of a week’s income in year t . We define a purchase of total durable goods as a purchase in either category (or both). Expenditures on nondurable goods are defined as total consumption expenditures less of expenditures on durable goods, jewelry and housing rents (imputed and actual).

We define households’ net financial assets as their financial assets net of debt owed to other households and debt for purchases of consumption goods, thus not including mortgage debt. The measure of financial assets includes all holdings in bank and deposit accounts as well as all directly held stocks, bonds and other financial instruments. We define total net assets as the sum of all assets and liabilities, including housing wealth.

The employment status of a household head in a year is defined as the employment status held for most part of that year. We show descriptive statistics of all economic variables used and some basic characteristics in Table 1.

2.6 Results

Table 2 shows the results from estimating (1) and (2). As our measure of unemployment risk is a generated regressor, the standard errors are bootstrapped.

In the first two columns of Table 2, we show the estimated effect on the probability of having purchased a durable good that results from estimating equation (1), with and without the inclusion of control variables. The coefficients show the average marginal effect, normalized by the unconditional purchase probability, and should thus be interpreted as the aggregate marginal effect on the number of purchases if all households in the sample are subject to a one-unit change in the corresponding independent variable. In particular, the

	Value/Mean	Std. Deviation	Minimum	Maximum
Share Males	0.81	.	.	.
Age	45.86	7.46	25.0	60.0
Share with Durable Purchase	0.41	.	.	.
Share with Vehicle Purchase	0.14	.	.	.
Share with Furniture Purchase	0.32	.	.	.
Nondurable Consumption/Income	0.57	0.23	0.07	4.26
Total Net Assets/Income	4.52	4.29	-3.51	40.22
Net Financial Assets/Income	0.43	0.89	-3.16	34.12
Unemployment risk	0.03	0.04	0.0	0.36
Unemployment risk growth	0.0	0.02	-0.2	0.22
Share denied/discouraged credit applicants	0.04	.	.	.

Table 1: Descriptive statistics of the sample used for the final regressions.

	Durables I	Durables II	Vehicles I	Vehicles II	Furniture I	Furniture II	Nondurables I	Nondurables II
Δ Unemployment risk _t	-3.24*** (0.65)	-2.54*** (0.69)	-3.2** (1.4)	-3.32** (1.59)	-3.32*** (0.76)	-2.51*** (0.81)	-0.27 (0.21)	-0.3 (0.23)
$\Delta \log Y_t$	0.61*** (0.07)	0.64*** (0.07)	1.1*** (0.15)	1.06*** (0.17)	0.5*** (0.08)	0.54*** (0.08)	0.38*** (0.03)	0.36*** (0.03)
D_t/Y_{t-2} , quartile 2	-0.2*** (0.05)	-0.22*** (0.05)	-1.2*** (0.11)	-1.27*** (0.1)	-0.16** (0.07)	-0.19*** (0.07)	0.02 (0.02)	0.02 (0.02)
D_t/Y_{t-2} , quartile 3	-0.21*** (0.06)	-0.25*** (0.06)	-1.33*** (0.12)	-1.39*** (0.12)	-0.07 (0.08)	-0.12 (0.07)	0.04** (0.02)	0.05*** (0.02)
D_t/Y_{t-2} , quartile 4	-0.18*** (0.06)	-0.24*** (0.06)	-1.53*** (0.12)	-1.65*** (0.13)	-0.08 (0.08)	-0.14* (0.08)	0.02 (0.02)	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 2	0.0 (0.05)	-0.03 (0.05)	0.12 (0.11)	0.1 (0.11)	-0.03 (0.07)	-0.06 (0.07)	-0.01 (0.02)	-0.01 (0.02)
FA_{t-2}/Y_{t-2} , quartile 3	0.13** (0.06)	0.1* (0.06)	0.17 (0.11)	0.15 (0.11)	0.14* (0.07)	0.1 (0.07)	0.01 (0.02)	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 4	0.16*** (0.06)	0.11* (0.06)	0.15 (0.12)	0.14 (0.13)	0.19** (0.08)	0.13 (0.08)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 2	0.0 (0.06)	-0.03 (0.06)	0.03 (0.12)	0.02 (0.12)	-0.03 (0.07)	-0.08 (0.07)	-0.01 (0.12)	-0.0 (0.2)
A_{t-2}/Y_{t-2} , quartile 3	-0.08 (0.06)	-0.1 (0.06)	-0.14 (0.12)	-0.15 (0.12)	-0.09 (0.08)	-0.1 (0.08)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 4	-0.11* (0.06)	-0.08 (0.06)	-0.18 (0.12)	-0.2 (0.13)	-0.12 (0.08)	-0.09 (0.08)	-0.01 (0.02)	-0.0 (0.02)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R ²	0.06	0.09	0.14	0.18	0.05	0.09	0.32	0.33
N	4574	4574	4574	4574	4574	4574	4574	4574

Table 2: Regression results from estimating (1) and (2). For the first six columns, the left-hand side variable is an indicator of whether a durable good in the category indicated by the column header has been purchased in the last 12 months. The coefficients show the average marginal effect normalized by the unconditional purchase probability, estimated with a probit model. D_t refers to the stock of durable goods in this durable good category, prior to any purchase in year t . In the last two columns, the left-hand side variable is the log growth of expenditures on nondurable goods, estimated by OLS. D_t is defined as in columns 1 and 2. The set of control variables includes indicator variables of 5-year age bins, sex, marital status, household size, education level, occupation, industry, region of residence, bins of the size of the town of residence, an indicator of a binding liquidity constraint as well as the log level of previous period income. Bootstrapped standard errors are shown in parenthesis. The bootstrap procedure computes the factors used for extracting unemployment risk based on the bootstrap sample, and reestimates unemployment risk using the bootstrap factors and the bootstrap sample. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.

coefficient for unemployment risk growth is the semi-elasticity of durable purchases to unemployment risk growth.

Our preferred specification is column 2, since the inclusion of the control variables indirectly control for the estimated level of unemployment risk. For this specification, a 1 percentage point increase in unemployment risk growth for all households is associated with an estimated fall of aggregate durable purchases by 2.5 percent. A 1 percent increase in income growth for all households is associated with a 0.6 percent increase in the number of durable purchases. Having a larger normalized stock of durable goods is associated with a smaller probability of a durable purchase. Having a larger normalized stock of net financial assets is associated with a larger probability of a durable purchase. There is no effect of total net assets.

Columns 3/4 and 5/6 show the regression results when we estimate Equation (1) for the two durable goods categories separately. The semi-elasticities of vehicle and furniture purchases to unemployment risk growth are 3.3 and 2.5, respectively. However, both effects are less precisely estimated, leaving the effect significant only at the 5 percent level for vehicle purchases. The loss of power is not surprising given that only 14 (32) percent of the sample have made a vehicle (furniture) purchase during the last 12 months, while the corresponding number is 41 percent if adding the two goods categories together. Overall, the coefficients for the other variables look similar. The most notable differences are the stronger effect of income growth and the steeper gradient in the stock of durable goods for the vehicles regression.

In the last two columns, we show the average marginal effect on the log of nondurable expenditure growth that results from estimating Equation (2). Here, the estimation is in OLS and the numbers are straightforwardly interpreted. A 1 percent increase in unemployment risk for all households in the sample is associated with a fall of nondurable expenditures by 0.3 percent, but we cannot distinguish the effect from zero. The effect of higher unemployment risk is clearly lower for nondurable goods than for durables. There is no effect from the durable wealth quintiles. The sole variable that has a large and significant impact on nondurable expenditure growth is income growth, with an estimated elasticity of 0.36.

In Appendix B, we address two remaining potential endogeneity concerns. First, with the variation in unemployment risk being driven by shocks at the industry/regional/education/occupation level, it is possible that unemployment risk correlates with expected future wage growth. Therefore, we control for future income growth. Second, we infer the probability of becoming unemployed from households that actually become unemployed. However, it could be the case that households that become unemployed know well in advance whether they will keep their employment or not and hence, that the employment status in period $t + 2$ does not have a meaningful stochastic component, but only masks individual private information. To address this, we restrict the sample to households that remain employed in period $t + 2$. Our results are not affected by either change in the specification. We also show that our results are robust to using any number between 4 and 12 factors in the estimation of unemployment probabilities and varying the income cutoff in the sample

selection.

3 Model

In this section, we propose a model that we will use to study aggregate consumption dynamics in Section 6. Before introducing aggregate risk, we will test the model performance at the micro level in Section 5 by repeating the regression analysis from Section 2 on model-generated data.

Our model extends a standard buffer-stock model (see, e.g., Carroll (1997)) to separate between non-durable and durable consumption goods with adjustment frictions for the durable good. Since the focus of the paper is the expenditure response to fluctuations in unemployment risk, the household's income process features time-varying unemployment risk.

We first describe the general formulation of the household optimization problem. Then, we specify and estimate the household income and unemployment processes. Finally, we calibrate the remaining parameters to match sample moments of the wealth and durable purchase distributions from the SHIW micro data used in Section 2.

3.1 The household problem

Time is infinite and discrete, each period corresponding to a quarter. The economy is populated by a continuum of households on the unit interval. All households are ex ante identical and face identical stochastic processes.

Preferences. Households have time-additive homothetic preferences over the consumption of nondurable goods C_{it} and the consumption of durable goods D_{it} . They have a subjective discount factor $\hat{\beta}$. To maintain a stationary income distribution (discussed below), households die with probability ω . The effective discount factor is thus $\beta = (1 - \omega)\hat{\beta}$.

Prices and technology. Households can purchase nondurable and durable goods at a unitary relative price and invest in a risk free liquid asset B_{it} at a price q .⁹ The durable good depreciates by δ each period.

Income process. In each period t , households receive income Y_{it} that depends on their employment status n_{it} and their earnings potential Y_{it} . Y_{it} is a continuous variable while n_{it} takes the value of 0 if the household is unemployed and 1 if the household is employed. The earnings potential Y_{it} and the employment status n_{it} are subject to several shock processes specified below.

⁹Under homothetic preferences, a constant relative price different from unity would only linearly rescale the decision functions.

Market frictions. Households face two market frictions. First, adjusting the durable stock is associated with an adjustment cost $A(D_{it}, D_{it-1})$. If not adjusting, households face no cost. Second, households cannot borrow more than a fraction χ of the pledgable part of their next period stock of durable goods $[(1 - \delta)D_{it} - A(0, D_{it})]$.

Formally, each household solves the problem

$$\max_{\{C_{it}, D_{it}, B_{it}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t u(C_{it}, D_{it})$$

$$\text{s.t.} \quad C_{it} + D_{it} + qB_{it} \leq Y_{it} + (1 - \delta)D_{it-1} + B_{it-1} - A(D_{it}, D_{it-1}), \quad (6)$$

$$B_{it} \geq -\chi [(1 - \delta)D_{it} - A(0, D_{it})], \quad (7)$$

$$C_{it}, D_{it} \geq 0, \quad (8)$$

and also subject to the laws of motion for Y_{it} and n_{it} .

Adjustment cost specification. We follow [Grossman and Laroque \(1990\)](#) and assume that, conditional on adjusting, the adjustment cost $A(D_{it}, D_{it-1})$ is linear in the stock of durable goods prior to the adjustment decision and zero otherwise:

$$A(D_{it}, D_{it-1}) = \begin{cases} 0 & \text{if } D_{it} = (1 - \delta)D_{it-1}, \\ hD_{it-1} & \text{if } D_{it} \neq (1 - \delta)D_{it-1}. \end{cases} \quad (9)$$

When households readjust, they can only recover a fraction of the value of their previous investments into their durable stock, making previous investments into the durable stock *partially irreversible*. For durables, the main sources of partial irreversibility are likely to be their illiquidity and the prevalence of rebate prices in the market for used goods.¹⁰ h can be interpreted as the average resale loss when selling the replaced stock D_{it-1} in the second hand market. With this interpretation of the adjustment cost, D_{it} should be interpreted as the stock of a “typical” durable good and not the total stock composed of different durable goods. We do not expect households to sell off their current stock of furniture when they purchase a new car, and vice versa. This interpretation is important when we choose the moments to which we calibrate our model, as described in Section 3.3.

There are other frictions in the household’s adjustment of the stock of durables, which are less well described by the assumption of a linear adjustment cost. For example, car buyers in Italy need to pay a flat fee to the Public Automobile Registry. The buyer’s fee is independent of the value of the car or any other characteristics of the household, and is better described as a fixed cost. The time spent purchasing a

¹⁰Such equilibria could be explained by, e.g., asymmetric information ([Akerlof, 1970](#)). In this paper, we are silent on the exact microeconomic source of these frictions, and focus on their implications for consumption behavior.

durable good is better modeled as a cost proportional to labor income. Although we cannot test it directly, our best guess is that such costs are small in relation to the resale loss, especially for large durable goods such as motor vehicles and large furniture.

3.2 The recursive household problem

We collect all exogenous state variables in \mathcal{S} and impose that these follow a Markov process. The household optimization problem then has a recursive representation. Denote the ingoing values of the durable stock, prior to depreciation, by D and the ingoing value of the liquid asset stock by B . Denote the choice of nondurable consumption, durables and liquid assets by C, D' and B' . Define $V_{NA}(\cdot)$ as the value function conditional on not adjusting the stock of durables, $V_A(\cdot)$ as the value function conditional on adjusting the stock of durables and the collateral requirement $\hat{\chi} \equiv \chi(1 - \delta - h)$. The recursive representation is then

$$\begin{aligned} V_{NA}(B, D; \mathcal{S}) = & \max_{C, B'} u(C, D') + \beta EV(B', D'; \mathcal{S}') & (10) \\ \text{s.t.} & D' = (1 - \delta)D, \\ & C + qB' \leq \Upsilon(Y_s, n_s) + B, \\ & B' \geq -\hat{\chi}D', \\ & C \geq 0, \end{aligned}$$

$$\begin{aligned} V_A(B, D; \mathcal{S}) = & \max_{C, B', D'} u(C, D') + \beta EV(B', D'; \mathcal{S}') & (11) \\ \text{s.t.} & C + qB' + D' \leq \Upsilon(Y_s, n_s) + (1 - \delta - h)D + B, \\ & B' \geq -\hat{\chi}D', \\ & C, D' \geq 0, \end{aligned}$$

$$V(B, D; \mathcal{S}) = \max\{V_{NA}(B, D; \mathcal{S}), V_A(B, D; \mathcal{S})\}. \quad (12)$$

and, while not stated, also subject to the laws of motion for the state vector \mathcal{S} .

Given this formulation, a solution to the household problem is a collection of policy functions g_C^{NA}, g_B^{NA} and a value function V_{NA} that solve (10), policy functions g_C^A, g_B^A, g_D^A and a value function V_A that solve (11), and a value function V that, given V_{NA}, V_A , solves (12).

We solve the model by value function iteration. In Appendix C, we describe the computational procedure in detail.

3.3 Parametric assumptions

Households receive their earnings potential, Y_{it} , if employed and a fraction of this earnings potential, bY_{it} , if unemployed:

$$\Upsilon(Y_{it}, n_{it}) = Y_{it} (n_{it} + b(1 - n_{it})).$$

The replacement rate is linear in the earnings potential Y_{it} , mainly for tractability. We set $b = 0.45$ to match the average replacement rate in Italy estimated by [Martin \(1996\)](#).

The process for employment The process for employment status n_{it} is governed by a constant job-finding probability λ and a time-varying job-separation probability ζ_{it} , which follows an AR(1) in logs,

$$\lambda_{it} = \lambda, \tag{13}$$

$$\log \zeta_{it} = \log \bar{\zeta} + \rho_{\zeta} \log \zeta_{it-1} + \sigma_{\zeta} \epsilon_{it}^{\zeta}, \quad \epsilon_{it}^{\zeta} \sim \mathbf{N}(0, 1). \tag{14}$$

Since ϵ_{it}^{ζ} is normal, ζ_{it} is log-normal with support $(0, \infty)$. This violates the economic restriction that $\zeta_{it} \in [0, 1]$. However, this theoretical inconsistency has no practical implications as ζ_{it} never exceeds unity in the estimated and discretized process.

We hold the job-finding rate constant, since the SHIW data is not sufficiently rich to identify the time variations in job-separation and job-finding rates separately. In addition, in the macroeconomic application of the model in [Section 6](#), we find that the separation rate alone accounted for the increase in the unemployment rate during the recent Eurozone crisis. By holding the cross-sectional job-finding rate constant, we keep the fluctuations in labor market risk that household face at the micro level consistent with the aggregate risk that households face in the business cycle experiment in [Section 6](#).

We calibrate $\bar{\zeta}$ and λ to match the average job-separation rate and the average job-finding rate for Italy in the period 1998-2013 (the latest date available), using aggregate labor market statistics from the OECD.¹¹ We estimate the job-finding rate and the job-separation rate using the method of [Elsby et al. \(2013\)](#). See [Appendix D](#) for details.

We calibrate ρ_{ζ} and σ_{ζ} by using the empirical estimates of unemployment risk, Urisk_{it} , from [Section 2](#). More specifically, we match the standard deviation and the autocorrelation of the change in unemployment risk, ΔUrisk_{it} with their model counterparts. In the data, Urisk_{it} corresponds to the conditional probability of being unemployed for "most part" of the year ranging from quarter $t + 5$ to quarter $t + 8$. In the model,

¹¹There is a small discrepancy in our computations. $\bar{\zeta}$ and λ are job-separation and job-finding probabilities. In our computations, those have been calibrated to equal the average job-separation and job-finding rates in the data. This means that we understate job-finding probability in the model by approximately 1.5 percentage points (a relative difference of approximately 10 percent). For the job-separation probability, the difference is negligible. The discrepancy will be corrected in the next revision of the paper, but we do not expect it to significantly affect any of our results.

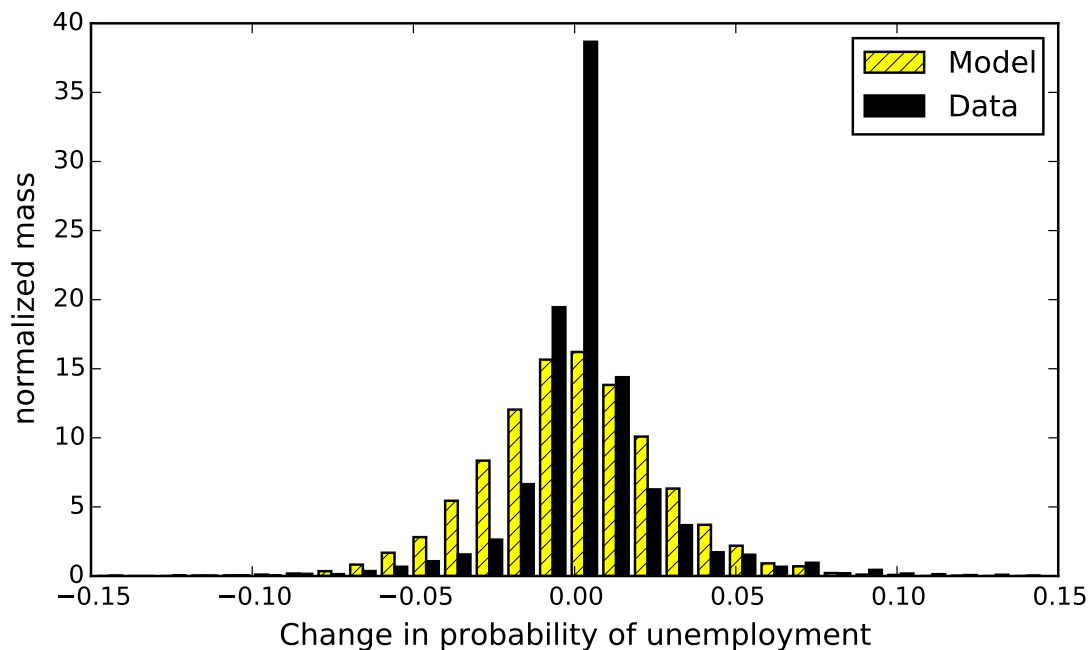


Figure 2: Comparison of the empirical distribution of unemployment risk growth to the model generated distribution of unemployment risk growth.

we define Urisk_{it} as the probability of being unemployed for at least two quarters in any of the quarters between $t + 5$ and $t + 8$.

The two target moments are matched exactly in the calibration. To see the fit of our estimated AR(1) process for the separation rate, we show the unconditional distribution of ΔUrisk_t in the model and in the data in Figure 2. The calibrated parameter values are reported in Table 3.

The earnings potential process The evolution of the earnings potential Y_{it} follows from the realizations of a permanent income shock η_{it} and a transitory income shock ϵ_{it} . Both are identically and independently distributed across time and households:

$$Y_{it} = Z_{it} e^{\epsilon_{it}}, \quad \epsilon_{it} \sim N(0, \sigma_\epsilon), \quad (15)$$

$$Z_{it} = Z_{it-1} e^{\eta_{it}}, \quad \eta_{it} \sim N(0, \sigma_\eta). \quad (16)$$

The permanent-transitory dichotomy of the earnings potential process Y_t is standard. Although the earnings potential process features a unit root, the positive death probability ω guarantees the existence of a stationary earnings potential distribution.

Our specification of the earnings potential process provides a parsimonious and tractable approximation

of the income processes faced by the households in the SHIW data. However, with our specified income process, we potentially ignore two important features of the income risks that the households are facing.

First, several studies have documented a high but less than unitary persistence in estimations of household income processes.¹² However, [Drue Dahl and Jørgensen \(2016\)](#) find that for the estimation of economic statistics such as marginal propensity to consume, the difference between a model with almost unitary persistence and a model with unitary persistence is small.

Second, we impose that the shocks to the log earnings potential are normally distributed. [Guvenen et al. \(2016\)](#) have shown in US administrative data that long-run changes in earnings are characterized by fat tails. If this is also true for Italy, we need to assume that the shocks are drawn from a process with excess kurtosis to match this. However, to make our model comparable to the vast majority of the literature on consumption dynamics, we opt for a log normal earnings potential shock distribution.

We estimate the parameters of the income process using the SHIW sample used for the regressions in Section 2, with the additional restriction that the household head remains employed between any two consecutive waves. As described in Section 2, the data provide annual estimates at a biennial frequency. Denote $y_{4,it}$ as the log of the total household income over the last four quarters in quarter t . We retrieve the residuals $\Delta y_{4,it}^{\text{res}}$ from regressing the two-year log growth $y_{4,it} - y_{4,it-8}$ on sex, education and region interacted with a four-degree polynomial of age and year fixed effects. We assume that $\Delta y_{4,it}^{\text{res}}$ follows the log of the process described by (15)-(16) at the biennial frequency. The biennial model moments are then identified by

$$\begin{aligned}\sigma_{\epsilon,\text{biennial}}^2 &= -\text{Cov}(\Delta y_{4,it}^{\text{res}}, \Delta y_{4,it-8}^{\text{res}}), \\ \sigma_{\eta,\text{biennial}}^2 &= (\text{Var}(\Delta y_{4,it}^{\text{res}}) - 2\sigma_{\epsilon,\text{biennial}}^2).\end{aligned}$$

After retrieving estimates of $\sigma_{\epsilon,\text{biennial}}^2, \sigma_{\eta,\text{biennial}}^2$, we rescale them to a quarterly frequency by setting

$$\begin{aligned}\sigma_{\epsilon}^2 &= \sigma_{\epsilon,\text{biennial}}^2, \\ \sigma_{\eta}^2 &= \sigma_{\eta,\text{biennial}}^2/8.\end{aligned}$$

The parameter values are reported in Table 3. We note that the parameter values are similar to several of the estimates provided in [Krueger et al. \(2010\)](#), which surveys the estimation of income processes across several countries.

In summary, the income process is described by the evolution of the labor market status n_{it} , shocks to the earnings potential ζ_{it} and ϵ_{it} , and shocks to the separation probability η_{it} . We collect these state

¹²For a recent example, see [Krueger et al. \(2016\)](#).

Employment process	Value	Target moment	Value	Data
λ	0.187	Mean find. rate	0.187	OECD, 1998-2013
$\bar{\zeta}$	0.671	Mean sep. rate	0.018	OECD, 1998-2013
σ_{ζ}	0.22	Sd($\Delta Urisk_t$)	0.023	SHIW 1998-2014
ρ_{ζ}	0.91	Corr($\Delta Urisk_t, \Delta Urisk_{t+8}$)	-0.28	SHIW 1998-2014
Potential earnings process	Value	Target moment	Value	Data
σ_{ϵ}	0.158	$-\text{Cov}(\Delta y_{4,it}^{\text{res}}, \Delta y_{4,it-8}^{\text{res}})$	0.158	SHIW 1998-2014
σ_{η}	0.073	$\frac{1}{8}(\text{Var}(\Delta y_{4,it}^{\text{res}}) - 2\sigma_{\epsilon}^2)$	0.073	SHIW 1998-2014

Table 3: Calibrated parameter values for the income process.

variables in $\mathcal{S}_{it} = \{n_{it}, \zeta_{it}, \epsilon_{it}, \eta_{it}\}$. The discretization of $\zeta_{it}, \epsilon_{it}, \eta_{it}$ is described in Appendix D.

Preference and technology parameters. The utility function is CRRA with a constant elasticity of substitution between durable and nondurable goods:

$$U(C_{it}, D_{it}) = \frac{1}{1-\sigma} \left(\left[\alpha C_{it}^{\frac{\gamma-1}{\gamma}} + (1-\alpha) D_{it}^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}} \right)^{1-\sigma}.$$

We follow the literature and assume a unitary intratemporal elasticity of substitution between the two goods, i.e., $\gamma = 1$, which means that the preference specification is Cobb-Douglas.¹³ There is scarce evidence on the intratemporal elasticity of substitution between nondurable and durable goods at the micro level, taking adjustment frictions associated with durable goods into account. Using time series data, [Ogaki and Reinhart \(1998\)](#) estimate that the intratemporal elasticity of substitution between durable and nondurable goods is approximately 1.

The combined assumptions of CRRA utility over homothetic preferences, an unemployment benefit that is linear in earnings potential Y_{it} and a credit constraint and an adjustment cost that are both linear in durable assets imply that the household policy functions are linear in the permanent earnings potential Z_{it} . Z_{it} can thus be eliminated as a state variable in the computation of the household value and policy functions (See Appendix C).

We set the risk aversion/inverse intertemporal elasticity of substitution, σ , to 2, the quarterly real interest rate, $1/q - 1$, to 1 percent and the mortality rate, ω , to generate an average working life of 50 years.

The rest of the parameters are calibrated to match moments from the SHIW data. For the discount factor β , we target the mean level of bond holdings in the model against the mean level of net financial assets, both normalized by total household income. For the credit constraint parameter $\hat{\chi}$, we target the share of households with negative net financial wealth.

¹³See, e.g., [Barsky et al. \(2007\)](#), [Monacelli \(2009\)](#), [Sterk \(2010\)](#), [Berger and Vavra \(2015\)](#) and [Druehl \(2015\)](#).

Parameters	Value	Target	Empirical	Model
Discount rate, β	0.969	Mean norm. fin. assets	1.72	1.74
Nondurable weight, α	0.934	Mean norm. dur. assets	1.24	1.23
Depreciation rate, δ	0.039	Mean yearly purch. freq.	0.14	0.14
Adjustment cost, h	0.24	Mean norm. purchase size	1.20	1.20
Collateral constraint, $\hat{\chi}$	0.73	Share neg. fin. wealth	0.11	0.09

Table 4: *The calibrated preference and technology parameters of the model. The targeted moments are computed from the SHIW sample used for the regressions in Section 2. For moments that concern the stock and flow of durable goods, we use the stock and flow of motor vehicles in the data.*

As discussed in Section 3, D_t in the model has the interpretation of a household’s stock of a typical durable good. Hence, we do not calibrate the model to match moments of households’ total stock of durable goods. Instead, we calibrate against moments of households’ total stock of motor vehicles. The Cobb-Douglas weight on nondurables α , the depreciation rate δ and the adjustment cost parameter h are set to match the mean level of wealth in motor vehicles normalized by income, the mean yearly purchase frequency of motor vehicles and the mean purchase size of motor vehicles normalized by income, respectively.

As shown in Table 4, the calibration yields moments that closely match the data.

4 Decision functions

We illustrate household behavior in Figure 3. In the upper and middle panel, we illustrate the decision functions of a household that is currently employed and faces the median level of unemployment risk. The vertical axis is the household stock of durables normalized by the permanent earnings potential Z_t and the horizontal axis is the household cash on hand (the sum of income and financial assets) normalized by the permanent earnings potential Z_t .

The shaded regions indicate whether or not the household will adjust its stock of durable goods. In the dark gray “inactivity region”, the household chooses not to adjust, while in the light gray “activity region”, it chooses to adjust. The dashed red lines constitute the adjustment thresholds.

In the upper panel, the arrows show the direction in which the households would be moving in the state space in the absence of any exogenous shocks in the next period, conditional on making an adjustment. The arrows are not drawn to scale, but the blue solid line indicates the next period cash on hand and durable goods that the household will hold conditional on making an adjustment.

The household decision rule over adjusting its durable stock can be considered as a two-dimensional (S,s)-decision rule. Because of the adjustment cost, the households will not make an adjustment if they are sufficiently close to their adjustment target. If the households are to the left of the leftward adjustment threshold, they downsize their durable stock to increase their stock of financial assets and consume nondurable

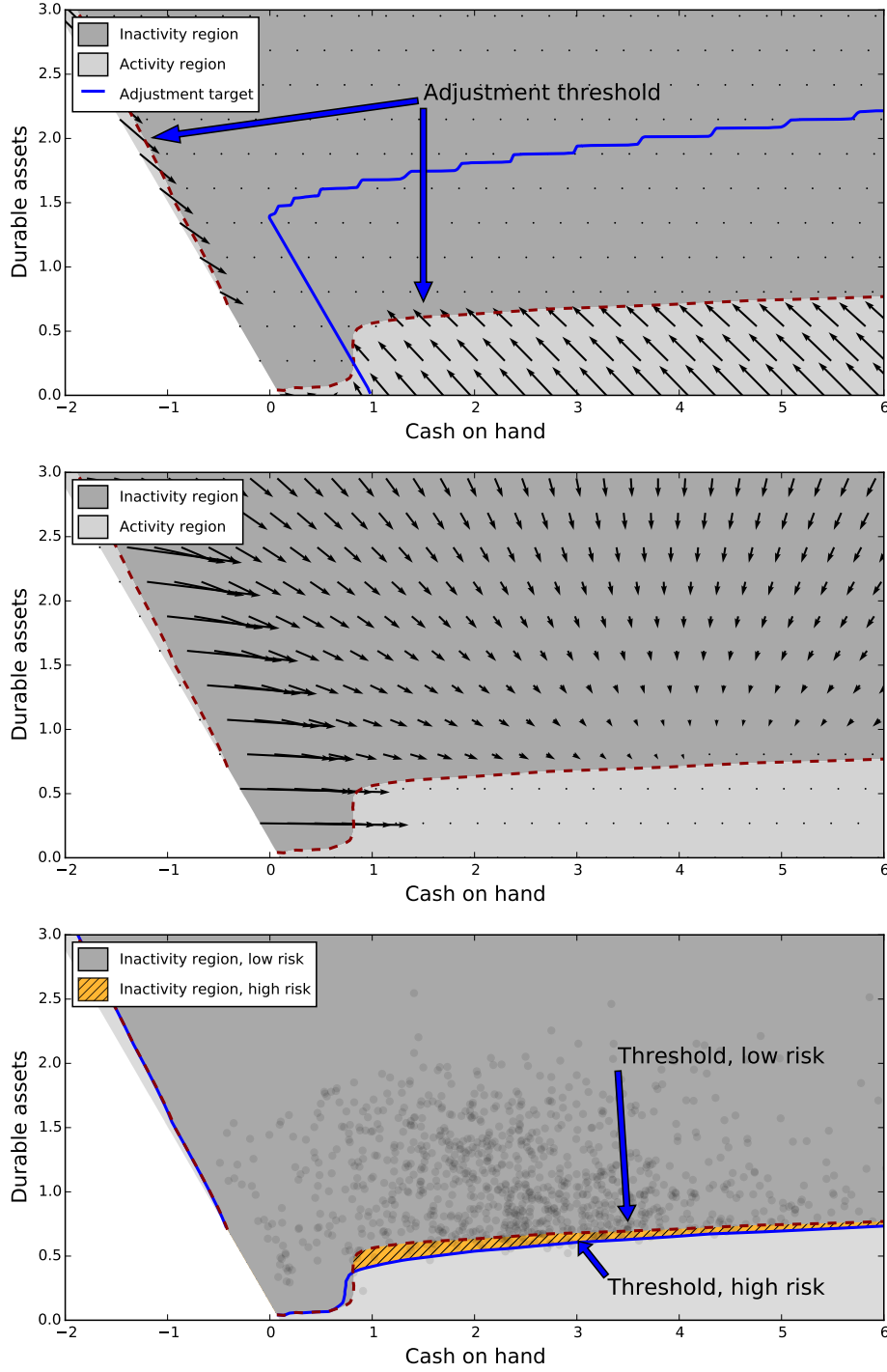


Figure 3: Illustrations of the household decision functions. The axes are normalized by the permanent earnings potential. The upper panel shows the direction of the drift in the activity region and the target conditional on adjusting the durable stock for a household with median unemployment risk. The middle panel shows the direction of the drift inside the inactivity region for the same household. The lower panel shows the stationary distribution of households together with the inactivity regions of a household with low unemployment risk (0.5 percent quarterly separation probability) and of a household with high unemployment risk (5 percent quarterly separation probability).

goods. If the households are below the bottom adjustment threshold, they upgrade their durable stock.

The middle panel illustrates the behavior inside the inactivity region. In the durable asset dimension, households drift downward as their stock of durable goods depreciates. In the cash-on-hand dimension, they pursue standard buffer-stock behavior. For a given stock of durables, there is a target stock of financial assets. With low financial wealth, the households save to insure against negative income shocks and unemployment shocks. With high financial wealth, the households divest and consume nondurables.

In the bottom panel, we illustrate how the households respond to an increase in unemployment risk. The dark gray area and the red dashed line show the inactivity region and the adjustment threshold of a household that is currently employed and faces a low level of unemployment risk. The orange area and the blue solid line show the inactivity region and the adjustment threshold of a household that is currently employed and face a high level of unemployment risk. Each dot represents a household drawn from the stationary distribution of the model.¹⁴ As seen from the figure, a household with high unemployment risk has an adjustment threshold below that of a household with low unemployment risk. Upon experiencing an adverse job-separation rate shock, it will thus take a longer time for a household that is currently inside the inactivity region to reach the activity region. Put differently, this household will postpone its purchases of durable goods.

Why does the adjustment threshold shift downward when a household experiences higher unemployment risk? In the adjustment decision, the household weighs the extra benefit of adjusting and a closer-to-optimal consumption today against the value of adjusting and a closer-to-optimal consumption in the next quarter. When the household experiences a temporary increase in unemployment risk, the value of postponing increases because 1) with higher unemployment risk, the desired level of consumption in the next quarter is more uncertain and because 2) this uncertainty will be resolved if drawing a lower separation probability in the next quarter. We refer to this mechanism as the *wait-and-see effect*.

5 Validation

In this section, we quantitatively evaluate the model performance at the micro level by comparing the implied elasticities of the model to those documented in the SHIW data in Section 2. Most importantly, we evaluate whether the model matches the estimated semi-elasticities to unemployment risk growth.

Our empirical approach in Section 2 is constrained by the idiosyncrasies of the SHIW. For example, since the SHIW is a biennial survey which asks questions regarding yearly variables, the empirical measure of unemployment risk is defined as the conditional probability of being unemployed for most of the year two years ahead. This is not the most natural measure of unemployment risk in our model, where we observe

¹⁴We obtain the stationary distribution by simulating 2000 households for 3000 quarters, discarding the first 1000 quarters of observations.

quarterly variables at a quarterly frequency. To compare the empirical results to the model, our approach is to construct the corresponding yearly variables at a biennial frequency from the model, and run exactly the same regressions on this model-generated data as run on the SHIW data.

Since our model is calibrated to match unconditional moments, there are no mechanical reasons why the model regression results, which capture correlations between individual-level growth rates of the relevant variables, should conform to the empirical regression results. To the extent that they do, we take it as evidence that the model captures key dimensions of the micro level consumption dynamics, and that the model can be used to infer aggregate consumption responses to business cycle and counterfactual policy shocks.

5.1 Setup

We simulate the baseline model to construct a panel sample for the regressions.¹⁵ A household that dies leaves the sample and is immediately replaced by a new household that starts with a permanent earnings potential $Z_{it} = 1$. The newborn household draws its assets from the cross-sectional normalized asset distribution.

A period in the model is a quarter while the panel from the SHIW is biennial. To conform with the SHIW, we construct a biennial panel sample from the model simulations. The time index t in this section refers to a given year. Our model estimate of household i 's unemployment risk in year t , $Urisk_{it}$, is the probability of the household being unemployed for at least two quarters in year $t + 2$. In the SHIW, the corresponding estimate is the year t probability of being unemployed for “most part” of year $t + 2$. All other variables are identically defined in both samples.

5.2 Regression specification

We use the same regression specifications for this exercise as those used in Section 2. For durables, we estimate a probit model of the probability of a durable purchase on the growth of unemployment risk:

$$P(DP_{it} = 1) = \Phi(\beta\Delta Urisk_{it} + \beta_x \mathbf{X}_{1it}), \quad (17)$$

where DP_{it} is an indicator variable that takes the value of 1 if a durable good has been purchased in year t , $\Phi()$ is a cumulative normal distribution, and \mathbf{X}_{1it} is a collection of relevant covariates. As in Section 2, \mathbf{X}_{1it} includes log income growth $\Delta \log Y_t$, previous period log income $\log Y_{t-2}$, quartile bins of the household's stock of durable goods excluding purchases in the last 12 months D_{it} , as well as net financial assets FA_{it-2} . The latter two variables are normalized by previous period income Y_{it-2} .

¹⁵More specifically, we populate the economy with 300,000 agents that live in the economy for 8,000 quarters, after a burn-in period of 1,000 quarters.

For nondurables, we estimate the effect of the growth in unemployment risk on log consumption expenditure growth in an OLS specification:

$$\Delta c_{it} = \alpha_0 + \alpha \Delta Urisk_{it} + \alpha_x \mathbf{X}_{1it} + \epsilon_t, \quad (18)$$

with the same set of covariates \mathbf{X}_{1it} .

5.3 Results

In Table 5, we show the results from estimating (17) and (18) together with the comparable regression results from Table 2. For durable goods, we show the estimated average marginal effect, normalized by the unconditional purchase probability. In the empirical exercise, we obtained separate empirical estimates for total durables, motor vehicles and furniture. We prefer to compare the regression results using the model-generated data to the empirical estimates for motor vehicles, as the model was calibrated to match moments of the households' stock and purchases of motor vehicles. However, for the estimated semi-elasticity to unemployment risk, the coefficient was estimated with a substantially higher precision for total durable goods. In this case, we therefore also compare the model estimate to the empirical estimate using purchases of total durable goods.

In the first row of Table 5, we see the estimated semi-elasticities of expenditures to unemployment risk growth. For durable goods, the model response to a 1 percent increase in unemployment risk growth is a decrease of 2.15 percent in the number of purchases. This decrease is smaller than, but within one standard deviation of, the corresponding empirical estimates of -3.33 for motor vehicles and -2.54 for total durable goods in columns 2 and 3, respectively. For nondurable goods, the model estimate of the response to unemployment risk growth is -0.39 , close to the empirical point estimate of -0.30 .

Turning to the second row, the model response to a 1 percent increase in income growth is an increase of 2.98 percent in the number of purchases of durable goods and an increase of 0.68 percent in nondurable expenditure growth. These numbers are substantially larger than the corresponding empirical estimates.

Turning to the durable asset variables, the model estimates for durable goods show a similar pattern to that in the data, with the probability of a purchase declining when moving up the quartile ladder. The gradient of this relationship is steeper in the model as compared to the data. The estimated effects of the durable asset variables on nondurable consumption are virtually zero in the model, consistent with the empirical estimates.

The picture is similar with respect to moving up the quartile ladder in financial assets. The model predicts a positive effect on the probability of a durable purchase. The same is true in the data, although the gradient is weaker. With respect to nondurable consumption, the model estimates of the effect of the

	Durables model	Vehicles SHIW	Durables SHIW	Nondurables model	Nondurable SHIW
$\Delta \text{Unemployment risk}_t$	-2.15	-3.32** (1.59)	-2.54*** (0.69)	-0.39	-0.30 (0.23)
$\Delta \log Y_t$	2.98	1.06*** (0.17)	0.64*** (0.07)	0.68	0.36*** (0.03)
D_t/Y_{t-2} , quartile 2	-1.40	-1.27*** (0.10)	-0.22*** (0.05)	0.01	0.02 (0.02)
D_t/Y_{t-2} , quartile 3	-2.41	-1.39*** (0.12)	-0.25*** (0.06)	0.00	0.05*** (0.02)
D_t/Y_{t-2} , quartile 4	-3.69	-1.65*** (0.13)	-0.24*** (0.06)	-0.01	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 2	0.19	0.10 (0.11)	-0.03 (0.05)	-0.00	-0.01 (0.02)
FA_{t-2}/Y_{t-2} , quartile 3	0.33	0.15 (0.11)	0.10* (0.06)	-0.00	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 4	0.52	0.14 (0.13)	0.11* (0.06)	-0.02	0.01 (0.02)
Time fixed effects		Yes	Yes		Yes
Controls		Yes	Yes		Yes
R2	0.59	0.18	0.09	0.75	0.33
N		4574	4574		4574

Table 5: Regression results from estimating (17) and (18) on model-generated data, together with regression results on SHIW data from Table 2. For the first three columns, the left-hand side variable is an indicator of whether a durable good has been purchased in the last 12 months. The model is probit and the coefficients show the average marginal effect, normalized by the unconditional purchase probability. For the last two columns, the left-hand side variable is the log growth of expenditures on nondurable goods and the model is OLS. D_t refers to the stock of durables in year t prior to any purchase in that year. For the set of control variables, see Table 2. Standard errors are shown in parenthesis. *, **, *** indicate that coefficients are significant at the 10%, 5% and 1% level, respectively.

financial asset variables are virtually zero, consistent with the empirical estimates.

Why does the level of financial wealth not affect nondurable consumption growth in the model? For a household that does not risk facing a binding borrowing constraint, the level of wealth affects the level of consumption, but has little influence on the consumption growth rate. However, being in the bottom quartile of the financial asset distribution could still indicate being close to a binding borrowing constraint, where the consumption growth rates are larger. However, in the model, only 2.5 (4.8) percent of the households have a normalized distance to the borrowing constraint less than 10 (30) percent of their permanent earnings potential. The low share of constrained households in the model is consistent with the data, where only 4 percent of the households report to have been denied or discouraged from applying credit.

In sum, the model comes close to matching the expenditure patterns documented in the SHIW data, especially with respect to the semi-elasticities of expenditures to unemployment risk growth, which are the key objects of interest in this paper. There are two exceptions: the model overshoots the elasticities of expenditure with respect to income growth, both with respect to nondurable and durable goods, and the gradients of the probability of purchasing a durable good along the two wealth margins.

Regarding the expenditure elasticities to income growth, a possible explanation for why the model overshoots is the large variance of permanent earnings potential shocks, with $\sigma_\eta = 0.073$. In the model, non-

durable consumption and the target stock of durables respond one-to-one to a shock to the permanent earnings potential. The lower empirical elasticities to income growth are possibly explained by changes in income in the data to a large extent being caused by shocks that are less than fully persistent, which we do not capture with the model income process.

Regarding the wealth gradients of durable purchases, a possible explanation for why the model overshoots is that there are more shocks, orthogonal to income and employment, that influence households' purchases in the data, e.g., break-down or taste shocks. Adding such shocks to the model will reduce the wealth gradients as it increases the probability that households with high (low) wealth in durable (financial) assets will make a purchase.

6 Aggregate consumption dynamics

In this section, we study the macroeconomic implications of the calibrated consumption model. We add an aggregate state variable to the model that shifts the economy between expansion and recession, and adjust the process for the separation rate so that a typical recession event in the model mimics the recent Eurozone crisis. Then, we study the consumption dynamics that follow a recession shock. We perform the experiments in partial equilibrium.

6.1 Aggregate risk

We add a process for aggregate risk to the model described in Section 3, capturing aggregate unemployment dynamics in the recent Eurozone crisis. Specifically, we add the variable A to the collection of state variables S . A takes two values; if $A = E$, the economy is in an expansion, if $A = R$, the economy is in a recession.

The aggregate state follows a Markov process with transition matrix T :

$$T = \begin{pmatrix} p_{EE} & 1 - p_{EE} \\ 1 - p_{RR} & p_{RR} \end{pmatrix}.$$

Of course, we cannot infer the ex-ante probability and the expected length of the Eurozone crisis. Instead, we set p_{EE} and p_{RR} to match the average length of recessions (9 quarters) and the share of total time spent in recessions (23%) in Italy for the period 1948-2016. We use recession indicators constructed by the Economic Cycle Research Institute, which dates recessions for a wide range of countries using methods similar to those of the NBER Business Cycle Dating Committee.

We extend the labor market transition process described by (13)-(14) to depend on the aggregate state

through the uniform shifters $\hat{\lambda}(\mathcal{A}_t)$, $\hat{\zeta}(\mathcal{A}_t)$:

$$\lambda_{it} = \lambda + \hat{\lambda}(\mathcal{A}_t) \tag{19}$$

$$\zeta_{it} = \exp(\log \bar{\zeta} + \rho_{\zeta} \log \zeta_{it-1} + \sigma_{\zeta} \epsilon_{it}^{\zeta}) + \hat{\zeta}(\mathcal{A}_t). \tag{20}$$

We set $\hat{\lambda}(\mathcal{A}_t)$ and $\hat{\zeta}(\mathcal{A}_t)$ so that entering a recession mimics the recent Eurozone crisis. In the appendix, we document that between the starting year of the recession, 2011, and 2013, the last year of observation, the separation rate increased by 106 percent, while there was no significant movement in the job finding rate. Accordingly, we set $\hat{\lambda}(\mathcal{R}) = \hat{\lambda}(\mathcal{E}) = 0$ and we set $\hat{\zeta}(\mathcal{R})$ and $\hat{\zeta}(\mathcal{E})$ so that the average separation rate increases by 106 percent upon entering a recession while keeping the unconditional mean unaffected. As a result, in a recession, the quarterly separation rate increases by 1.3 percentage points. With the added state variable, we solve the model using the calibrated parameters from Section 3.3.

To investigate how the adjustment frictions for durable goods affect aggregate consumption dynamics, we will compare the simulation outcome of our model to that of a corresponding model without adjustment frictions. The flexible-adjustment model is identical in all dimensions except that we set the adjustment cost h to 0 and recalibrate the preference and technology parameters. In doing so, we assume that the depreciation rate δ is the same in the flexible-adjustment model as in the baseline model, but calibrate (without the aggregate state variable) β , α and $\hat{\chi}$ to match the mean level of normalized net financial assets, the mean level of normalized durable assets and the share of households with negative net financial wealth in the data. Without this recalibration, the wealth distribution in the flexible-adjustment model would differ greatly from the wealth distribution of the baseline model (and the data), which would obscure any comparison between the two. The recalibrated parameters are shown in Table 12 in Appendix D.2.

6.2 Consumption dynamics in a recession

We analyze the impulse-response functions to a recession shock. We populate the economy with 1,000 households, and let the recession shock hit the economy at $t = 0$. Prior to feeding the recession shock, we simulate the economy for 1,000 quarters with the aggregate state drawn from its stochastic law of motion. After these burn-in periods, the economy enters into an expansion which lasts 30 quarters (the average length of an expansion). At $t = 0$, the economy enters into a recession that lasts 9 quarters (the average length of a recession) after which it reverts to the expansion regime for 30 quarters and then once more evolves stochastically.¹⁶

The impulse-response functions are shown in Figure 4. The recession periods are indicated by the shaded area. The figures also depict a decomposition of the total response into an *ex-ante risk channel* and an

¹⁶To gain precision, we compute and report averages from repeating this experiment 24,000 (4,500) times for the baseline (flexible adjustment) model.

ex-post income channel. The ex-ante risk channel (the dashed line) is the impulse-response function that results when households believe that they are in the recession state in periods 0 – 8, but actually draw the shocks consistent with being in the expansion state during these periods. This channel captures the effect that is solely due to households *believing* that the separation probability is higher when in a recession. In contrast, the ex-post income channel (the dotted line) is the impulse-response function that results when households believe that they are in the expansion state in periods 0 – 8, but draw the shocks consistent with being in the recession state during these periods. The ex-post income channel captures the effect that is solely due to households experiencing the more frequent separation shocks when in a recession, without affecting households’ beliefs regarding the riskiness of their environment. The decomposition is not exact as the two channels can interact. However, as seen from the graphs, the two channels approximately add up to the total response.

Starting with the top row, expenditures on durable goods fall by approximately 55 percent on impact in the baseline economy. There is a gradual recovery until the economy leaves the recession in period 9, when expenditures spike. We see a similar pattern in the flexible-adjustment model, albeit with smaller magnitudes and less persistence. Inferring the size of the difference is easier if looking at the evolution of the cumulative response, depicted in the second row. In the baseline economy at the end of the recession, the cumulative loss in expenditures of durables, as a fraction of the expenditures in quarter $t - 1$, is close to 130 percent. In the flexible-adjustment model, the cumulative loss is close to 90 percent. Over the whole recession, the presence of adjustment frictions thus amplifies the response of durable purchases to the aggregate separation rate shock by roughly 40 percent.

Moreover, and in our view more importantly, the presence of adjustment frictions changes the mechanism through which the total response is generated. In the baseline model, the total response is almost entirely driven by the ex-ante risk channel, producing a cumulative fall of 100 percent in the final period of the recession, whereas in the flexible-adjustment model, the ex-ante response produces a cumulative fall of only 30 percent. In contrast, the ex-post income channel produces a cumulative fall of 40 percent in the baseline model and a cumulative fall of 60 percent in the flexible-adjustment model.

Why is the ex-ante risk channel for durable goods approximately three times as strong in the baseline model compared to the model without adjustment frictions? In the flexible-adjustment model, expenditures respond due to the standard precautionary savings motive, arising from prudent preferences and the potentially binding credit constraint, leading households to invest in liquid assets and thus insure themselves against the higher probability of experiencing an unemployment spell. Consumption expenditures drop in the first period of the recession. After the initial drop, the households have increased their buffer stock of liquid savings, and the expenditure rate recovers. This precautionary savings motive is also present in the baseline model. In addition, the presence of the adjustment frictions produces the wait-and-see effect,

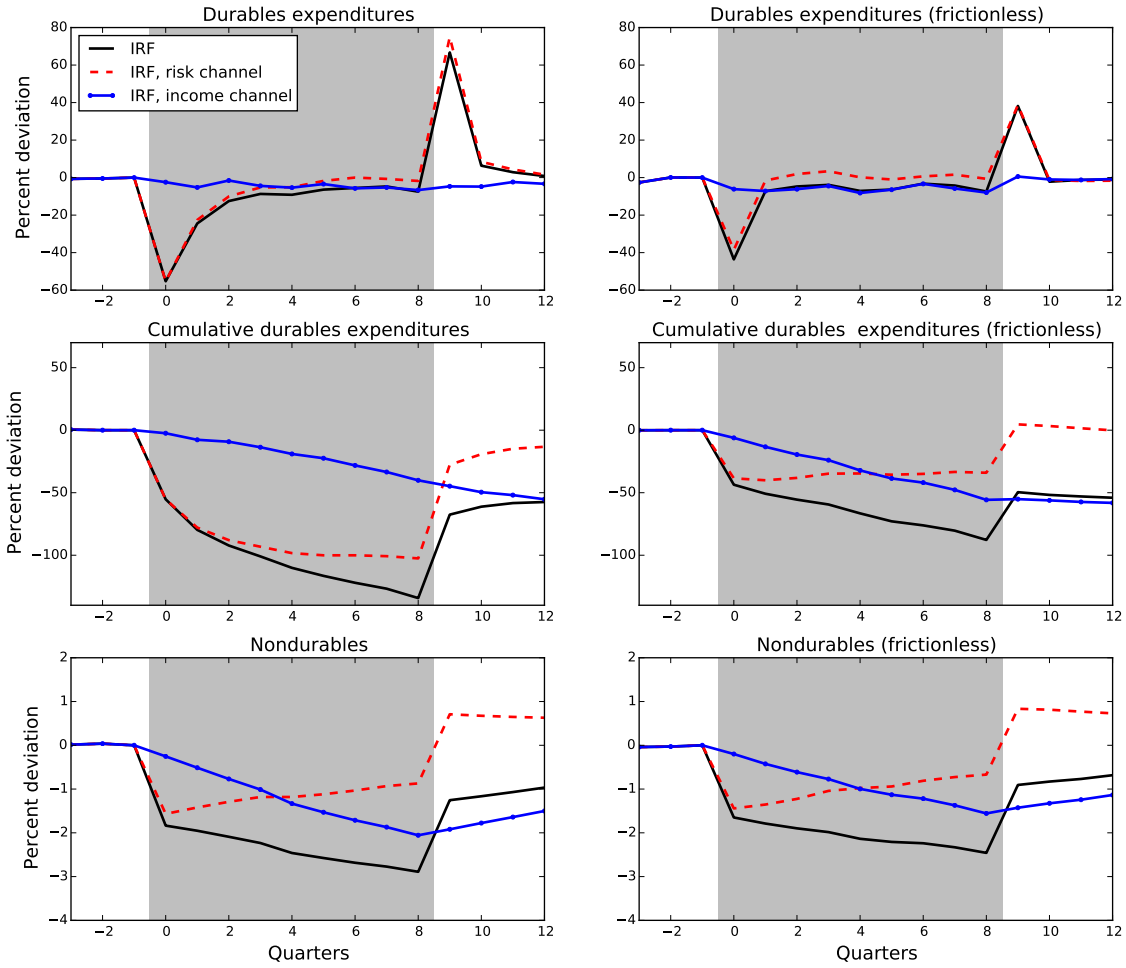


Figure 4: Impulse-response functions to a recession shock. The recession periods are indicated by the shaded area. The left-hand column depicts the outcome in the baseline model, the right-hand column depicts the outcome in the flexible-adjustment model. The percentage deviation refers to the percentage deviation compared to the expenditure level in period -1 , before the economy enters the recession.

as discussed in Section 4. The adjustment frictions make it costly for the households to frequently adjust their durable stock. In the adjustment decision, the household weigh the extra benefit of a closer-to-optimal consumption today against the value of adjusting and a closer-to-optimal consumption level in the next quarter. Entering a recession increases the value of postponing, because 1) with higher unemployment risk, the desired level of consumption in the next quarter is more uncertain and 2) because this uncertainty will be resolved if the economy leaves the recession in the next quarter. This makes an additional incentive for the households to decrease their purchases of durable goods upon entering a recession.

Turning to the third row of Figure 4, we see that the two model economies deliver very similar impulse responses for expenditures on nondurable goods, both with respect to the total response and the decomposition into the ex-ante risk channel and the ex-post income channel. Thus, the presence of adjustment frictions for durable goods does not significantly alter the consumption behavior for nondurable goods.

6.3 State dependency

In the previous subsection, we analyzed the expenditure response to an aggregate shock to unemployment risk, induced by a temporarily higher probability of separation. Here, we study the aggregate responsiveness of expenditures to an unexpected transitory income shock, i.e., the *marginal propensity to spend*, and the real interest rate, conditioning on the shock to the separation probability. The aggregate marginal propensity to spend and the aggregate responsiveness to the real interest rate are two key statistics in evaluating the effect of monetary and fiscal transfer policies; the investigation here thus speaks to how and whether the expenditure responses documented in the previous subsection can be stabilized.

To estimate the aggregate marginal propensity to spend, we repeat the simulation exercise of the previous subsection with the addition that in each period, we give the households an unexpected transfer corresponding to x percent of their quarterly permanent earnings potential. We compute the marginal propensity to spend as the share of that transfer that is spent on durable goods for each household and compute the aggregate marginal propensity to spend as the simple average of these shares.

We show the results in the left-hand panel of Figure 5. We depict the aggregate marginal propensity to spend for two different sizes of the transfer: 1 and 5 percent of each household's quarterly permanent earnings potential. As seen in the figure, the aggregate marginal propensity to spend for durable goods falls upon entering a recession. The fall is concentrated to the first few quarters of the recession, recovers gradually, and spikes upon leaving the recession, similar to the expenditure response of durables in Figure 4. The size of the initial fall is roughly the same for the two different sizes of the transfer. In the first period of the recession, the marginal propensity to spend for durable goods falls from 0.13 to 0.09, a relative difference of approximately 30 percent.

To estimate the aggregate responsiveness to the real interest rate, we repeat the simulation exercise of

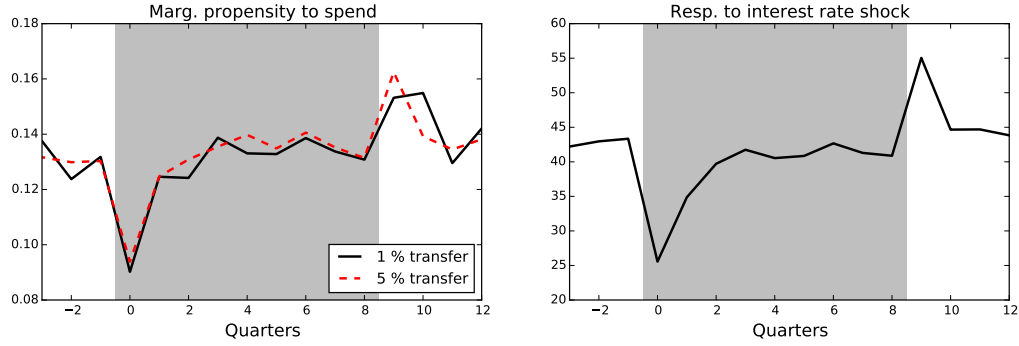


Figure 5: *Left-hand panel: The aggregate marginal propensity to spend on durable goods following a recession shock, when feeding the households an unexpected transfer of 1 and 5 percent of their permanent earnings potential, respectively. Right-hand panel: The response of expenditures on durable goods, as a share of the expenditure level in period $t-1$, to an unexpected transitory cut in the yearly interest rate of 1 percent. The recession periods are indicated by the shaded areas.*

the previous subsection with the addition that in each period, we unexpectedly cut the yearly real interest rate by 1 percent for one quarter. We then compute the difference between the total expenditure response on durable goods in the case with and without the interest rate cut, as a fraction of the expenditure rate in period $t = -1$, before entering the recession.

We show the results in the right-hand panel of Figure 5. Similarly to the evolution of the marginal propensity to spend, the fall is concentrated to the first few quarters of the recession. In the first period of the recession, the expenditure response falls from 40–45 percent to 25 percent of the quarterly expenditure rate prior to the recession, a relative difference of approximately 40 percent.

What explains the state dependency of the aggregate marginal propensity to spend and the aggregate responsiveness to the real interest rate in the model? Inside the inactivity region, households do not adjust their holdings of durable goods. If further away from the adjustment threshold, they become less responsive to any small shift in the incentives to adjust. As emphasized in the previous subsection, upon entering a recession and experiencing an increase in unemployment risk, the adjustment threshold shifts down. Some of the households that were planning to adjust are now inside the inactivity region and the households that were already inside the inactivity region are now further from the adjustment threshold. The aggregate marginal propensity to spend and the aggregate responsiveness to the real interest rate for durable goods fall for both reasons.

What are the implications of the fall in the aggregate marginal propensity to spend and the aggregate responsiveness to the real interest rate in recessions? With regard to fiscal policy, an immediate implication of the procyclical marginal propensity to spend is that fiscal transfers, such as the 2001 federal income tax rebate and the 2008 Economic Stimulus Act employed in the US, have less of an effect on durable expenditures

in recessions as compared to expansions. With regard to monetary policy, the responsiveness of expenditures to the real interest rate is the standard transmission channel of interest rate changes to consumption in new Keynesian models. In addition, the marginal propensity to spend captures the consumption response to the additional indirect income effects that monetary policy may generate in general equilibrium, as recently emphasized in [Kaplan et al. \(2016\)](#). In effect, both the fall in the aggregate marginal propensity to spend and in the aggregate responsiveness to the real interest rate for durable goods during recessions suggest that the stabilizing effect of monetary policy is also weaker in recessions as compared to expansions. Consistent with this finding, [Tenreyro and Thwaites \(2015\)](#) find that the responses of all aggregate variables to monetary policy shocks are weaker in recessions as compared to expansions.

7 Concluding Remarks

We have argued that adjustment frictions in households' purchases of durable goods amplify the response of aggregate expenditures on durable goods to fluctuations in unemployment risk and dampens the response to realized unemployment shocks. The effect is quantitatively important, raising the demand response through the ex-ante risk channel by approximately 200 percent, and reducing the demand response through the ex-post income channel by approximately 30 percent. In addition, we have also shown that when unemployment risk increases, the marginal propensity to spend and the responsiveness to the real interest rate for durable goods fall, thus constraining monetary and fiscal transfer policies in stabilizing shortfalls in durable goods demand during recessions.

Although our results carry a negative message for monetary and fiscal transfer policies, they are also indicative of how other policies might be more effective in stabilizing consumption. If consumption expenditures are more reactive to perceived income risk rather than realized income losses, a natural conjecture is that stabilization policy should focus on reducing the perceived income risks associated with entering a recession. A generous and/or countercyclical unemployment insurance scheme could, for example, achieve this. A recent literature has investigated the stabilizing effect of unemployment insurance in models with a single nondurable consumption good ([McKay and Reis, 2016](#), [Kekre, 2016](#)). Extending the analysis to incorporate adjustment frictions for durable goods would likely change the quantitative assessment. Another example is work-sharing arrangements, in which workers cut back on hours to avoid layoffs in response to a temporary decline in business activity (see [Hijzen and Venn \(2011\)](#) for a documentation of subsidized short-time work policies in the OECD during the Great Recession). In principle, such arrangements could minimize the transmission of adverse firm shocks to worker income risk and translate them into transitory income shocks (shared by all workers). To the best of our knowledge, their implication for aggregate consumption volatility has not yet been analyzed.

Throughout the paper, our analysis has been maintained in partial equilibrium. An open question is how

the demand responses uncovered here affect consumption dynamics in general equilibrium.¹⁷ In particular, the response of the demand for durable goods relative to nondurables might be sensitive to temporary changes in the relative price and the interest rate, prices that may respond endogenously to demand shocks originating from the labor market.¹⁸ Given our findings on the amplifying role of non-convex adjustment costs in partial equilibrium, a natural next step is to incorporate a separation between nondurable and durable goods in existing general equilibrium frameworks used for analyzing aggregate consumption dynamics under countercyclical income risk, e.g., [Ravn and Sterk \(2013\)](#) and [McKay \(2016\)](#). In this context, the state dependence of the consumption dynamics becomes important: if the responsiveness of the demand for durable goods is procyclical, then general equilibrium movements in the interest rate and the relative price might play a smaller role in recessions than in expansions.

¹⁷Our investigation parallels the literature on firm investment, in which a key question has been whether general equilibrium feedback will undo any demand effects induced by non-convex adjustment frictions, see [Khan and Thomas \(2008\)](#). Notably, [Bloom et al. \(2014\)](#) find a strong response of firm investment to uncertainty shocks in a calibrated general equilibrium model featuring non-convex adjustment frictions.

¹⁸For an elucidating investigation of the relative price sensitivity in the context of monetary policy shocks, see [Barsky et al. \(2007\)](#)

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A Data description

In this appendix, we describe the SHIW data in more detail and give precise definitions of all variables used.

A.1 Sampling structure

Since 1998, the survey includes approximately 8000 households in each wave, of which about half has been interviewed in previous surveys, with gradual replacement over time. Table 6 shows the structure of the panel.

Year	1998	2000	2002	2004	2006	2008	2010	2012	2014
1998	7147	3873	2591	1855	1476	1284	1088	915	634
2000	0	8001	3605	2522	1951	1682	1418	1171	804
2002	0	0	8011	3604	2623	2207	1834	1511	1025
2004	0	0	0	8012	3957	3202	2620	2142	1420
2006	0	0	0	0	7768	4345	3476	2790	1834
2008	0	0	0	0	0	7977	4621	3596	2315
2010	0	0	0	0	0	0	7951	4611	2894
2012	0	0	0	0	0	0	0	8151	4459
2014	0	0	0	0	0	0	0	0	8156

Table 6: *The sampling structure of the SHIW, 1998-2014. Each row corresponds to one survey wave. In each row, the columns show the number of households that have also been surveyed in the year indicated by the column.*

A.2 Data quality

To gauge the quality of the SHIW data, we compare aggregate statistics from the survey with corresponding variables from the national accounts. The results are shown in Figure 6. As seen, disposable income and durable expenditures are well aligned. Total and nondurable expenditures show a significant increase between the years 2002 and 2004 in the SHIW, which is not apparent in the national accounts data. Otherwise, these series also seem well-aligned.

A.3 Comparison to US consumption surveys

Compared to the US survey data sources, such as the Consumption Expenditure Survey (CEX) and the Panel Study of Income Dynamics (PSID), which have been used for studying expenditure patterns separately for nondurable and durable goods (e.g. in [Attanasio \(2000\)](#), [Berger and Vavra \(2015\)](#), [Suzuki \(2016\)](#)), the SHIW has several advantages. Among all durable goods, the PSID only contains information on car purchases. Cars are typically purchased at a very low frequency, so that credibly separating the characteristics of buyers from those of non-buyers requires a large sample size. The PSID only samples 2000 households in

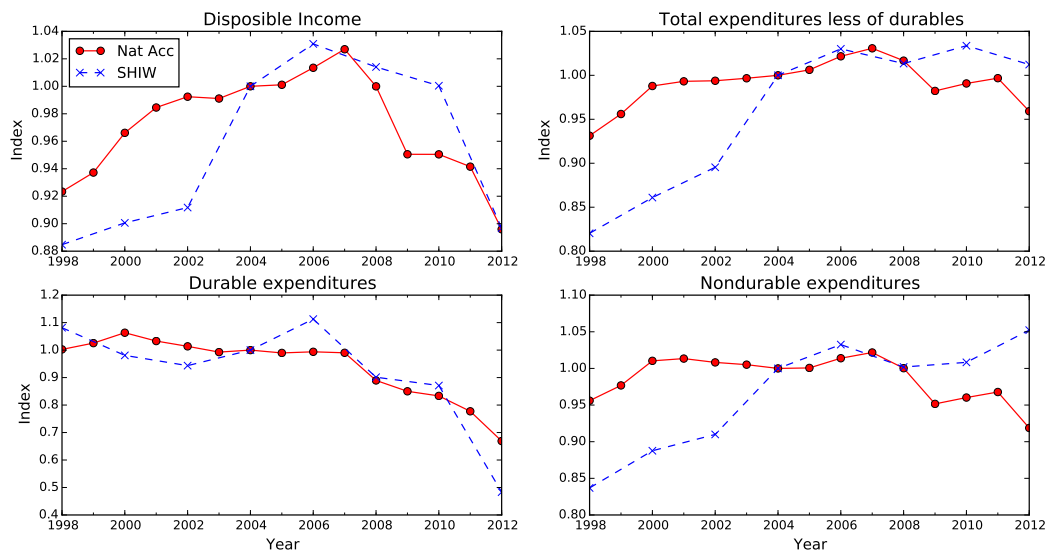


Figure 6: Comparison of aggregate SHIW data to the national accounts. Total expenditures less of durables is defined as total household expenditure on all items, including housing maintenance cost, actual and imputed rents, less of durable goods. Nondurable expenditures is defined as expenditure on all items, excluding housing maintenance costs, actual rents, imputed rents and durable goods. All variables are deflated by the CPI. National accounts variables have been divided by population size, while SHIW variables are calculated as means using sample weights and dividing by household size. The national accounts and CPI data have been retrieved from OECD statistics.

each wave, however. The CEX contains more information on durable goods purchases but less on household characteristics. One can only indirectly, and therefore imperfectly, identify the employment status of the respondent and is not given detailed information on household wealth. In addition, households are part of the sample for at a maximum of only four consecutive quarters, thus restricting panel-based identification strategies. Finally, it is likely that the CEX suffers from severe measurement error. [Carroll \(2009\)](#) reports that the times series of consumption generated by aggregating CEX data exhibit weak co-movement with the corresponding NIPA tables.

A.4 Definition of all variables used

In this subsection, we provide definitions of all variables used that are non self-explanatory.

Marital status. Category variable that takes 4 values: Married, Single, Separated or Widow/er.

Education level. Category variable that takes 8 values: None, Primary school certificate, Lower secondary school certificate, Vocational secondary school diploma, Upper secondary school diploma, 3-year university degree, 5-year university degree and Postgraduate qualification.

2-digit region indicator. Category variable with 20 values, one for each administrative region of Italy.

1-digit superregion indicator. Category variable with 3 values: North, Centre and South-Islands.

Town size. Category variable with 4 values: 0-20,000, 20,000-40,000, 40,000-500,000 and 500,000+.

Occupation. Category variable that take 5 values conditioned on being employed by second party. Refers to the situation of the person for most of the last 12 months.

Industry. Category variable that take 21 values and indicates where the person currently works.

Household Income. Defined as total net disposable income over the last 12 months from summing labor income, pensions and transfers, income from self-employment and income from financial assets and property.

Labor Income. Defined as total net payroll income over the last 12 months, including fringe benefits.

Binding liquidity constraint. Indicator variable that takes the value of 1 if the household has reported 1) that a member of the household has applied for a loan and been partly or fully refused and/or 2) a member of the household considered applying for a loan but later changed his/her mind in anticipation that the loan would be refused.

Furniture Stock. The self-estimated value of all household belongings of furniture, furnishings, household appliances and sundry equipment.

Vehicle Stock. The self-estimated value of all household belongings of cars and other means of transport.

Durable Stock. The sum of furniture and vehicle stock.

Financial Assets. The sum of all financial assets, e.g. deposit accounts, savings accounts, stocks, bonds, funds, shares in partnerships etc.

Total Assets. The sum of real assets (property, jewellery, business equity), financial assets and liabilities.

Non-durable expenditures. Self-estimated total spending less of expenditures on durable goods and extraordinary maintenance costs. Does not include actual or imputed rents. Does include fringe benefits.

Vehicle expenditures. Net expenditures on cars and other means of transport.

Furniture expenditures. Net expenditures on furniture, furnishings, household appliances and sundry equipment.

Durable expenditures. The sum of vehicle and furniture expenditures.

B Robustness exercises to the empirical analysis

In this section, we perform various robustness checks to the empirical exercise in Section 2. To save computing time, standard errors are computed in the standard fashion, and not by the bootstrap procedure used for the main results in Table 2 (for that estimation, the bootstrapped standard errors were somewhat smaller as compared to those computed in the standard fashion).

Endogeneity of unemployment risk to future income growth With variation in unemployment risk being driven by shocks at the industry/regional/education/occupation level, it is possible that unemployment risk correlates with expected future wage growth. In this case, our estimated coefficient of unemployment risk growth on expenditures could be biased by the response of expenditures to expected wage growth. To overcome the omitted variable bias, we add income growth between periods t and $t + 2$ as a control variable to the expenditures regressions. The results are shown in Table 7. As seen, the inclusion of this variable does not affect our results. Moreover, the estimated coefficient on future income growth is small, suggesting that the value of this variable is likely to be unknown to the households in period t .

	Durables I	Durables II	Vehicles I	Vehicles II	Furniture I	Furniture II	Nondurables I	Nondurables II
Δ Unemployment risk _t	-3.23*** (0.77)	-2.57*** (0.82)	-3.23** (1.65)	-3.47* (1.78)	-3.33*** (0.96)	-2.54** (1.01)	-0.30 (0.24)	-0.33 (0.26)
$\Delta \log Y_t$	0.65*** (0.07)	0.68*** (0.07)	1.22*** (0.14)	1.21*** (0.15)	0.51*** (0.08)	0.55*** (0.09)	0.39*** (0.02)	0.37*** (0.02)
$\Delta \log Y_{t+2}$	0.09* (0.05)	0.08 (0.05)	0.29** (0.12)	0.29** (0.12)	0.03 (0.06)	0.02 (0.06)	0.01 (0.02)	0.01 (0.02)
D_t/Y_{t-2} , quartile 2	-0.20*** (0.05)	-0.23*** (0.05)	-1.21*** (0.09)	-1.27*** (0.09)	-0.16*** (0.06)	-0.19*** (0.06)	0.02 (0.02)	0.02 (0.02)
D_t/Y_{t-2} , quartile 3	-0.21*** (0.05)	-0.25*** (0.05)	-1.33*** (0.09)	-1.39*** (0.09)	-0.07 (0.06)	-0.12* (0.06)	0.04** (0.02)	0.05*** (0.02)
D_t/Y_{t-2} , quartile 4	-0.19*** (0.05)	-0.25*** (0.05)	-1.55*** (0.10)	-1.67*** (0.10)	-0.09 (0.06)	-0.14** (0.06)	0.01 (0.02)	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 2	-0.00 (0.05)	-0.03 (0.05)	0.10 (0.10)	0.08 (0.10)	-0.03 (0.06)	-0.06 (0.06)	-0.01 (0.02)	-0.01 (0.02)
FA_{t-2}/Y_{t-2} , quartile 3	0.12** (0.05)	0.09* (0.05)	0.15 (0.10)	0.14 (0.10)	0.13** (0.06)	0.10 (0.06)	0.01 (0.02)	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 4	0.16*** (0.05)	0.11* (0.06)	0.13 (0.11)	0.12 (0.11)	0.19*** (0.06)	0.13* (0.07)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 2	-0.00 (0.05)	-0.03 (0.05)	0.02 (0.10)	0.02 (0.10)	-0.04 (0.06)	-0.08 (0.07)	-0.01 (0.02)	-0.00 (0.02)
A_{t-2}/Y_{t-2} , quartile 3	-0.09 (0.05)	-0.10* (0.05)	-0.14 (0.11)	-0.15 (0.11)	-0.09 (0.07)	-0.11 (0.07)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 4	-0.11** (0.05)	-0.09 (0.06)	-0.19* (0.11)	-0.21* (0.11)	-0.12* (0.07)	-0.09 (0.07)	-0.01 (0.02)	-0.00 (0.02)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R ²	0.06	0.09	0.14	0.18	0.05	0.09	0.32	0.33
N	4571	4571	4571	4571	4571	4571	4571	4571

Table 7: Regression results from estimating (1) and (2), when adding future income growth as a control. For the first six columns, the left-hand side variable is an indicator of whether a durable good in the category indicated by the column header has been purchased in the last 12 months using a probit model. The coefficients show the average marginal effect normalized by the unconditional purchase probability. D_t refers to the stock of durable goods in this durable good category, prior to any purchase in year t . In the last two columns, the left-hand side variable is the log growth of expenditures on nondurable goods, estimated by OLS. D_t is defined as in columns 1 and 2. The set of control variables includes indicator variables of 5-year age bins, sex, marital status, household size, education level, occupation, industry, region of residence, bins of the size of the town of residence, an indicator of a binding liquidity constraint as well as the log level of previous period income. Standard errors are shown in parenthesis. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.

	Durables I	Durables II	Vehicles I	Vehicles II	Furniture I	Furniture II	Nondurables I	Nondurables II
$\Delta \text{Unemployment risk}_t$	-3.40*** (0.79)	-2.71*** (0.83)	-3.32** (1.67)	-3.55** (1.80)	-3.51*** (0.98)	-2.73*** (1.03)	-0.27 (0.25)	-0.28 (0.26)
$\Delta \log Y_t$	0.60*** (0.07)	0.63*** (0.07)	1.04*** (0.13)	1.00*** (0.14)	0.49*** (0.08)	0.54*** (0.09)	0.38*** (0.02)	0.36*** (0.02)
D_t/Y_{t-2} , quartile 2	-0.20*** (0.05)	-0.23*** (0.05)	-1.21*** (0.09)	-1.27*** (0.09)	-0.17*** (0.06)	-0.20*** (0.06)	0.02 (0.02)	0.02 (0.02)
D_t/Y_{t-2} , quartile 3	-0.22*** (0.05)	-0.26*** (0.05)	-1.31*** (0.09)	-1.37*** (0.09)	-0.08 (0.06)	-0.13** (0.06)	0.04*** (0.02)	0.05*** (0.02)
D_t/Y_{t-2} , quartile 4	-0.18*** (0.05)	-0.24*** (0.05)	-1.55*** (0.10)	-1.67*** (0.10)	-0.09 (0.06)	-0.15** (0.06)	0.02 (0.02)	0.03 (0.02)
FA_{t-2}/Y_{t-2} , quartile 2	-0.01 (0.05)	-0.04 (0.05)	0.12 (0.10)	0.11 (0.10)	-0.05 (0.06)	-0.07 (0.06)	-0.01 (0.02)	-0.01 (0.02)
FA_{t-2}/Y_{t-2} , quartile 3	0.12** (0.05)	0.08* (0.05)	0.17 (0.10)	0.15 (0.10)	0.13** (0.06)	0.09 (0.06)	0.02 (0.02)	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 4	0.15*** (0.05)	0.10* (0.06)	0.15 (0.11)	0.14 (0.11)	0.18*** (0.07)	0.12* (0.07)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 2	0.00 (0.05)	-0.03 (0.05)	0.03 (0.10)	0.03 (0.10)	-0.03 (0.07)	-0.09 (0.07)	-0.01 (0.02)	-0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 3	-0.09 (0.05)	-0.10* (0.05)	-0.16 (0.11)	-0.17 (0.11)	-0.09 (0.07)	-0.11* (0.07)	0.01 (0.02)	0.00 (0.02)
A_{t-2}/Y_{t-2} , quartile 4	-0.11** (0.06)	-0.09 (0.06)	-0.21* (0.11)	-0.23** (0.11)	-0.12* (0.07)	-0.09 (0.07)	-0.01 (0.02)	-0.00 (0.02)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.06	0.09	0.14	0.18	0.05	0.09	0.32	0.33
N	4461	4461	4461	4461	4461	4461	4461	4461

Table 8: Regression results from estimating (1) and (2), when excluding households that become unemployed in period $t+2$ from the sample. For the first six columns, the left-hand side variable is an indicator of whether a durable good in the category indicated by the column header has been purchased in the last 12 months using a probit model. The coefficients show the average marginal effect normalized by the unconditional purchase probability. D_t refers to the stock of durable goods in this durable good category, prior to any purchase in year t . In the last two columns, the left-hand side variable is the log growth of expenditures on nondurable goods, estimated by OLS. D_t is defined as in columns 1 and 2. The set of control variables includes indicator variables of 5-year age bins, sex, marital status, household size, education level, occupation, industry, region of residence, bins of the size of the town of residence, an indicator of a binding liquidity constraint as well as the log level of previous period income. Standard errors are shown in parenthesis. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.

Endogeneity of unemployment risk to private information We infer the probability of becoming unemployed from households that actually become unemployed. However, it could be the case that households that become unemployed know well in advance whether they will keep their employment or not and hence, that the employment status in period $t+2$ does not have a meaningful stochastic component, but only masks individual private information. If this is the case, the estimated coefficient of unemployment risk growth on expenditures should be driven by those households that actually do become unemployed in period $t+2$. Therefore, we rerun the regressions excluding households that became unemployed in period $t+2$ from our sample. The results are shown in Table 8. Comparing the coefficients to Table 2, this adjustment does not affect the results.

Number of factors used for estimation of unemployment risk. In the estimation of unemployment probabilities, we used 6 factors based on maximizing the adjusted predictive power of our regressions. How-

	Durables I	Durables II	Vehicles I	Vehicles II	Furniture I	Furniture II	Nondurables I	Nondurables II
Δ Unemployment risk (4 factors)	-3.25*** (0.91)	-2.88*** (0.95)	-4.56** (1.95)	-5.17** (2.04)	-2.83** (1.13)	-2.43** (1.18)	0.16 (0.29)	0.11 (0.30)
Δ Unemployment risk (6 factors)	-3.24*** (0.77)	-2.54*** (0.82)	-3.20* (1.64)	-3.33* (1.78)	-3.32*** (0.96)	-2.51** (1.01)	-0.27 (0.24)	-0.30 (0.26)
Δ Unemployment risk (8 factors)	-2.53*** (0.71)	-1.94*** (0.74)	-3.18** (1.49)	-3.37** (1.60)	-2.70*** (0.88)	-2.10** (0.92)	-0.39* (0.22)	-0.47** (0.24)
Δ Unemployment risk (10 factors)	-2.35*** (0.65)	-1.76*** (0.67)	-2.16 (1.39)	-2.22 (1.50)	-2.51*** (0.80)	-1.92** (0.82)	-0.18 (0.20)	-0.22 (0.21)
Δ Unemployment risk (12 factors)	-1.91*** (0.59)	-1.36** (0.60)	-1.56 (1.25)	-1.40 (1.34)	-2.33*** (0.72)	-1.80** (0.74)	-0.05 (0.18)	-0.05 (0.19)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control set 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control set 2	No	Yes	No	Yes	No	Yes	No	Yes

Table 9: Regression results from estimating (1) and (2), when using between 4 and 12 factors for the estimation of unemployment probabilities. For the first six columns, the left-hand side variable is an indicator of whether a durable good in the category indicated by the column header has been purchased in the last 12 months using a Probit model. The coefficients show the average marginal effect normalized by the unconditional purchase probability. In the last two columns, the left-hand side variable is the log growth of expenditures on nondurable goods, estimated by OLS. Control set 1 includes log income growth, the stock of durables, financial and total assets. Control set 2 includes indicator variables of 5-year age bins, sex, marital status, household size, education level, occupation, industry, region of residence, bins of the size of the town of residence, an indicator of a binding liquidity constraint as well as the log level of previous period income. Standard errors are shown in parenthesis. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.

ever, and as discussed earlier, for this number of factors, the marginal contribution of adding additional factors to the fraction of the variation in the underlying covariates is substantial.

We reestimate Equations (1) and (2) using between 4 and 12 factors. Reassuringly, our results are robust, although the estimated effect of unemployment risk on durable purchases levels off as we increase the number of factors. When using 8 factors, we also find a significant negative effect of unemployment risk growth on nondurable expenditure growth.

Income cutoff in sample selection. The sample only includes households where the labor income of the household head is at least 40 percent of total household income, so that an unemployment spell would likely have a substantial effect on household income. The exact cutoff is somewhat arbitrary. We rerun the regression when setting this cutoff to 35 and 45 percent, respectively. The results are shown in Tables 10 and 11. The estimated coefficients of unemployment risk on durable purchases are slightly smaller in both cases, but still sizable. Increasing the cutoff further up, the sample size shrinks fast.

C Solving the consumption model

In this appendix, we provide a description of how we solve the consumption model presented in Section 3. The description has three parts. First, we describe how the consumption problem can be rewritten in a

	Durables I	Durables II	Vehicles I	Vehicles II	Furniture I	Furniture II	Nondurables I	Nondurables II
$\Delta \text{Unemployment risk}_t$	-2.29*** (0.71)	-1.62** (0.74)	-2.60* (1.53)	-2.70 (1.65)	-2.15** (0.88)	-1.38 (0.91)	-0.04 (0.23)	-0.11 (0.24)
$\Delta \log Y_t$	0.60*** (0.06)	0.64*** (0.06)	1.17*** (0.12)	1.15*** (0.13)	0.49*** (0.07)	0.54*** (0.08)	0.40*** (0.02)	0.38*** (0.02)
D_t/Y_{t-2} , quartile 2	-0.19*** (0.04)	-0.22*** (0.04)	-1.14*** (0.08)	-1.20*** (0.08)	-0.16*** (0.05)	-0.19*** (0.05)	0.02 (0.01)	0.02 (0.02)
D_t/Y_{t-2} , quartile 3	-0.19*** (0.05)	-0.23*** (0.05)	-1.28*** (0.08)	-1.35*** (0.08)	-0.04 (0.06)	-0.09* (0.05)	0.03** (0.02)	0.04** (0.02)
D_t/Y_{t-2} , quartile 4	-0.21*** (0.05)	-0.28*** (0.05)	-1.51*** (0.09)	-1.63*** (0.09)	-0.08 (0.06)	-0.15** (0.06)	0.02 (0.02)	0.03* (0.02)
FA_{t-2}/Y_{t-2} , quartile 2	0.01 (0.05)	-0.02 (0.05)	0.13 (0.09)	0.09 (0.09)	-0.03 (0.06)	-0.05 (0.06)	-0.00 (0.01)	-0.00 (0.02)
FA_{t-2}/Y_{t-2} , quartile 3	0.15*** (0.05)	0.12*** (0.05)	0.16* (0.09)	0.13 (0.09)	0.17*** (0.06)	0.13** (0.06)	0.01 (0.02)	0.01 (0.02)
FA_{t-2}/Y_{t-2} , quartile 4	0.18*** (0.05)	0.14*** (0.05)	0.13 (0.10)	0.12 (0.10)	0.22*** (0.06)	0.17*** (0.06)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 2	-0.03 (0.05)	-0.06 (0.05)	0.05 (0.09)	0.05 (0.09)	-0.07 (0.06)	-0.11* (0.06)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 3	-0.10** (0.05)	-0.10** (0.05)	-0.17* (0.10)	-0.17* (0.10)	-0.11* (0.06)	-0.11* (0.06)	0.01 (0.02)	0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 4	-0.14*** (0.05)	-0.11** (0.05)	-0.15 (0.10)	-0.19* (0.10)	-0.16*** (0.06)	-0.12* (0.06)	-0.00 (0.02)	0.00 (0.02)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.06	0.09	0.14	0.17	0.05	0.08	0.32	0.33
N	5178	5178	5178	5178	5178	5178	5178	5178

Table 10: Regression results from estimating (1) and (2) when the income cutoff is 35 percent. For the first six columns, the left-hand side variable is an indicator of whether a durable good in the category indicated by the column header has been purchased in the last 12 months using a probit model. The coefficients show the average marginal effect normalized by the unconditional purchase probability. D_t refers to the stock of durable goods in this durable good category, prior to any purchase in year t . In the last two columns, the left-hand side variable is the log growth of expenditures on nondurable goods, estimated by OLS. D_t is defined as in columns 1 and 2. The set of control variables includes indicator variables of 5-year age bins, sex, marital status, household size, education level, occupation, industry, region of residence, bins of the size of the town of residence, an indicator of a binding liquidity constraint as well as the log level of previous period income. Standard errors are shown in parenthesis. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.

	Durables I	Durables II	Vehicles I	Vehicles II	Furniture I	Furniture II	Nondurables I	Nondurables II
$\Delta \text{Unemployment risk}_t$	-2.34*** (0.81)	-1.53* (0.84)	-2.77 (1.71)	-2.30 (1.86)	-2.14** (1.00)	-1.35 (1.03)	-0.30 (0.25)	-0.30 (0.26)
$\Delta \log Y_t$	0.60*** (0.07)	0.61*** (0.08)	1.05*** (0.15)	1.02*** (0.16)	0.51*** (0.09)	0.53*** (0.10)	0.37*** (0.02)	0.35*** (0.02)
D_t/Y_{t-2} , quartile 2	-0.22*** (0.05)	-0.25*** (0.05)	-1.20*** (0.10)	-1.25*** (0.10)	-0.13** (0.07)	-0.16** (0.07)	0.01 (0.02)	0.02 (0.02)
D_t/Y_{t-2} , quartile 3	-0.17*** (0.06)	-0.21*** (0.06)	-1.31*** (0.10)	-1.36*** (0.10)	-0.04 (0.07)	-0.10 (0.07)	0.04** (0.02)	0.05*** (0.02)
D_t/Y_{t-2} , quartile 4	-0.20*** (0.06)	-0.26*** (0.06)	-1.60*** (0.11)	-1.73*** (0.11)	-0.10 (0.07)	-0.15** (0.07)	0.01 (0.02)	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 2	-0.01 (0.06)	-0.04 (0.06)	0.19* (0.11)	0.13 (0.11)	-0.05 (0.07)	-0.08 (0.07)	-0.01 (0.02)	-0.01 (0.02)
FA_{t-2}/Y_{t-2} , quartile 3	0.14** (0.06)	0.09 (0.06)	0.22* (0.12)	0.16 (0.12)	0.11 (0.07)	0.07 (0.07)	0.02 (0.02)	0.02 (0.02)
FA_{t-2}/Y_{t-2} , quartile 4	0.17*** (0.06)	0.10 (0.06)	0.13 (0.12)	0.08 (0.13)	0.19** (0.07)	0.11 (0.08)	0.02 (0.02)	0.02 (0.02)
A_{t-2}/Y_{t-2} , quartile 2	-0.02 (0.06)	-0.04 (0.06)	0.12 (0.12)	0.10 (0.12)	-0.06 (0.07)	-0.09 (0.07)	-0.01 (0.02)	-0.01 (0.02)
A_{t-2}/Y_{t-2} , quartile 3	-0.07 (0.06)	-0.07 (0.06)	0.01 (0.12)	-0.01 (0.12)	-0.09 (0.07)	-0.10 (0.08)	0.00 (0.02)	0.00 (0.02)
A_{t-2}/Y_{t-2} , quartile 4	-0.11* (0.06)	-0.08 (0.06)	-0.13 (0.12)	-0.17 (0.13)	-0.12 (0.08)	-0.07 (0.08)	-0.01 (0.02)	-0.00 (0.02)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.06	0.10	0.14	0.18	0.05	0.10	0.33	0.34
N	3871	3871	3871	3871	3871	3871	3871	3871

Table 11: Regression results from estimating (1) and (2) when the income cutoff is 45 percent. For the first six columns, the left-hand side variable is an indicator of whether a durable good in the category indicated by the column header has been purchased in the last 12 months using a probit model. The coefficients show the average marginal effect normalized by the unconditional purchase probability. D_t refers to the stock of durable goods in this durable good category, prior to any purchase in year t . In the last two columns, the left-hand side variable is the log growth of expenditures on nondurable goods, estimated by OLS. D_t is defined as in columns 1 and 2. The set of control variables includes indicator variables of 5-year age bins, sex, marital status, household size, education level, occupation, industry, region of residence, bins of the size of the town of residence, an indicator of a binding liquidity constraint as well as the log level of previous period income. Standard errors are shown in parenthesis. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.

simplified form with fewer state variables, greatly reducing the computational burden. Second, we describe the solution method. Finally, we describe how it is implemented in practice.

C.1 State space reduction in the recursive formulation

Due the combined assumptions of a linear replacement rate, a linear adjustment cost and preferences with constant relative risk aversion over a homothetic bundle of the two goods, the household problem can be normalized with respect to the permanent income state Z_t , similar to a standard buffer-stock model with only one good (see e.g. [Carroll \(1997\)](#)). In addition, since transitory shocks have no dependence on past variables, ϵ can also be eliminated as a state variable. Finally, conditional on adjusting, one more state variable can be eliminated as the optimization problem only depends on the total available resources today. We describe each of these simplifications in turn.

Before describing the normalization with respect to Z_t , we make the variable substitution $\hat{B} = B + \hat{\chi}D$. This normalizes the borrowing constraint to $\hat{B} \geq 0$:

$$\begin{aligned}
V_{NA}(\hat{B}, D; Z, \epsilon, n, \zeta) = & \max_{C, \hat{B}^*} u(C, D^*) + \beta EV(\hat{B}', D'; Z', \epsilon', n', \zeta') \\
\text{s.t.} & \hat{B}' = \hat{B}^* \\
& D' = D^* \\
& D^* = (1 - \delta)D \\
& C + q\hat{B}^* \leq Y(n + b(1 - n)) + \hat{B} - \hat{\chi}(1 - q(1 - \delta))D, \\
& \hat{B}^*, C \geq 0, \\
& Y = Z\epsilon, \\
V_A(\hat{B}, D; Z, \epsilon, n, \zeta) = & \max_{C, D^*, \hat{B}^*} u(C, D^*) + \beta EV(\hat{B}', D'; Z', \epsilon', n', \zeta') \\
\text{s.t.} & \hat{B}' = \hat{B}^* \\
& D' = D^* \\
& C + (1 - q\hat{\chi})D^* + q\hat{B}^* \leq Y(n + b(1 - n)) + \hat{B} + (1 - \delta - h - \hat{\chi})D, \\
& \hat{B}^*, C, D^* \geq 0, \\
& Y = Z\epsilon, \\
V(\hat{B}, D; Z, \epsilon, n, \zeta) = & \max\{V_{NA}(\hat{B}, D; Z, \epsilon, n, \zeta), V_A(\hat{B}, D; Z, \epsilon, n, \zeta)\}.
\end{aligned}$$

Now we normalize the household problem with respect to permanent income Z_t . We make the following definitions:

- $\mathbf{v} = \mathbf{V}Z^{-(1-\sigma)}$ for variables $\mathbf{V} = V, V_{NA}, V_A$

- $x = X/Z$ for any other variable X
- $x' = X'/Z'$ for any variable X'

Using that $u(\cdot)$ is homothetic, the recursive problem can be reformulated in terms of v, x, x' without dependence of the state variable Z :

$$\begin{aligned}
v_{NA}(\hat{b}, d; \epsilon, n, \zeta) = & \max_{c, \hat{b}^*} u(c, d^*) + \beta E \eta^{1-\sigma} v(\hat{b}', d'; \epsilon', n', \zeta') & (21) \\
\text{s.t.} & \hat{b}' = \eta'^{-1} \hat{b}^* \\
& d' = \eta'^{-1} d^* \\
& d^* = (1 - \delta) d \\
& c + q \hat{b}^* \leq \epsilon(n + b(1 - n)) + \hat{b} - \hat{\chi}(1 - q(1 - \delta))d, \\
& b^*, c \geq 0,
\end{aligned}$$

$$\begin{aligned}
v_A(\hat{b}, d; \epsilon, n, \zeta) = & \max_{c, d^*, \hat{b}^*} u(c, d^*) + \beta E \eta^{1-\sigma} v(\hat{b}', d'; \epsilon', n', \zeta') & (22) \\
\text{s.t.} & \hat{b}' = \eta'^{-1} \hat{b}^* \\
& d' = \eta'^{-1} d^* \\
& c + (1 - q\hat{\chi})d^* + q\hat{b}^* \leq \epsilon(n + b(1 - n)) + \hat{b} + ((1 - \delta)(1 - h) - \hat{\chi})d, \\
& \hat{b}^*, c, d^* \geq 0, \\
v(\hat{b}, d; \epsilon, n, \zeta) = & \max\{v_{NA}(\hat{b}, d; \epsilon, n, \zeta), v_A(\hat{b}, d; \epsilon, n, \zeta)\}.
\end{aligned}$$

Second, ϵ can be eliminated as a state variable as it enters through the sufficient state variable $\mathbf{a} = \epsilon(n + b(1 - n)) + \hat{b}$. Using this, we can write the problem as

$$\begin{aligned}
v_{NA}(\mathbf{a}, d; n, \zeta) = & \max_{c, \hat{b}^*} u(c, (1 - \delta)d) + \beta E \eta^{1-\sigma} v(\epsilon'(n' + b(1 - n')) + \eta'^{-1} \hat{b}^*, \eta'^{-1}(1 - \delta)d; n', \zeta') \\
\text{s.t.} & c + q \hat{b}^* \leq \mathbf{a} - \hat{\chi}(1 - q(1 - \delta))d, \\
& b^*, c \geq 0, \\
v_A(\mathbf{a}, d; n, \zeta) = & \max_{c, d^*, \hat{b}^*} u(c, d^*) + \beta E \eta^{1-\sigma} v(\epsilon'(n' + b(1 - n')) + \eta'^{-1} \hat{b}^*, \eta'^{-1} d^*; n', \zeta') \\
\text{s.t.} & c + (1 - q\hat{\chi})d^* + q\hat{b}^* \leq \mathbf{a} + ((1 - \delta)(1 - h) - \hat{\chi})d, \\
& \hat{b}^*, c, d^* \geq 0, \\
v(\hat{b}, d; n, \zeta) = & \max\{v_{NA}(\hat{b}, d; \epsilon, n, \zeta), v_A(\hat{b}, d; n, \zeta)\}.
\end{aligned}$$

Finally, note that conditional on adjusting, the sole state variable is $w = \mathbf{a} + ((1 - \delta)(1 - h) - \hat{\chi})d$, such

that

$$\begin{aligned}
v_A(w; n, \zeta) = & \max_{c, d^*, \hat{b}^*} u(c, d^*) + \beta E \eta^{1-\sigma} v(\epsilon'(n' + b(1 - n')) + \eta'^{-1} \hat{b}^*, \eta'^{-1} d^*; n', \zeta') \\
\text{s.t.} & c + (1 - q\hat{\chi})d^* + q\hat{b}^* \leq w \\
& \hat{b}^*, c, d^* \geq 0.
\end{aligned}$$

C.2 Computation

We solve the recursive problem by value function iteration. The convergence criterion is specified in terms of the distance between two consecutive value functions under the sup norm. We set the criterion to 10^{-5} when extracting decision rules used for the simulations in Sections 5 and 6, and to 10^{-2} for the calibration.

We discretize the processes for the labor market transition rates and the income shocks. For the labor market transition rates, we use the method by [Tauchen and Hussey \(1991\)](#) with seven states. For the income shocks, we use Hermite-Gauss polynomials with five states.

The grids for the endogenous states \mathbf{a} , \mathbf{d} , \mathbf{w} are linear up to a cutoff value and exponential in a sparse grid above the cutoff value. Given a value function v^i , we solve the expectation over the future value function by linear interpolation. Then, we compute v_{NA}^{i+1}, v_A^{i+1} by nonlinear optimization methods using several initial guesses. We then compute $v_A^{i+1}(\hat{b}, d; n, s)$ from $v_A^{i+1}(w; n, s)$ by cubic interpolation, and retrieve v^{i+1} by taking the maximum of $\{v_{NA}^{i+1}, v_A^{i+1}\}$.

We implement the computations in Python. The linear interpolation operations are executed in C via the Numba package.

D Details of calibration procedure

D.1 Estimation of average job-separation and job-finding rate

We estimate the quarterly separation and job-finding rates using the method developed by [Elsby et al. \(2013\)](#) (EHS) using annual data for the Italian unemployment rate, grouped by the duration of the unemployment spell. We retrieve the data from the OECD for the period 1984-2014, allowing us to estimate the quarterly rates for the period 1984-2013. The EHS method for estimating the separation and the job-finding rate is an extension of the method popularized by [Shimer \(2012\)](#). The method is robust to temporal aggregation bias, as it is inferred from an underlying continuous time process.

Let t denote a quarter. To estimate the quarterly job finding rate f_t , define $F_t^{<d}$ as the probability that

an unemployed worker exits unemployment within d quarters. $F_t^{<d}$ is estimated from

$$F_t^{<d} = 1 - \frac{u_{t+d} - u_{t+d}^{<d}}{u_t}$$

with an associated outflow rate given by

$$f_t^{<d} = -\log(1 - F_t^{<d})/d$$

Normalizing the time scale, we observe $u_{t+d}^{<d}$, u_{t+d} in year $t+d$. We infer u_t by taking the weighted geometric average of u_{t+d} and u_{t+d-4} ,

$$u_t = u_{t+d}^{d/4} u_{t+d-4}^{(4-d)/4}.$$

The OECD data allow us to observe unemployment rates with duration less than 1, 3, 6 and 12 months. Accordingly, we estimate the flow rates $f_t^{<1/3}$, $f_t^{<1}$, $f_t^{<2}$, $f_t^{<4}$. Then, we compute the average job finding rate f_t as the simple average of these four variables.¹⁹

Given f_t and u_t we can infer s_t from the law of motion for the aggregate unemployment rate:

$$\frac{\partial u}{\partial t} = s_t(1 - u_t) - f_t u_t. \quad (23)$$

Assuming that the flows are constant over a year and solving (23) one year forward, we have

$$u_t = \kappa_t u_t^* + (1 - \kappa_t) u_{t-4}, \quad (24)$$

where $\kappa_t = 1 - e^{-4(s_t + f_t)}$ and $u_t^* = \frac{s_t}{s_t + f_t}$. Given f_t , we use (24) to solve for the separation rate s_t .

The resulting quarterly job-finding and job-separation rates are shown in Figure 7. Between the start of the Eurozone crisis in 2011 and the last period of observation in 2013, the separation rate increased from 1.01 percent to 2.08 percent, a relative increase of 106 percent.

D.2 Calibration of flexible-adjustment model

For the calibration of the flexible-adjustment model used in Section 6, we set $h = 0$ and take the calibrated depreciation rate of the baseline model. We then calibrate (without the aggregate state variable) β , α and $\hat{\chi}$ to match the mean level of normalized financial assets, the mean level of normalized durable assets and the share of households with negative wealth in the data. The recalibrated parameters are shown in Table 12.

¹⁹Elsby et al. (2013) use an optimal weighting scheme based on minimizing the mean squared error of the estimate. For simplicity, we compute the unweighted average.

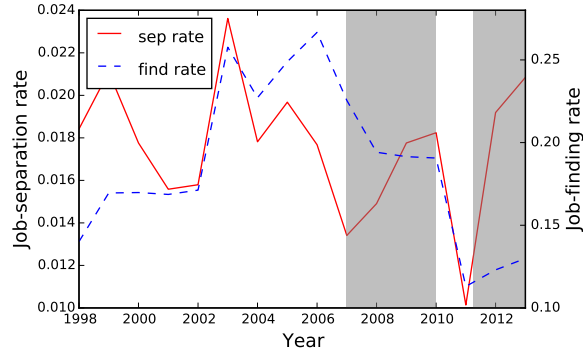


Figure 7: Estimated quarterly job-separation and job-finding rates, Italy 1998-2013. ECRI recession dates are indicated by the Shaded areas.

Parameters	Value	Target	Empirical	Model
Discount rate, β	0.971	Mean norm. fin. assets	1.72	1.72
Nondurable weight, α	0.946	Mean norm. dur. assets	1.24	1.23
Depreciation rate, δ	0.039			
Adjustment cost, h	0			
Collateral constraint, $\hat{\chi}$	0.40	Share neg. fin. wealth	0.11	0.012

Table 12: The calibrated parameters of the flexible-adjustment model. The targeted moments are computed from the SHIW sample used in Section 2. For moments that concern the stock and flow of durable goods, we use the stock and flow of motor vehicles in the data.