Consumption Dynamics under Time-Varying Unemployment Risk*

Karl Harmenberg† Erik Öberg‡

October 16, 2020

Abstract

In response to an adverse labor-market shock, a calibrated heterogeneous-agent model predicts that aggregate spending on durable goods falls mainly due to the ex-ante increase in income uncertainty caused by higher unemployment risk. In contrast, aggregate spending on nondurable goods falls mainly due to the ex-post income losses associated with realized unemployment spells. When households hold little liquid assets, the nondurable spending response is amplified, whereas the durable spending response is dampened. These differences stem from micro-level adjustment frictions involved in purchases of durable goods. The model is corroborated with evidence from micro survey data.

*We are very grateful for helpful comments from the editor Yuriy Gorodnichenko, the associate editor Joe Vavra, one anonymous referee, Adrien Auclert, Marco Bassetto, Christian Bayer, Tobias Broer, Mikael Carlsson, Chris Carroll, Russell Cooper, Jeppe Druedahl, Peter Fredriksson, Fatih Guvenen, John Hassler, Paul Klein, Per Krusell, Kurt Mitman, Benjamin Moll, Luca Repetto, José-Victor Ríos-Rull, Hans-Henrik Sievertsen, David Strömberg and participants in numerous conferences and seminars. Financial support from Handelsbanken's Research Foundations is gratefully acknowledged. All errors are our own.

†Copenhagen Business School. kha.eco@cbs.dk.

‡Uppsala University. erik.oberg@nek.uu.se.

1 Introduction

A recent strand of the business-cycle literature has stressed the importance of building models of household consumption-saving decisions that are consistent with the rich heterogeneity seen in micro data.[1] A key insight from this literature is that fluctuations in aggregate demand are not well described by a representative household. For example, worsening conditions in the labor market —a salient feature of recessions— only affects the representative household's consumption through its effect on the net-present value of the aggregate future income stream, which is typically small.[2] A more realistic view is that, due to the lack of insurance instruments and the presence of credit constraints, such shocks will also affect aggregate consumption demand via its effect on individual households' income paths. In particular, an increase in the unemployment rate raises the idiosyncratic uncertainty of households' future income *ex ante*, due to the higher risk of becoming unemployed, and generates large and concentrated income losses *ex post*, due to the realized unemployment spells. From this perspective, an important task for business-cycle research is to gauge the importance of these different micro-level channels in accounting for aggregate expenditure dynamics and to identify the determinants of their relative strength.

So far, most of the literature on this topic has focused on the dynamics of expenditure on nondurable goods, which constitute the largest goods category in household consumption.[3] However, from a business-cycle perspective, consumer durable goods are at least as important as nondurables, owing to the high volatility of durable-goods spending. For example, between 1947 and 2007, the contribution of spending on consumer durable goods to the shortfalls in aggregate GDP during US recessions is as large as the contribution of total spending on nondurables and services combined (Leamer, 2007). In the first year of the Great Recession,

[1] For surveys, see Krueger, Mitman, and Perri (2016) and Kaplan and Violante (2018).

[2] This statement is of course only true ceteris paribus. If the shock has equilibrium effects on prices, the expenditure dynamics will also depend on these effects.

[3] See, e.g., Carroll, Slacalek, Tokuoka, and White (2017), Kaplan, Moll, and Violante (2018), Auclert, Rognlie, and Straub (2018) and Berger et al. (2018) for models of the nondurable consumption response to changes in current income/liquidity. See, e.g., Challe and Ragot (2016), McKay (2017), Den Haan, Rendahl, and Riegler (2018), Ravn and Sterk (2018) and Bayer et al. (2019) for models of the nondurable consumption response to changes in income uncertainty.

expenditures on cars alone dropped by almost one percent of total GDP (Dupor, Li, Saif, and Tsai, 2018).

In this paper, we consider a heterogeneous-agent model that includes both durable and nondurable goods, with realistic frictions to make the model expenditure patterns consistent with key features of the micro data. In particular, we stress that durables are different from nondurables in that purchases of durables are lumpy. We use the model to estimate the aggregate demand response to an adverse labor-market shock, and attribute the demand response to the changes in realized income losses (due to more households becoming unemployed) as well as the changes in expected future income and income uncertainty (both due to an increased risk of becoming unemployed). Our main finding is that the spending response through these three channels is both qualitatively and quantitatively different for durable goods compared to nondurable goods. In particular, whereas the realized income losses account for most of the response for nondurables, the heightened income uncertainty accounts for most of the response for durables. Moreover, we show that the degree of household insurance, a key dimension of heterogeneity in the micro data, has different implications for nondurable and durable expenditure dynamics. In a comparative-statics sense, more households having small liquid-assets holdings increases the aggregate response of nondurable spending to the labor-market shock, whereas it decreases the aggregate response of durable spending.

Our model extends a standard buffer-stock savings model to include both nondurable and durable consumption, with durable purchases subject to a nonconvex adjustment cost.[4] Because of the adjustment cost, it is costly for households to frequently adjust their durable stock, which generates lumpy purchase behavior consistent with the data. The adjustment cost affects durable-expenditure dynamics in two distinct ways. First, in response to income shocks, the adjustment cost smoothens the aggregate expenditure response (Chetty and Szeidl, 2016). At any given moment, few households adjust their durable stock, and it

[4] A recent literature has investigated the role of similar adjustment costs for shaping business-cycle dynamics of firm investment, see Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) and references therein.

therefore takes time before all households have responded to the shock. Second, in response to shocks to income uncertainty, the adjustment cost amplifies the expenditure response for durables. Without the adjustment cost, households respond to heightened income uncertainty because of prudent preferences and the potentially binding credit constraint, which cause them to increase their buffer-stock savings target and cut back on all expenditures. With the adjustment cost, households have an additional motive to cut durable expenditures. In case of an adverse income shock, readjustment of the durable stock is costly. Anticipating this, a forward-looking household delays its durable-goods purchases in response to increased income uncertainty (Bernanke, 1983, Dixit and Pindyck, 1994).

We estimate the model processes for employment and income, and calibrate the preference and technology parameters to match sample moments in Italian micro survey data (which we also use for a reduced-form empirical investigation, see below). We then compute, in partial equilibrium, the aggregate-expenditure response to a large and persistent increase in the job-separation rate, in line with the Italian experience during the recent Eurozone crisis. The shock raises the risk of becoming unemployed ex ante for all households, thereby decreasing expected income and raising income uncertainty, and depresses income ex post for the subset of households that do become unemployed. Although the realized income losses always produce the largest expenditure responses at the household level, it is a priori unclear which channel dominates in the aggregate.

We decompose the aggregate expenditure response into these three separate channels. Whereas the *income-uncertainty* channel accounts for 30 percent of the aggregate nondurable response, the same channel accounts for 60 percent of the aggregate durable response. For nondurables, the most important channel is the ex-post *unemployment channel*. The difference stems primarily from the adjustment-cost amplification of the durable-spending response to income uncertainty. In a model without the adjustment cost, the income-uncertainty response for durables is reduced by 85 percent. The *expected-income channel* is small for nondurables and negligible for durables.

By varying the model discount factor, in a comparative-statics sense, we trace out how the expenditure responses depend on the households' holdings of liquid assets. Since the nondurable response is primarily driven by the unemployment channel and the households' marginal propensity to consume (MPC) increases as households come close to a binding credit constraint, the aggregate nondurable spending response is monotonically decreasing in the amount of liquidity in the economy. For durables, in contrast, the total response is primarily driven by the income-uncertainty channel, and is hump shaped. When households have plenty of liquid assets and are well insured, they do not respond to the uncertainty component of the adverse labor-market shock; when households face a binding credit constraint, they do not respond to changes in future income at all. The income-uncertainty response is maximized for intermediate values, where households are simultaneously forward-looking and not well insured.

We corroborate our findings with reduced-form evidence using the same Italian survey data that we employ for calibrating our model. Based on observable household characteristics, we estimate a factor model for predicting idiosyncratic changes in household-level unemployment risk. We then estimate the effect of a change in predicted unemployment risk on purchases of consumer durable goods and nondurable goods separately.[5] Durable purchases respond strongly to changes in unemployment risk, with a semi-elasticity around 3, while the semi-elasticity for nondurable expenditures is considerably smaller, around 0.5. We relate these estimates to our model by running the same regressions on model-generated data. Although not targeted in the calibration, the expenditure responses to changes in unemployment risk are close to the empirical estimates, both for durable and nondurable expenditures.

Taken together, our results suggest that the formation of households' beliefs about their income processes is key for shaping aggregate consumption dynamics, especially their perceived uncertainty regarding their future income path. In this paper, we do not present evidence on household belief formation and simply assume rational expectations, but our

[5]Most previous micro-level studies on the relation between expenditures and income risk have only used cross-sectional variation, see, e.g., Carroll, Dynan, and Krane (2003), Eberly (1994) and Bertola, Guiso, and Pistaferri (2005). In our context, having panel data is important, as it is only to temporary increases in income uncertainty that our model predicts a large response of durable purchases.

findings reinforce the importance of understanding household belief formation and how it varies with the business cycle. In this sense, our paper motivates the growing literature on how households learn about their income processes (Guvenen and Smith, 2014, Druedahl and Jorgensen, 2018, Rozsypal and Schlafmann, 2019) and about the aggregate state of the economy (Bhandari, Borovička, and Ho, 2019, Carroll, Crawley, Slacalek, Tokuoka, and White, 2019). Our findings also reinforce the hypothesis that the distribution of liquid assets is key for determining the size of the expenditure response to labor-market shocks. Several previous studies have emphasized that having many liquidity-constrained households tends to amplify the expenditure response of nondurables to labor-market shocks, see, e.g., Kaplan, Moll, and Violante (2018) and Auclert, Rognlie, and Straub (2018). In contrast, we find that for durables, having many liquidity-constrained households depresses the expenditure response by eliminating the otherwise large response to income uncertainty.

Our paper adds to the growing literature that emphasizes the importance of adjustment frictions and incomplete markets for the business-cycle dynamics of durable-goods spending. Berger and Vavra (2015) show that such frictions generate state-dependent responses to policy shocks. McKay and Wieland (2019) show that such frictions generate an intertemporal trade-off for monetary policy in stabilizing aggregate demand. Gavazza and Lanteri (2018) show that equilibrium dynamics in the second-hand market imply that these adjustment frictions become more severe during recessions. We show that adjustment frictions change the relative importance of the different channels that generate fluctuations in durable-goods demand, and how this depends on households' liquid asset position.

2 Model

Our model extends a standard buffer-stock model (see, e.g., Carroll (1997)) to separate between nondurable and durable consumption goods, with an adjustment cost for the durable good. The economy has a continuum of ex-ante identical households. Time is discrete and a period corresponds to a quarter. Each household solves

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

$$
C_{it} + D_{it} + qB_{it} \leqslant \Upsilon(Y_{it}, n_{it}) + (1-\delta)D_{it-1} + B_{it-1} - A(D_{it}, D_{it-1}), \tag{1}
$$

$$
B_{it} \geqslant -\chi \left[(1-\delta)D_{it} - A(0, D_{it-1})\right], \tag{2}
$$

$$
C_{it}, D_{it} \geqslant 0. \tag{3}
$$

Households have time-additive homothetic preferences over the consumption of nondurable goods C_{it} and the consumption of durable goods D_{it}, with discount factor β. They 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. The durable good depreciates by δ each period. In each period, households receive income Υ_{it} that depends on their employment status n_{it} and their earnings potential Y_{it}.

The households face two market frictions. First, households face a credit constraint, given by Equation (2). Specifically, households cannot borrow more than a fraction χ of the pledgeable part of their next-period stock of durable goods, $(1-\delta)D_{it} - A(0, D_{it})$. Second, and importantly for this paper, adjusting the durable stock is associated with a nonconvex adjustment cost on the form,[6]

$$
A(D_{it}, D_{it-1}) = \begin{cases} 0 & \text{if } D_{it} = (1-\delta)D_{it-1}, \\ hD_{it-1} & \text{if } D_{it} \neq (1-\delta)D_{it-1}. \end{cases} \tag{4}
$$

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*. The adjustment-cost parameter h can be interpreted as the average resale loss when selling the replaced stock D_{it-1} in the second-hand market. The adjustment cost generates lumpy purchases of consumer durables, consistent with the micro data.

[6] The specification follows Grossman and Laroque (1990) and Berger and Vavra (2015).

2.1 Calibration

We estimate the income processes and calibrate parameters to match moments from the Italian Survey of Household Income and Wealth (SHIW) for the years 1998-2014 (using the same sample as we use for the empirical analysis in Section 4) as well as to a selected set of Italian macro statistics.

Details of the estimations and the computational method for solving and simulating the model are described in Appendix A.

Income process Households receive their earnings potential, Y_{it}, if employed and a constant fraction, bY_{it}, if unemployed. The process for earnings potential Y_{it} has permanent and transitory shocks. Both are identically and independently distributed across time and households.

$$\Upsilon(Y_{it}, n_{it}) = Y_{it}\left(n_{it} + b(1 - n_{it})\right), \tag{5}$$

$$Y_{it} = Z_{it}e^{\epsilon_{it}}, \qquad \epsilon_{it} \sim N\left(-\sigma_{\epsilon}^2/2, \sigma_{\epsilon}\right) \tag{6}$$

$$Z_{it} = Z_{it-1}e^{\eta_{it}}, \qquad \eta_{it} \sim N\left(-\sigma_{\eta}^2/2, \sigma_{\eta}\right). \tag{7}$$

We set $b = 0.45$ to match the average replacement rate in Italy estimated by Martin (1996).

Employment process and aggregate state The process for employment status n_{it} is governed by a job-finding probability λ_t and a job-separation probability ζ_t. We aim for a process that captures the unemployment dynamics in Italy during the recent Eurozone crisis.

The aggregate state takes two values, expansion (E) and recession (R), and follows a Markov process. We set the transition probabilities 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.[7]

We estimate the job-finding and job-separation rates for Italy 1998-2013 using OECD

[7] Recession indicators are retrieved from the Economic Cycle Research Institute.

Potential-earnings process				
Parameter	Value	Target moments	Value	Data
σ_ϵ	0.158	$-\mathrm{Cov}(\Delta y_{it}^{annual}, \Delta y_{it-2}^{annual})$	0.158	SHIW
σ_η	0.073	$\frac{1}{8}(\mathrm{Var}(\Delta y_{it}^{annual}) - 2\sigma_\epsilon^2)$	0.073	SHIW

Job-finding process				
Parameter	Value	Target moments	Value	Data
$\lambda(E)$	0.17	Mean find. rate 1998-2013	0.17	OECD
$\lambda(R)$	0.17	Find. rate(2013)/Find. rate(2011)	~ 1	OECD

Job-separation process				
Parameter	Value	Target moments	Value	Data
$\zeta(E)$	0.012	Mean sep. rate 1998-2013	0.018	OECD
$\zeta(R)$	0.024	Sep. rate(2013)/Sep. rate(2011)	~ 2	OECD

Table 1: *Calibrated parameter values for the income process.* Δy_{it}^{annual} *is the residual from regressing the two-year annual-earnings growth on sex, education and region, all interacted with a four-degree polynomial of age, and year fixed effects. Here, the time subscript* t *refers to a year, and not a quarter.*

data. Between the starting year of the recession, 2011, and 2013, the last year of observation, the quarterly job-separation rate increased from 1.01 to 2.08 percent, while there was no significant movement in the job-finding rate. Accordingly, we impose that our process satisfies $\lambda(R)/\lambda(E) = 1$ and $\zeta(R)/\zeta(E) = 2$, and that the means, $E(\lambda)$ and $E(\zeta)$, equal the average job-finding and job-separation probability in the period 1998-2013. The resulting parameter values are reported in Table 1.

In the business-cycle literature, it is common to model a recession as a uniform fall in income (e.g., the wage) and/or an increase in the variance of the income process. Here, we do not consider all changes to the household income process during a recession but only focus on changes induced by a higher job-separation rate. Still, it might be useful to compare the size of our job-separation rate recession in terms of the shocks considered in the previous literature. In our model recession, the higher job-separation rate induces a fall in per-period aggregate income by 2.1 percent and an increase in the standard deviation of income growth equivalent to an increase by 71 percent in the standard deviation of permanent earnings-potential shocks.[8] The fall in aggregate income is comparable to the average falls in US HP-filtered real quarterly GDP during the early-90s recession, the early-00s recession, and the Great Recession, which were 1.9, 1.8 and 1.9 percent, respectively.[9] The variance increase is close to the estimate of Storesletten, Telmer, and Yaron (2004), which has that the standard deviation of the highly persistent income shock increases by 75 percent during recessions.

Other parameters The period utility function is CRRA over a Cobb-Douglas aggregator of the nondurable and durable good, $U(C_{it}, D_{it}) = \frac{1}{1-\sigma}\left(C_{it}^{\alpha} D_{it}^{1-\alpha}\right)^{1-\sigma}$, motivated by Ogaki and Reinhart (1998), who estimate that the intratemporal elasticity of substitution between durable and nondurable goods is approximately 1. We set the risk-aversion parameter $\sigma = 2$, in the middle of the standard range $[1, 5]$, and the quarterly real interest rate to 1 percent.

The rest of the parameters are calibrated to match moments from the SHIW data. We target the average level of net financial assets and durable assets as multiples of total household income, the annual durable purchase frequency, the average size of durable purchases as a multiple of the durable stock and the share of households with negative net financial wealth.

A durable purchase in the data is a yearly expenditure on goods in the motor vehicle category or furniture/appliance category (including electronics, furnishings and sundry equipment) that corresponds to at least two weeks of mean household income. The annual purchase frequency and purchase size matches the weighted average of the purchase frequencies and purchases sizes for vehicles and furniture/appliances, weighted by the share of the total durable stock belonging to the two categories. The calibrated parameter values and the target moments are shown in Table 2.

[8]The fall in mean income is computed by comparing average unemployment rates in expansions and recessions. The increase in the standard deviation is computed by matching the shift in the standard deviation of the log income growth distribution associated with a recession.

[9]These numbers are computed comparing the average HP-filtered GDP during the NBER recession quarters to the HP-filtered GDP in the quarter prior to each recession.

Parameter	Value	Target	Value
Discount rate, β	0.975	Mean norm. fin. assets	0.46
Nondurable weight, α	0.920	Mean norm. dur. assets	0.73
Depreciation rate, δ	0.023	Mean yearly purch. freq.	0.16
Adjustment cost, h	0.086	Mean norm. purchase size	0.55
Collateral constraint, χ	0.359	Share neg. fin. wealth	0.11

Table 2: *The calibrated preference and technology parameters of the model. The targeted moments are computed from the SHIW sample used for the empirical analysis in Section 4. The calibrated model moments are all within* 0.1% *of their targets.*

2.2 Household decision functions

The main features of our model are the inclusion of durable goods, subject to a non-convex adjustment cost, and the lack of a complete asset market. Here, we highlight how these features interact in shaping households' decisions over durable purchases. Figure 1 illustrates the household decision function for durable goods and how it varies with the household employment status and aggregate state. Because of the adjustment cost, households employ a two-dimensional (S,s)-type decision rule. Only households that are sufficiently poor in durable assets increase their durable stock, and only household sufficiently poor in cash decrease it, as indicated by the shaded regions. If adjusting, households jump to the adjustment target.

Because markets are incomplete, households may respond strongly to both unemployment and unemployment-risk shocks. Compared to a flexible-adjustment model, the (S,s)-type decision rule implies a smoother response of aggregate expenditures to unemployment shocks, illustrated in the left panel of Figure 1. At any given time, only a subset of households are in the region where they would have purchased a durable if employed but not if unemployed, and it therefore takes considerable time before all households have responded to the shock. The (S,s)-type decision rule also implies a wait-and-see effect that amplifies the expenditure response to unemployment-risk shocks, through its effect on income uncertainty. This is illustrated in the right panel of Figure 1. If a household experiences an unemployment

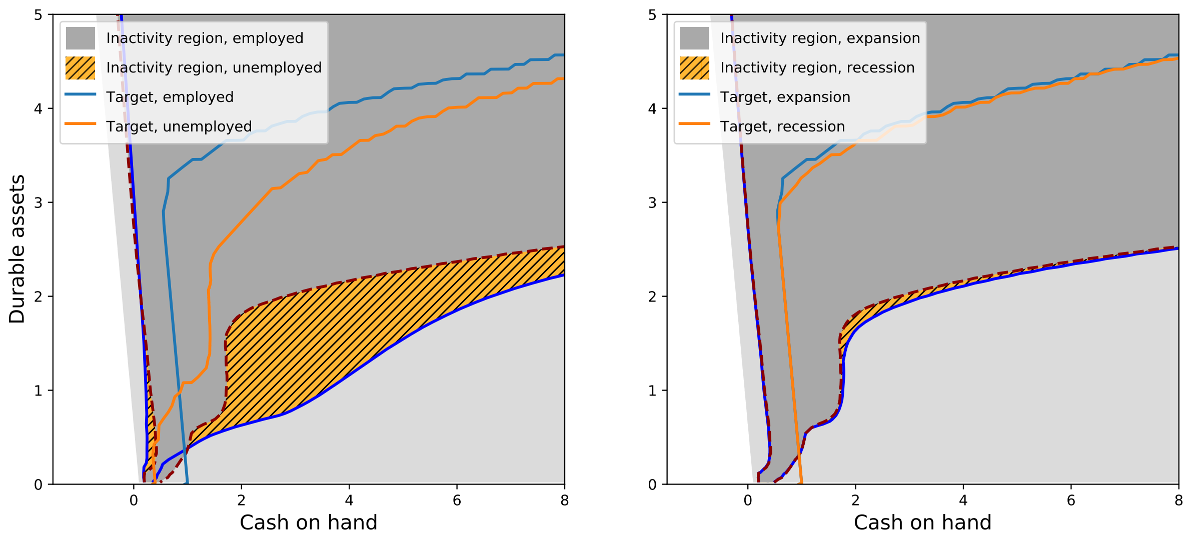

Figure 1: *Household decision functions. The model state space is composed of the household stock of durables and cash on hand (the sum of income and financial assets), both normalized by the permanent-earnings potential. The state space is tilted since households face a collateral constraint: with more durable assets, the households can borrow more. Left panel: Decision functions for an employed and an unemployed household in the expansion state. Right panel: Decision functions for an employed household in the expansion state and in the recession state.*

shock, readjustment of the durable stock is costly. Anticipating this, a forward-looking household delays its durable-goods purchases in response to increased unemployment risk, and the inactivity region shifts outward. For a theoretical characterization of how non-convex adjustment costs affect investment decisions in response to income shocks and income-uncertainty shocks, see Chetty and Szeidl (2016) and Dixit and Pindyck (1994), respectively.

As seen by comparing the figures, an actual unemployment shock triggers a larger response than a shock to unemployment risk. However, in response to an aggregate shock to the job-separation rate, only a subset of households lose their job while all households experience an increase in unemployment risk. The relative importance of the two channels for aggregate expenditure dynamics is theoretically ambiguous, motivating the quantitative investigation in the next section.

3 Model Results

We study the demand response to a recession shock. We populate the economy with a continuum of households, and let the recession shock hit the economy at $\mathtt{t} = 0$. Prior to feeding the recession shock, the economy starts with the ergodic distribution of households who then experience 30 quarters of expansion (the average length of an expansion). The recession lasts 9 quarters (the average length of a recession) after which the economy reverts back to the expansion regime.

A decomposition method To understand the mechanisms behind the aggregate expenditure responses, we decompose them into two components, an ex-ante *unemployment-risk channel* and an ex-post *unemployment channel*,

$$\text{Consumption response} \approx \text{Unemployment-risk channel} + \text{Unemployment channel}. \tag{8}$$

The unemployment channel captures the mechanical effect of more households becoming unemployed during the recession. It answers the question: "What is the consumption response if the economy is in a recession but households believe they are in an expansion?" We compute the unemployment channel by having households employ the expansion decision function while feeding them shocks drawn from the recession distribution. The unemployment-risk channel captures the change in behavior in response to the job-separation rate shock. It answers the opposite question: "What is the consumption response if the economy is in an expansion but households believe they are in a recession?" We compute the unemployment-risk channel by having the households employ the recession decision functions while feeding them shocks drawn from the expansion distribution.

The unemployment-risk channel can be further decomposed into two components, the *expected-income channel* and the *income-uncertainty channel*:

$$\text{Unemployment-risk channel} \approx \text{Expected-income channel} + \text{Income-uncertainty channel}. \quad (9)$$

When entering the recession, the net-present-value of the income stream for employed households is unaffected if combined with a per-period increase of income by 2.2 percent during the recession. We compute the income-uncertainty channel by tracking the change in behavior of households who believe that their per-period income will be 2.2 percent higher paired with the higher job-separation rate for the duration of the recession. Conversely, we compute the expected-income channel by tracking the change in behavior of households who believe that their income will be 2.2 percent lower for the duration of the recession but that the job-separation rate is unaffected.[10]

Decomposed responses We show the aggregate and decomposed responses in Figure 2, expressed as percentages of expenditures in the pre-recession quarter $\mathtt{t} = -1$. We also depict the expenditure responses when cumulated over the recession period.

Comparing durables to nondurables, there are four clear differences. First, the total

[10] These "counterfactual" recessions are ex-ante probability zero events in our computations. Therefore, our decomposition understates both the expected-income channel and the income-uncertainty channel. Entering one of the counterfactual recessions means that the risk of entering a true recession, in which the job-separation rate spikes and there is no compensation in households' income, is lower since the economy must transit via an expansion to get there.

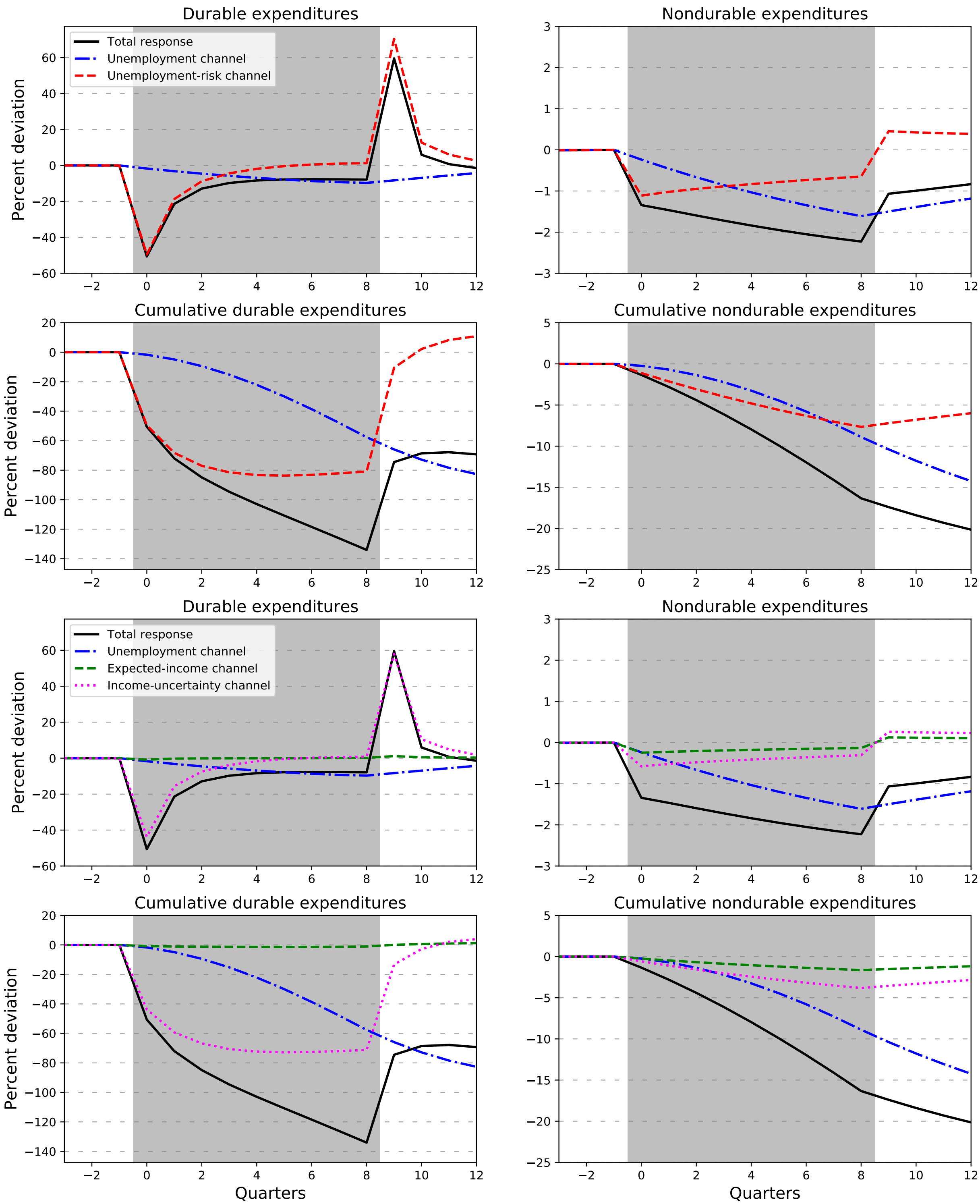

Figure 2: *Expenditure responses to a recession shock. The recession periods are indicated by the shaded area. The percentage deviation refers to the percentage deviation compared to the expenditure level in period* -1*, before the economy enters the recession.*

expenditure response for durables is much larger than for nondurables. This primarily reflects that durables are investment goods: to achieve the same fall in the consumption of durables as for nondurables, durable expenditures need to fall by approximately a multiple $1/\delta$ of the nondurable expenditure response in the first period. Second, the relative contribution of the unemployment-risk channel is larger for durables than for nondurables. While the unemployment-risk channel accounts for about 60 percent of total cumulative expenditure loss for durables at the end of the recession, it only accounts for about 45 percent for nondurables. Third, the response of durables to unemployment risk stems entirely from the income-uncertainty channel. This channel accounts for the majority (60 percent) of the cumulative expenditure response in durables at the end of the recession, while it only accounts for 30 percent of the nondurable response. In contrast, for nondurable expenditures, the most important channel is the unemployment channel, accounting for about 55 percent of the total response. Fourth, the dynamics are different: for durables, the income-uncertainty channel response is more concentrated to the early part of the recession. The expected-income channel is small for nondurables and negligible for durables.

Comparison to a flexible-adjustment model In our model, the non-convex adjustment cost is the primary reason that the expenditure pattern differ for durables and nondurables. Without the adjustment cost, and unless the credit constraint binds, our preference specification implies that households will hold the ratio of durable to nondurable consumption constant. In this case, the cumulative expenditure loss in durables, which is approximately proportional to the change in the stock, closely resembles a rescaling of the per-period nondurable expenditure response, both in terms of the total response and the underlying channels.

We show the responses for our baseline model together with a corresponding model without the adjustment cost in Figure 3.[11] Without the adjustment cost, the relative magnitudes

[11] The flexible-adjustment model has the adjustment cost parameter set to $h = 0$. In Figure 3, we show the flexible-adjustment model with the collateral parameter $\chi = 1$, recalibrated to match the target moments for financial and durable asset holdings. In Appendix A, we show the responses of a flexible-adjustment model with χ equal to its baseline value. With more constrained households, the contribution of the unemployment-channel is somewhat larger, which further magnifies the difference to the baseline model.

of the different channels in the response of cumulative durable expenditure are very similar to that of nondurable expenditures. Comparing our baseline model to the flexible-adjustment model, the income-uncertainty channel response of durables is amplified by a factor 7, due to the wait-and-see effect. In contrast, due to the smoothing effect, the unemployment-channel response is reduced by 15 percent by the end of the recession, but also continues to decline after the recession has ended. The response of nondurable expenditures is very similar across the two models.

We also depict the response of total expenditures. The inclusion of the adjustment cost for durable purchases is quantitatively important for total expenditure dynamics: at the end of the recession, it increases the cumulative income-uncertainty response of total expenditures by 100 percent.

3.1 The role of insurance

Besides the adjustment cost, the second key feature of our model is the lack of a complete insurance market, which leads households to self-insure by accumulating liquid assets. To study the role of limited insurance, we compute the expenditure responses for 15 different values of the households' discount factor β, which, in our model, is the primary determinant of households' level of liquid-asset holdings. The expenditure responses are displayed in Figure 4.

The degree of self-insurance affects the expenditure responses for durables and nondurables differently. For durable expenditures, the total response is U-shaped: the magnitude of the total response, both in terms of the first-period and the cumulative response, is increasing for low levels of liquid asset holdings, and decreasing for large values of liquid-asset holdings. For nondurable expenditures, the magnitude of the total response is monotonically decreasing in liquid-asset holdings.

The difference stems from two effects. First, the income-uncertainty channel is more important for the response of durables while the unemployment channel is more important for the response of nondurables. Second, the response through the unemployment channel

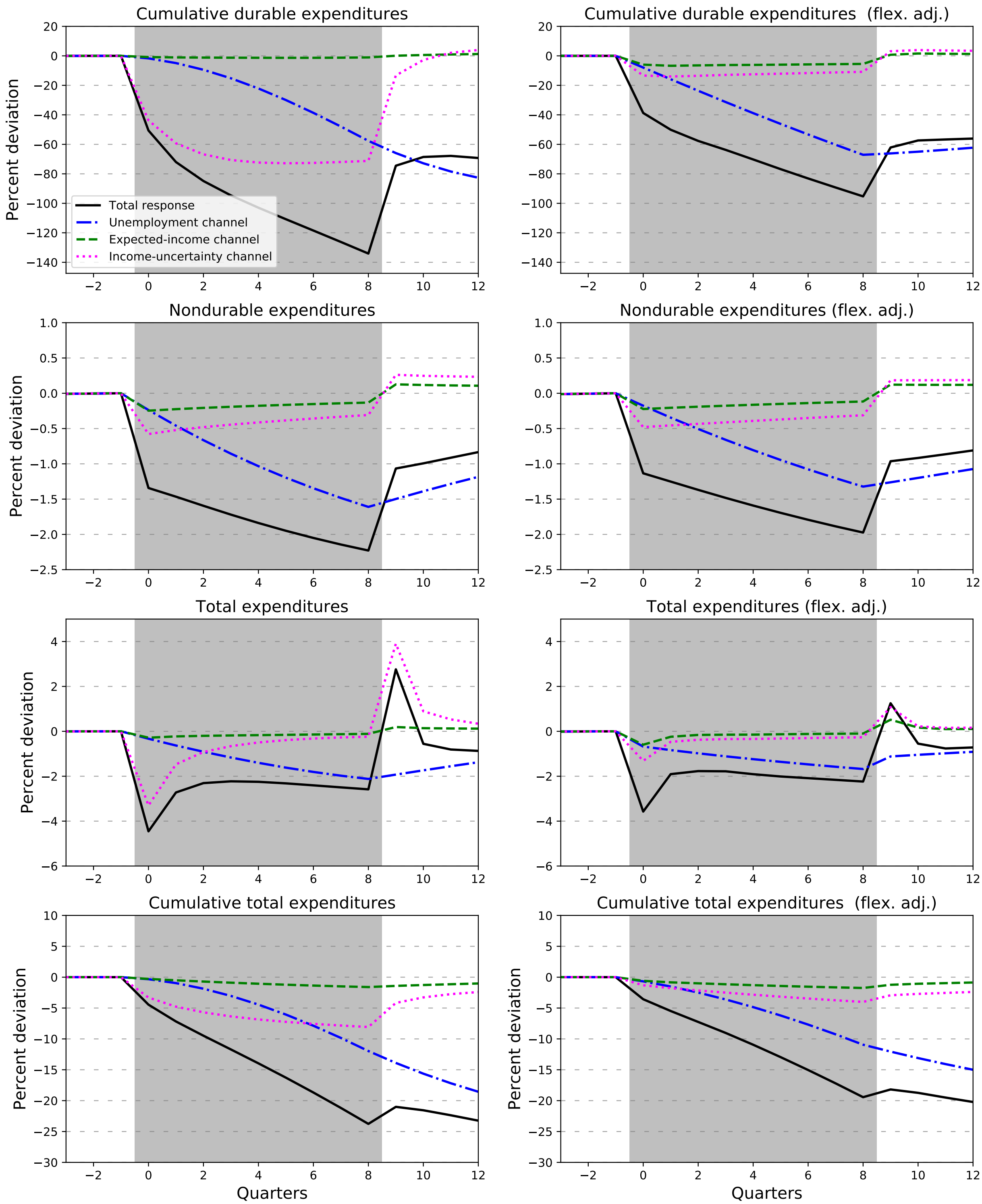

Figure 3: *Expenditure responses to a recession shock, comparing the baseline model to a model with no adjustment cost (the flexible-adjustment model). The recession periods are indicated by the shaded area. The percentage deviation refers to the percentage deviation compared to the expenditure level in period* -1*, before the economy enters the recession.*

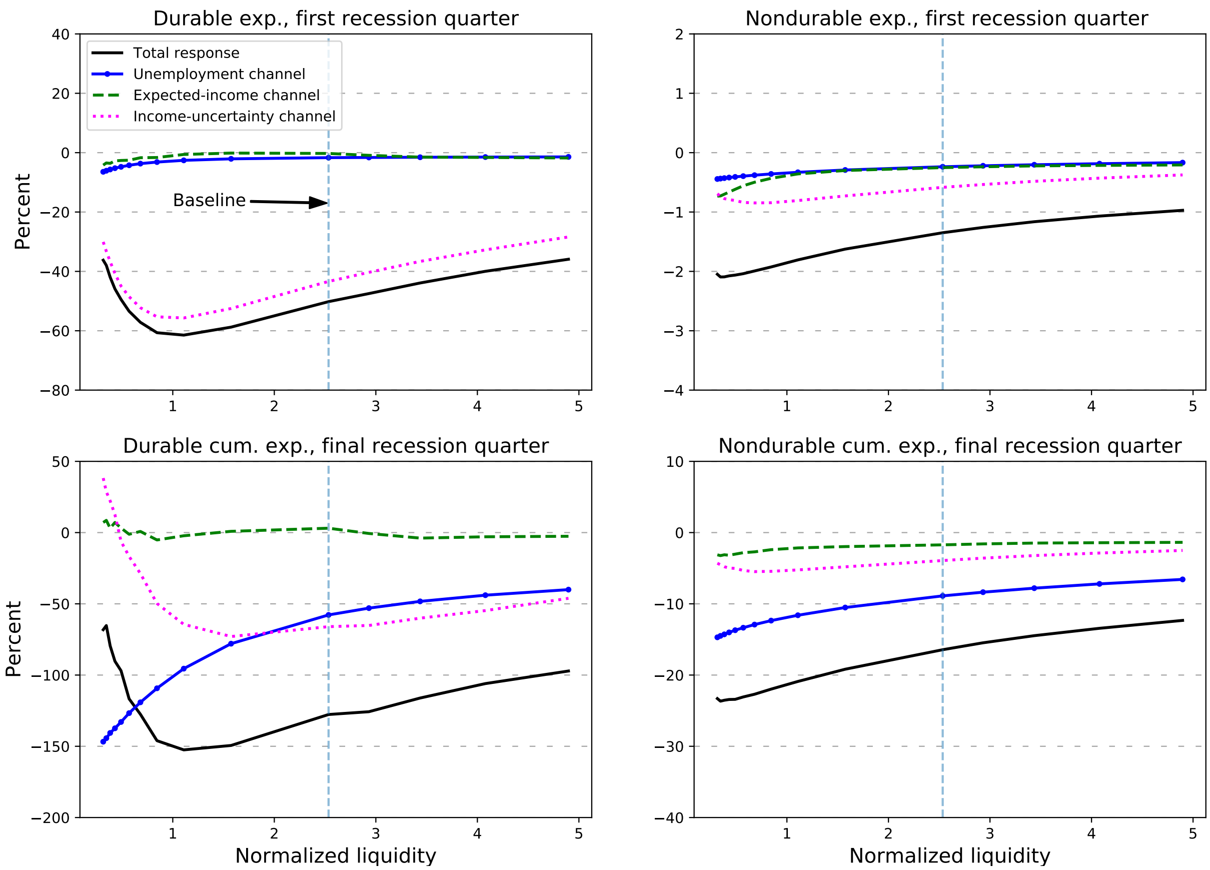

Figure 4: *Decomposed expenditure responses to the aggregate job-separation shock as functions of households' mean asset holdings. The horizontal axis represents the mean level of* normalized liquidity*: the sum of households' financial assets and collateral value of their durable assets, where the normalization is with respect to permanent-earnings potential. When this sum takes the value of* 0*, the credit constraint is binding for all households. Each data point is an expenditure response calculated for an economy with a given discount factor* β*, using 15 different values of* $\beta \in [0.9495, 0.9770]$*. Top row: expenditure response in the first period of the recession. Bottom row: cumulative expenditure response in the final period of the recession.*

is monotonic, while the response through the income-uncertainty channel is U-shaped, and this U-shape is also much more pronounced for durables.

The monotonicity of the unemployment channel reflects that i) unemployment primarily affects households by reducing their near-term income and ii) households' marginal propensity to consume (MPC) decreases in their liquid-asset holdings. The U-shape of the income-uncertainty channel reflects that i) at high levels of liquidity, households are well insured and do not respond strongly to the increase in income uncertainty, and ii) at low levels of liquidity, households are constrained and do not respond to changes in their future income at all. The income-uncertainty response is maximized for intermediate values, where most households are simultaneously forward-looking and not well insured. Further, the magnitude of the income-uncertainty response is maximized for different values for durable and nondurable expenditures. Due to the adjustment cost, households adjust their durable stock by making sizable lumpy purchases, which means that they become liquidity constrained in terms of their durable purchases at higher levels of liquidity compared to when they become constrained in terms of their nondurable expenditures.

4 Model Meets Data

In this section, we estimate expenditure responses, for nondurable and durable goods separately, to household-level fluctuations in unemployment risk, using a biennial panel for 1998-2014 from the SHIW. The empirical expenditure responses are then compared with corresponding model regressions.

To estimate the empirical expenditure responses, the main challenge is that household-level unemployment risk is not observed in the SHIW data. To construct a proxy measure of unemployment risk, we estimate the probability of becoming unemployed in the subsequent wave, given observed household characteristics in the current wave (different regions, industries, occupations, education levels, etc.) as summarized by a set of factors. For identification, we study the expenditure response to *changes* in unemployment risk, exploiting variation in households' exposure to unemployment-rate shocks across the observed characteristics.

Variables are yearly, and the time subscript t in this section refers to a year. Consistent with the calibration targets, a purchase of durable goods is defined as yearly expenditures on motor vehicles and furniture/appliances (including electronics, furnishings and sundry equipment) that sum to at least two weeks of mean household income. The sample restrictions are described in Table 3.

4.1 Econometric framework

Durable purchases are lumpy, and we estimate the expenditure response to unemployment-risk fluctuations in terms of the probability of a purchase. For nondurables, the response is in terms of the growth rate in log expenditures. For a household i in year t, denote a durable purchase by the indicator variable DP_{it}, nondurable expenditures by C_{it}, the year-t probability that the household is unemployed in year $t+2$ by $\mathsf{URISK}_{i,t+2|t}$, and let $\Delta\mathsf{URISK}_{i,t+2|t} = \mathsf{URISK}_{i,t+2|t} - \mathsf{URISK}_{i,t|t-2}$. Our models are

$$\mathrm{DP}_{it} = \beta_0^d + \beta_1^d \Delta\mathsf{URISK}_{i,t+2|t} + \boldsymbol{\beta}_z^d \mathbf{Z}_{it} + \epsilon_{it}^d, \tag{10}$$

$$\Delta \log C_{it} = \beta_0^c + \beta_1^c \Delta\mathsf{URISK}_{i,t+2|t} + \boldsymbol{\beta}_z^c \mathbf{Z}_{it} + \epsilon_{it}^c, \tag{11}$$

where $\mathbf{Z}_{it}$ is a vector of control variables.

Measurement of unemployment risk The variable $\mathsf{URISK}_{i,t+2|t}$ refers to the probability that household i in year t will be unemployed in year $t+2$. At time t, this is a forward-looking variable. The main challenge of estimating (10) and (11) is that $\mathsf{URISK}_{i,t+2|t}$ is not observed in the data. To construct a measure of $\mathsf{URISK}_{i,t+2|t}$, we compute the probability of a household becoming unemployed based on observable characteristics $\mathbf{X}_{it}$ of the household heads' work and basic demographic information, listed in Table 3.

In practice, with the small sample size of our survey data, predicting $\mathsf{URISK}_{i,t+2|t}$ by directly regressing an unemployment indicator on the full set of observable household characteristics, which together make 82 dummy variables, will likely overfit the data. To still be able to use a rich set of observable household characteristics for estimating $\mathsf{URISK}_{i,t+2|t}$, we pool the entire panel and project the characteristics on a smaller set of time-invariant factors. A household i's characteristics at time t are then summarized by the household's factor loadings $\hat{\boldsymbol{\lambda}}_{it}$. We use the estimated factor loadings $\hat{\boldsymbol{\lambda}}_{it}$ to impute the households' probability of being unemployed in the subsequent survey wave, for each year in the sample. Let U_{it+2} be an indicator of unemployment in year $t+2$. Our model is

$$U_{it+2} = \alpha_t + \boldsymbol{\gamma}_t \hat{\boldsymbol{\lambda}}_{it} + \xi_{it}, \quad \text{for } t = 1998, 2000, ..., 2012. \tag{12}$$

Note that a household i with the same characteristics across two waves, meaning that $\hat{\boldsymbol{\lambda}}_{it-2} = \hat{\boldsymbol{\lambda}}_{it}$, may still face a different probability of being unemployed in years t and $t+2$, due to the time-variation in the intercept α_t and slope coefficients $\boldsymbol{\gamma}_t$. For example, if the unemployent rate in a particular industry increases in a particular year, then the slope coefficients for the factors loading on that industry increase in that particular year.

We retrieve the factors by multiple-correspondence analysis, which is analogous to principal-component analysis but adapted to categorical variables (Greenacre 2007). The baseline specification uses 10 factors, we later check the robustness of our results to both more and fewer factors. We report results from the factor analysis and estimation of Equation (12) in Appendix B. Having estimated Equation (12) for each wave in the sample, our measure of the change in unemployment risk is the first difference of the fitted values:

$$\Delta\mathsf{URISK}_{i,t+2|t} = \hat{\mathsf{P}}(\mathrm{U}_{it+2}|\hat{\boldsymbol{\lambda}}_{it}) - \hat{\mathsf{P}}(\mathrm{U}_{it}|\hat{\boldsymbol{\lambda}}_{it-2}) = \Delta\hat{\alpha}_t + \Delta\left(\hat{\boldsymbol{\gamma}}_t \hat{\boldsymbol{\lambda}}_{it}\right). \tag{13}$$

Identification To identify the effect of a change in unemployment risk on expenditures, our imputed measure of unemployment risk should i) affect consumption behavior through households' perceived unemployment risk and ii) not affect consumption behavior through any other channel, given the set of control variables $\mathbf{Z}_{it}$.

The first condition means that variation in our imputed measure of unemployment risk

Sample restrictions
Household head is in prime age (25-54) in year $\mathtt{t}$ Household head is employed in year $\mathtt{t}$ Household head is part of the labor force in year $\mathtt{t}+2$
Household characteristics, $\mathbf{X}_{\mathtt{it}}$
Occupation Industry Superregion of residence (north, center and south/islands) Region of residence (the 20 administrative regions of Italy) Town size (binned) Education level Five-year age bins Sex Marital status Household size
Control variables, $\mathbf{Z}_{\mathtt{it}}$
Time fixed effect Change in factor loadings All variables from $\mathbf{X}_{\mathtt{it}}$ except superregion Growth rate of log income between year $\mathtt{t}$ and year $\mathtt{t}-2$ Quartiles of net financial assets in year $\mathtt{t}-2$ Quartiles of total assets in year $\mathtt{t}-2$ Quartiles of ingoing durable goods assets in year $\mathtt{t}$ Credit constraint

Table 3: *For complete definitions of all variables, see Appendix B. The superregion is omitted as a control variable because of colinearity with region of residence. Net financial assets, total assets and durable goods are measured as multiples of income in the year* $\mathtt{t}-2$*. The credit-constraint variable reports if the household has been denied or discouraged from applying for credit in the past year.*

must affect households' perceived unemployment risk. We cannot test the causal relationship, but we can test whether the two variables are correlated using the 1998 survey wave of the SHIW. In this wave, a subset of the households were asked to state their perceived risk of non-employment over the next 12 months.[12] Figure 5 displays a scatter plot of the elicited

[12] Specifically, households were asked: "If you had to give a score from 0 to 100 to the chances that you

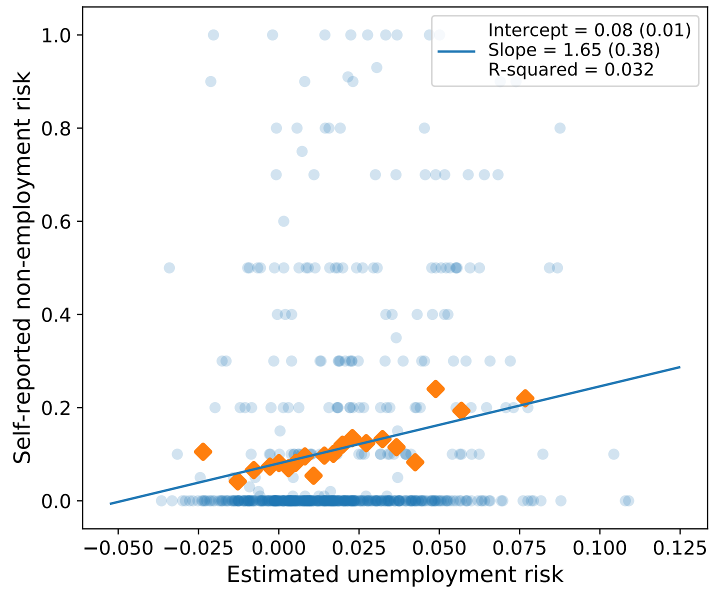

Figure 5: *Scatter plot of estimated unemployment risk and self-reported non-employment risk for the 1998 survey wave, together with an estimated regression line. Blue circles: raw data (590 observations). Orange diamonds: binned data (20 bins).*

beliefs and imputed unemployment risk. The two measures are positively and significantly related, and we cannot reject that the coefficient is 1.

The second condition means that we need to control for all omitted variables that are correlated with our imputed measure of unemployment-risk growth and household expenditure decisions. To do so, we proceed in two steps. First, we decompose the variation in unemployment-risk growth, and eliminate all variation that does not stem from heterogeneous growth rates in unemployment across observable characteristics. Second, we add an additional set of control variables to deal with remaining identification concerns.

Since we estimate the response to unemployment-risk growth, and not levels, we can

will remain in or find employment in the next 12 months, what would it be?". Note that the survey question refers to the probability of being *non-employed* in the period *0-12 months* ahead, whereas our measure is an estimate of the probability of being *unemployed* during the period *12-24 months* ahead. Still, since our sample is restricted to employed household heads in prime working age, non-employment is very likely to be associated with unemployment. Moreover, given the low job-finding rate in Italy, unemployment spells are likely to be long term.

decompose the variation in unemployment risk into three parts.

$$\begin{aligned}\Delta \mathsf{URISK}_{i,t+2|t} &= \Delta\hat{\alpha}_t + \Delta\left(\hat{\boldsymbol{\gamma}}_t \hat{\boldsymbol{\lambda}}_{it}\right) \\ &= \underbrace{\Delta\hat{\alpha}_t}_{\text{agg. variation}} + \underbrace{\hat{\boldsymbol{\gamma}}_t \times \Delta\hat{\boldsymbol{\lambda}}_{it}}_{\text{change in factor loadings}} + \underbrace{\Delta\hat{\boldsymbol{\gamma}}_t \times \hat{\boldsymbol{\lambda}}_{it-1}.}_{\text{change in unemp. exposure}} \end{aligned} \tag{14}$$

At the aggregate level, low spending may cause high unemployment through Keynesian demand effects, implying reverse causation, and fluctuations in unemployment risk may also be correlated with changes in the interest rate and other prices. Hence, we control for time fixed effects to eliminate the aggregate variation captured by $\Delta\hat{\alpha}_t$.

The variations in factor loadings, i.e., changes in household characteristics, are also likely endogenous to household expenditure decisions. For example, a household relocating to a new region may change both its likelihood of acquiring a motor vehicle and its unemployment risk. We therefore also include $\hat{\boldsymbol{\gamma}}_t \times \Delta\hat{\boldsymbol{\lambda}}_{it}$ as a control.

After these controls, the variation in $\Delta \mathsf{URISK}_{i,t+2|t}$ stems from different regions, industries, occupations etc. experiencing heterogeneous changes in unemployment rates. To this, we add the variables $\mathbf{X}_{it}$ used to retrieve the factors as control variables, which take out the trends of these heterogeneous growth rates. The remaining variation likely reflects aggregate shocks with heterogeneous treatment intensity, e.g., that blue-collar workers face more volatile employment prospects than white-collar workers over the business cycle, or disaggregate shocks, e.g., a fall in the foreign demand for certain manufacturing goods that are produced in a particular region.

In exploiting this variation, two concerns for identification remain. First, any shock that affects the unemployment rate for some group of households may affect other economic conditions for that group. For example, an adverse region-specific shock may depress local house prices and an industry-specific shock may depress industry wage growth. In our preferred specification, we therefore control for log income growth, measures of the households' wealth and households' credit availability. The control variables are listed in Table 3.

Second, if the heterogeneous changes in unemployment rates across regions result from local spending shocks, then using this variation does not overcome the aforementioned reverse-causation problem. For durable goods, local spending shocks do not likely cause local unemployment, since most durables are traded across different regions. However, for nondurable goods, which to a large extent are produced locally, such effects cannot be excluded. Therefore, as a robustness check, we also control for time-region fixed effects.

Inference Since our regressor is generated in multiple steps, we compute standard errors by bootstrapping the entire three-step estimation procedure (estimation of factors and factor loadings, estimation of unemployment risk, estimation of expenditure equations). The bootstrap samples are clustered at the two-digit regional level.

4.2 Regressions on model-generated data

To compare the evidence with our model, we run the regressions (10) and (11) on model-generated data. To do so, we eliminate the aggregate shock and add idiosyncratic fluctuations in unemployment risk to the model. Specifically, we assume that there are idiosyncratic and persistent shocks to the job-separation rate, and calibrate the parameters of an $\mathsf{AR}(1)$ process to match the variance and autocorrelation of the estimated unemployment-risk growth $\Delta \mathsf{URISK}_{it+2|t}$. We simulate the model, aggregate the resulting quarterly panel to the biennial frequency, and construct variables as they are defined in the SHIW data. The set of financial control variables are the same as those we use for the empirical regressions. We repeat the simulation and regression estimation 1000 times, and report means of all estimates. For details, see Appendix B.

4.3 Results

Table 4 shows the results from estimating Equations (10) and (11), both on actual and model-generated data. The top row shows the effect on the log of nondurable expenditure growth that results from estimating Equation (11). Our preferred empirical specification is column (3), as the inclusion of all the control variables makes it more likely that the variation in $\Delta\mathsf{URISK}_{i,t+2|t}$ is exogenous to expenditure decisions in period t. A one percent increase in unemployment risk is associated with a fall of nondurable expenditures by 0.56 percent. In the model, the corresponding estimate is 0.21 percent. The standard error is large in the empirical regression, and we cannot reject the two coefficients being equal.

		Data		Model
	(1)	(2)	(3)	(4)
Nondurables	-0.32	-0.60***	-0.56**	-0.21***
	(0.21)	(0.23)	(0.23)	(0.07)
R^2	0.27	0.27	0.32	0.73
Durables	-2.84***	-3.38***	-2.84***	-2.81*
	(0.96)	(0.96)	(0.91)	(1.67)
R^2	0.01	0.01	0.08	0.15
Time fixed effects	Yes	Yes	Yes	-
Change in factor loadings	No	Yes	Yes	-
Household characteristics	No	No	Yes	-
Financial variables	No	No	Yes	Yes
N	5095	5095	5095	5220

Table 4: *Regression results from estimating (10) and (11) on actual and model-generated data. The coefficients show the effect of a change in unemployment risk growth on the expenditure on nondurable goods and the purchase probability of durable goods, where the latter is normalized by the unconditional purchase probability. For the empirical regressions, the standard errors are bootstrapped, clustered at the 2-digit regional level. For the model regressions, all estimates are averages from 1,000 simulations. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.*

The second row shows the estimated effect on the probability of purchasing a durable good, normalized by the unconditional purchase probability. For our preferred specification in column (3), a one percentage point increase in unemployment risk is associated with a fall of the aggregate number of durable purchases by 2.84 percent. The estimate is close to the model estimate of 2.81 percent. Since the left-hand side variable is a binary variable, the empirical estimate for durable goods cannot be straightforwardly compared with the expenditure semi-elasiticty estimated for nondurable goods. Under the assumption that the intensive margin, i.e., the durable purchase size, is unaffected by unemployment risk, the two outcome variables are equivalent. Given that there is likely also an intensive-margin effect, the estimated semi-elasticity for the number of purchases provides a lower bound for the semi-elasticity of expenditures.

Since our model is calibrated to match unconditional moments in the data, and not any dynamic responses, there are no mechanical reasons why the model regression results should conform to the empirical regression results. The fact that they do suggests that the model provides reliable estimates of the strength of the unemployment-risk channel, for both durable and nondurable goods.

Robustness In estimating unemployment risk and its effect on expenditures, we made two subjective choices: i) the exact value of the size restriction for durable expenditures to be treated as a durable purchase, which we set to two weeks of mean household income, and ii) the number of factors used for estimating Equation (12). Moreover, our results may be driven by the households who experience the largest changes in unemployment risk. To explore the sensitivity of our results, we estimate the expenditure responses for all combinations of five different numbers of factors, three different cutoff sizes for durable purchases, and three different winsorization cutoffs for $\Delta\mathsf{URISK}_{i,t+2|t}$. The results are shown in the specification graphs in Figure 6, where we order the different specifications from lowest to largest point estimate. The results are largely insensitive to the purchase cutoff and winsorization, but the estimate for nondurables is sensitive to using a lower number of factors. The estimates from our model regressions are in the middle range of the empirical estimates across the different specifications.

In Appendix B, we show specification curves for estimating Equation (10) separately for purchases of vehicles and furniture/appliances, respectively. We also estimate Equation (10) using a Probit model and provide results for a specification where we include time-region fixed effects. With time-region fixed effects, the standard errors of the estimates are in general higher, but the general pattern for the point estimates is the same.

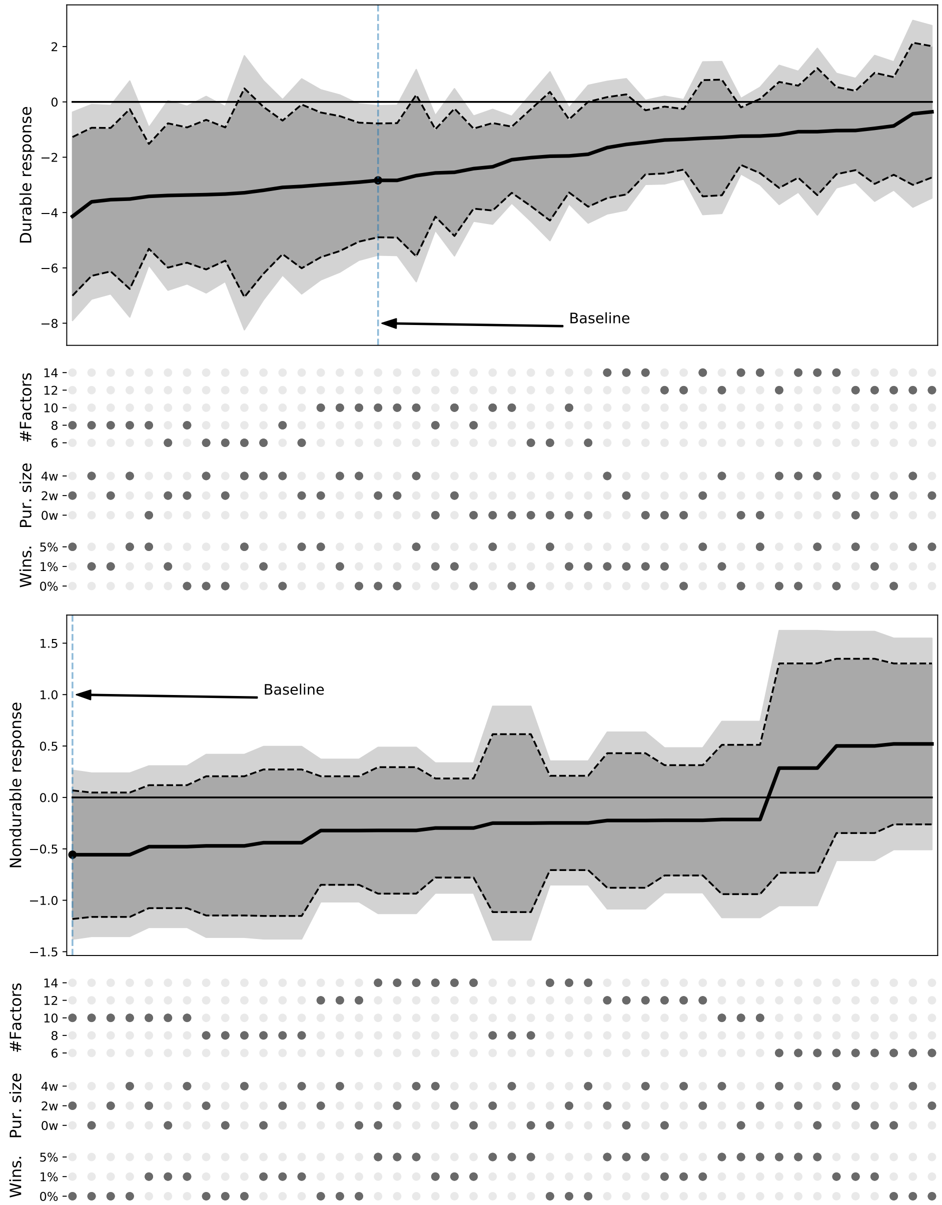

Figure 6: *Empirical specification graphs. The solid line indicates the point estimate from estimating Equations (10) and (11), across different specifications. The shaded areas indicate 95% and 99% bootstrapped confidence intervals. The colored circles below each graph indicate the specification used when varying a) the number of factors in estimating Equation (12), b) the size cutoff for durable purchases (in terms of weekly household income) and c) the winsorization cutoffs for* $\Delta\mathsf{URISK}_{\mathsf{it+2|t}}$ *(1% means that we drop the 0.5 % highest and smallest values of* $\Delta\mathsf{URISK}_{\mathsf{it+2|t}}$*, respectively). The vertical line indicates the baseline empirical specification.*

5 Concluding Remarks

The main message of this paper is that the mechanisms behind aggregate durable-expenditure dynamics are different from those of aggregate nondurable-expenditure dynamics. The difference stems from the interaction of uninsurable income risk and adjustment costs involved in purchases of durable goods. Until recently, most of the studies of fluctuations in durable-goods demand have employed representative-agent models without such frictions. Conversely, most of the incomplete-markets literature has focused on nondurable spending. Going forward, given the importance of durable goods in accounting for aggregate expenditure fluctuations, it seems vital to include both incomplete markets and frictional durable goods adjustment in the study of aggregate demand.

References

A. Auclert, M. Rognlie, and L. Straub. The Intertemporal Keynesian Cross. *Mimeo*, 2018.

C. Bayer, R. Lütticke, L. Pham-Dao, and V. Tjaden. Precautionary Savings, Illiquid Assets, and the Aggregate Consequences of Shocks to Household Income Risk. *Econometrica*, 87 (1):255–290, 2019.

D. Berger and J. Vavra. Consumption Dynamics During Recessions. *Econometrica*, 83(1): 101–154, 2015.

D. Berger, V. Guerrieri, G. Lorenzoni, and J. Vavra. House Prices and Consumer Spending. *The Review of Economic Studies*, 85(3):1502–1542, jul 2018.

B. S. Bernanke. Irreversibility, uncertainty and cyclical investment. *Quarterly Journal of Economics*, 98(1):85–106, 1983.

G. Bertola, L. Guiso, and L. Pistaferri. Uncertainty and consumer durables adjustment. *Review of Economic Studies*, 72(4):973–1007, 2005.

A. Bhandari, J. Borovička, and P. Ho. Survey data and subjective beliefs in business cycle models. *Mimeo*, 2019.

N. Bloom, M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. Terry. Really Uncertain Business Cycles. *Econometrica*, 86(3):1031–1065, 2018.

C. Carroll, E. Crawley, J. Slacalek, K. Tokuoka, and M. White. Sticky Expectations and Consumption Dynamics. *Mimeo*, 2019.

C. D. Carroll. Buffer-Stock Saving and the Life Cycle/Permanent Income Hypothesis. *Quarterly Journal of Economics*, 112(1):1–55, 1997.

C. D. Carroll, K. Dynan, and S. Krane. Unemployment Risk and Precautionary Wealth: Evidence from Households' Balance Sheets. *Review of Economics and Statistics*, 85:586–604, 2003.

C. D. Carroll, J. Slacalek, K. Tokuoka, and M. N. White. The distribution of wealth and the marginal propensity to consume. *Quantitative Economics*, 8(3):977–1020, 2017.

E. Challe and X. Ragot. Precautionary Saving Over the Business Cycle. *The Economic Journal*, 126(590):135–164, 2016.

R. Chetty and A. Szeidl. Consumption Commitments and Habit Formation. *Econometrica*, 84(2):855–890, 2016.

W. J. Den Haan, P. Rendahl, and M. Riegler. Unemployment (Fears) and Deflationary Spirals. *Journal of the European Economic Association*, 16(5):1281–1349, nov 2018.

A. K. Dixit and R. S. Pindyck. *Investment under uncertainty*. Princeton University Press, 1994.

J. Druedahl. A Guide On Solving Non-Convex Consumption-Saving Models. 2020.

J. Druedahl and T. H. Jorgensen. Can Consumers Distinguish Persistent from Transitory Income Shocks? *Mimeo*, 2018.

B. Dupor, R. Li, M. M. Saif, and Y.-C. Tsai. The 2008 U.S. Auto Market Collapse. *Mimeo.*, 2018.

J. C. Eberly. Adjustment of consumers' durables stocks: Evidence from automobile purchases. *Journal of Political Economy*, 102(3):403–436, 1994.

M. W. L. Elsby, B. Hobijn, and A. Şahin. Unemployment Dynamics in the OECD. *Review of Economics and Statistics*, 95(2):530–548, 2013.

A. Gavazza and A. Lanteri. Credit Shocks and Equilibrium Dynamics in Consumer Durable Goods Markets. *Mimeo*, dec 2018.

M. Greenacre. *Correspondence Analysis in Practice*. Chapman & Hall/CRC, 2nd edition, 2007.

S. J. Grossman and G. Laroque. Asset Pricing and Optimal Portfolio Choice in the Presence of Illiquid Durable Consumption Goods. *Econometrica*, 58(1):25, jan 1990.

F. Guvenen and A. A. Smith. Inferring Labor Income Risk and Partial Insurance From Economic Choices. *Econometrica*, 82(6):2085–2129, nov 2014.

K. Harmenberg. Aggregating Heterogeneous-Agent Models with Permanent Income Shocks. 2020.

G. Kaplan and G. L. Violante. Microeconomic heterogeneity and macroeconomic shocks. *Journal of Economic Perspectives*, 32(3):167–194, jun 2018.

G. Kaplan, B. Moll, and G. L. Violante. Monetary Policy According to HANK. *American Economic Review*, 108(3):697–743, 2018.

D. Krueger, F. Perri, L. Pistaferri, and G. L. Violante. Cross Sectional Facts for Macroeconomists. *Review of Economic Dynamics*, 13(1):1–14, 2010.

D. Krueger, K. Mitman, and F. Perri. Macroeconomics and Household Heterogeneity. In J. Taylor and H. Uhlig, editors, *Handbook of Macroeconomics, Vol. 2*. 2016.

E. E. Leamer. Housing Is the Business Cycle. *NBER Working Paper*, 2007.

J. P. Martin. Measures of replacement rates for the purpose of international comparisons: a note. *OECD Economic Studies*, 1(26):99–115, 1996.

A. McKay. Time-varying idiosyncratic risk and aggregate consumption dynamics. *Journal of Monetary Economics*, 88:1–14, 2017.

A. McKay and J. F. Wieland. Lumpy Durable Consumption Demand and the Limited Ammunition of Monetary Policy. *Mimeo.*, 2019.

S. Ng. Constructing Common Factors from Continuous and Categorical Data. *Econometric Reviews*, 34(6-10):1141–1171, 2015.

M. Ogaki and C. Reinhart. Measuring Intertemporal Substitution: The Role of Durable Goods. *Journal of Political Economy*, 106(5):1078–1098, 1998.

M. O. Ravn and V. Sterk. Macroeconomic Fluctuations with HANK&SAM: An Analytical Approach. *Mimeo*, 2018.

F. Rozsypal and K. Schlafmann. Overpersistence Bias in Individual Income Expectations and its Aggregate Implications. *Mimeo*, 2019.

R. Shimer. Reassessing the ins and outs of unemployment. *Review of Economic Dynamics*, 15(2):127–148, 2012. doi: 10.1016/j.red.2012.02.001.

K. Storesletten, C. I. Telmer, and A. Yaron. Cyclical Dynamics in Idiosyncratic Labor Market Risk. *Journal of Political Economy*, 112(3):695–717, 2004.

G. Tauchen and R. Hussey. Quadrature-Based Methods for Obtaining Approximate Solutions to Nonlinear Asset Pricing Models. *Econometrica*, 59(2):371–396, 1991.

E. R. Young. Solving the incomplete markets model with aggregate uncertainty using the Krusell-Smith algorithm and non-stochastic simulations. *Journal of Economic Dynamics and Control*, 34(1):36–41, 2010.

A Model

In this appendix, we describe the details of the computation and calibration of the model and also provide an additional result.

A.1 Solution Method

In this appendix, we provide a description of how we solve the consumption model presented in Section 2. First, we recast the household problem on recursive form and describe how the consumption problem can be rewritten in a simplified form with fewer state variables. Second, we describe the solution method and how it is implemented in practice.

Recursive formulation We collect all exogenous state variables in the state $\mathcal{S}$. 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 and $V_A(\cdot)$ as the value function conditional on adjusting the stock of durables and the collateral requirement parameter $\hat{\chi} \equiv \chi(1-\delta-h)$. The recursive representation is then

$$
\begin{aligned}
V_{NA}(B, D; \mathcal{S}) = \quad & \max_{C,B'} u(C, D') + \beta E V(B', D'; \mathcal{S}') && (15)\\
\text{s.t.} \quad & D' = (1-\delta)D, \\
& C + qB' \leqslant \Upsilon(Y_{\mathcal{S}}, n_{\mathcal{S}}) + B, \\
& B' \geqslant -\hat{\chi}D', \\
& C \geqslant 0, \\
V_A(B, D; \mathcal{S}) = \quad & \max_{C,B',D'} u(C, D') + \beta E V(B', D'; \mathcal{S}') && (16)\\
\text{s.t.} \quad & C + qB' + D' \leqslant \Upsilon(Y_{\mathcal{S}}, n_{\mathcal{S}}) + (1-\delta-h)D + B, \\
& B' \geqslant -\hat{\chi}D', \\
& C, D' \geqslant 0, \\
V(B, D; \mathcal{S}) = \quad & \max\{V_{NA}(B, D; \mathcal{S}), V_A(B, D; \mathcal{S})\}. && (17)
\end{aligned}
$$

and, while not stated, also subject to the law 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 (15), policy functions g_C^A, g_B^A, g_D^A and a value function V_A that solve (16), and a value function V that, given V_{NA}, V_A, solves (17).

State space reduction Due the combined assumptions of a constant 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 earnings-potential Z_t, similar to a standard buffer-stock model with only one good (see e.g. Carroll (1997)). In addition, since the 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 $\hat{B} \geqslant 0$:

$$\begin{aligned} V_{NA}(\hat{B}, D; Z, \epsilon, n, \Theta) = \quad & \max_{C, \hat{B}^*} u(C, D^*) + \beta E V(\hat{B}', D'; Z', \epsilon', n', \Theta') \\ \text{s.t.} \quad & \hat{B}' = \hat{B}^* \\ & D' = D^* \\ & D^* = (1-\delta)D \\ & C + q\hat{B}^* \leqslant Y(n + b(1-n)) + \hat{B} - \hat{\chi}(1 - q(1-\delta))D, \\ & \hat{B}^*, C \geqslant 0, \\ & Y = Z\epsilon, \end{aligned} \tag{18}$$

$$\begin{aligned} V_A(\hat{B}, D; Z, \epsilon, n, \Theta) = \quad & \max_{C, D^*, \hat{B}^*} u(C, D^*) + \beta E V(\hat{B}', D'; Z', \epsilon', n', \Theta') \\ \text{s.t.} \quad & \hat{B}' = \hat{B}^* \\ & D' = D^* \\ & C + (1 - q\hat{\chi})D^* + q\hat{B}^* \leqslant Y(n + b(1-n)) + \hat{B} + (1 - \delta - h - \hat{\chi})D, \\ & \hat{B}^*, C, D^* \geqslant 0, \\ & Y = Z\epsilon, \end{aligned} \tag{19}$$

$$V(\hat{B}, D; Z, \epsilon, n, \Theta) = \max\{V_{NA}(\hat{B}, D; Z, \epsilon, n, \Theta), V_A(\hat{B}, D; Z, \epsilon, n, \Theta)\}. \tag{20}$$

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

- $v = VZ^{-(1-\sigma)}$ for variables $V = V, V_{NA}, V_A$
- $x = X/Z$ 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:

$$
\begin{aligned}
v_{NA}(\hat{b}, d; \epsilon, n, \Theta) = \quad & \max_{c,\hat{b}^*} u(c, d^*) + \beta E \eta'^{1-\sigma} v(\hat{b}', d'; \epsilon', n', \Theta') && (21)\\
\text{s.t.} \quad & \hat{b}' = \eta'^{-1}\hat{b}^* \\
& d' = \eta'^{-1} d^* \\
& d^* = (1-\delta)d \\
& c + q\hat{b}^* \leqslant \epsilon(n + b(1-n)) + \hat{b} - \hat{\chi}(1 - q(1-\delta))d, \\
& b^*, c \geqslant 0, \\
v_A(\hat{b}, d; \epsilon, n, \Theta) = \quad & \max_{c,d^*,\hat{b}^*} u(c, d^*) + \beta E \eta'^{1-\sigma} v(\hat{b}', d'; \epsilon', n', \Theta') && (22)\\
\text{s.t.} \quad & \hat{b}' = \eta'^{-1}\hat{b}^* \\
& d' = \eta'^{-1} d^* \\
& c + (1 - q\hat{\chi})d^* + q\hat{b}^* \leqslant \epsilon(n + b(1-n)) + \hat{b} + ((1-\delta)(1-h) - \hat{\chi})d, \\
& \hat{b}^*, c, d^* \geqslant 0, \\
v(\hat{b}, d; \epsilon, n, \Theta) = \quad & \max\{v_{NA}(\hat{b}, d; \epsilon, n, \Theta), v_A(\hat{b}, d; \epsilon, n, \Theta)\}. && (23)
\end{aligned}
$$

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

$$\begin{aligned}
v_{NA}(a,d;n,\Theta) = \quad & \max_{c,\hat{b}^*} u(c,(1-\delta)d) \\
& +\beta E \eta'^{1-\sigma} v(\epsilon'(n'+b(1-n'))+\eta'^{-1}\hat{b}^*, \eta'^{-1}(1-\delta)d; n', \Theta') \\
\text{s.t.} \quad & c + q\hat{b}^* \leqslant a - \hat{\chi}(1-q(1-\delta))d, \\
& b^*, c \geqslant 0,
\end{aligned} \tag{24}$$

$$\begin{aligned}
v_A(a,d;n,\Theta) = \quad & \max_{c,d^*,\hat{b}^*} u(c,d^*) + \beta E \eta'^{1-\sigma} v(\epsilon'(n'+b(1-n'))+\eta'^{-1}\hat{b}^*, \eta'^{-1}d^*; n', \Theta') \\
\text{s.t.} \quad & c + (1-q\hat{\chi})d^* + q\hat{b}^* \leqslant a + ((1-\delta)(1-h)-\hat{\chi})d, \\
& \hat{b}^*, c, d^* \geqslant 0,
\end{aligned} \tag{25}$$

$$v(a,d;n,\Theta) = \max\{v_{NA}(a,d;\epsilon,n,\Theta), v_A(a,d;n,\Theta)\}. \tag{26}$$

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

$$\begin{aligned}
v_A(w;n,\Theta) = \quad & \max_{c,d^*,\hat{b}^*} u(c,d^*) + \beta E \eta'^{1-\sigma} v(\epsilon'(n'+b(1-n'))+\eta'^{-1}\hat{b}^*, \eta'^{-1}d^*; n', \Theta') \\
\text{s.t.} \quad & c + (1-q\hat{\chi})d^* + q\hat{b}^* \leqslant w \\
& \hat{b}^*, c, d^* \geqslant 0.
\end{aligned} \tag{27}$$

Given this formulation, a solution to the household problem is a collection of policy functions h_c^{NA}, h_b^{NA} and a value function v_{NA} that solve (25), policy functions h_c^A, h_b^A, h_d^A and a value function v_A that solve (27), and a value function v that, given v_{NA}, v_A, solves (26).

Computation We solve the recursive problem by the endogenous-grid method developed by Druedahl (2020). 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^{-6} for all value functions.

We discretize the income shocks, using Hermite-Gauss polynomials with five states. For the model augmented with idiosyncratic fluctuations in labor market transition rates used fro the regressions in Section 4, we discretize the process for the transition rates using the method by Tauchen and Hussey (1991) with seven states.

The grids for the endogenous states a, d, w are linear up to a cutoff value and exponential in a sparse grid above the cutoff value. For the calibration, we use 100 grid points for each variable. For the impulse responses, we use 200 grid points.

We simulate the model using non-stochastic simulation (Young, 2010) and the permanent-income-neutral measure (Harmenberg, 2020). For the discrete choice of durable adjustment, we compute the adjustment share at a particular grid point in the following way:

- A grid point is a representative for a rectangle in the state space. Compute $V_A - V_{NA}$ at the four points of the rectangle by linear interpolation.
- If $V_A - V_{NA} > 0$ at none of the four points, then the adjustment share is 0.
- If $V_A - V_{NA} > 0$ at one point, then compute (by linear interpolation) where $V_A - V_{NA} = 0$ along the sides of the rectangle connected to the point. The area of the triangle connecting the point with the two points where $V_A - V_{NA} = 0$ represents the share of adjusters.
- If $V_A - V_{NA} > 0$ at two points, then do a similar computation for the quadrangle of adjusters in the rectangle. The remaining cases are analogous.

The simulation method of Harmenberg (2020) allows us to sidestep keeping track of the permanent earnings-potential distribution. Therefore, we do not *need* to introduce a perpetual-youth structure as in, e.g., McKay (2017) and Carroll, Slacalek, Tokuoka, and White (2017) in order to have a well-defined permanent earnings-potential distribution. The dynamics of aggregate variables can be described without reference to the permanent earnings-potential distribution and we can therefore present our model with infinitely-lived households.

A.2 Calibration: The Permanent-Earnings Potential Process

We estimate the parameters of the income process using the SHIW sample used for the regressions in Section 4, with the additional restriction that the household head remains employed between any two consecutive waves. As described in Section 4, the data provide annual estimates at a biennial frequency. Denote Δy_{it}^{annual} as the residual from regressing the two-year log growth of annual household income in year t (note that this differs from the quarterly time subscript in the consumption-savings model). Our regressors are sex, education and region, all interacted with a four-degree polynomial of age, and year fixed effects. We assume that Δy_{it}^{annual} follows the log of the process described by (6)-(7) at the biennial frequency. The biennial model moments are then identified by

$$\sigma^2_{\epsilon,\text{biennial}} = -\text{Cov}(\Delta y_{it}^{annual}, \Delta y_{it-2}^{annual}),$$
$$\sigma^2_{\eta,\text{biennial}} = \text{Var}(\Delta y_{it}^{annual}) - 2\sigma^2_{\epsilon,\text{biennial}}.$$

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

$$\sigma^2_{\epsilon} = \sigma^2_{\epsilon,\text{biennial}},$$
$$\sigma^2_{\eta} = \sigma^2_{\eta,\text{biennial}}/8.$$

The parameter values presented in Table 1 are similar to several of the estimates provided in Krueger et al. (2010), who survey the estimation of income processes across several countries.

A.3 Calibration: Estimation of Aggregate Labor Market Transition Rates

We estimate the quarterly separation and job-finding rates using the method developed by Elsby, Hobijn, and Şahin (2013), which extends Shimer (2012), using annual data for the

Italian unemployment rate, grouped by the duration of the unemployment spell. A key advantage of the method is that it is robust to temporal aggregation bias, as the rates are inferred from an underlying continuous-time process. We retrieve the data from the OECD for the period 1984-2014, allowing us to estimate the quarterly rates for the period 1984-2013.

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.[13]

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

$$\frac{\partial u}{\partial t} = s_t(1 - u_t) - f_t u_t. \tag{28}$$

[13] Elsby, Hobijn, and Şahin (2013) use an optimal weighting scheme based on minimizing the mean squared error of the estimate.

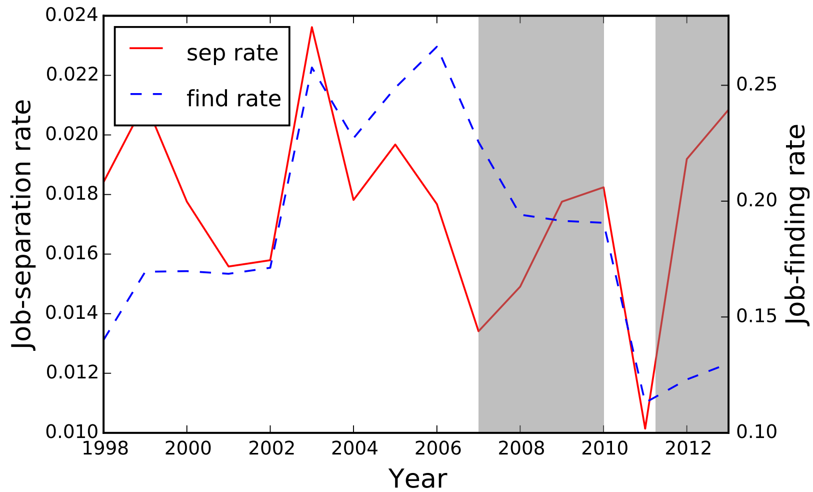

Figure 7: *Estimated quarterly job-separation and job-finding rates, Italy 1998-2013. Recession indicators are retrieved from the Economic Cycle Research Institute and indicated by the Shaded areas.*

Assuming that the flows are constant over a year and solving (28) one year forward, we have

$$u_t = \kappa_t u_t^* + (1 - \kappa_t) u_{t-4}, \tag{29}$$

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 (29) 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.

A.4 Additional model results

In Figure 8, we show the expenditure response of the baseline model alongside an alternatively calibrated flexible-adjustment model. In this flexible-adjustment model, the collateral constraint parameter χ is set to the same value as in the baseline model, and not 1. This results in more households being close to binding credit constraint compared to the flexible-adjustment model used for Figure 3. With more constrained households, the contribution of the unemployment-channel is somewhat larger, which further magnifies the difference to the baseline model.

B Model meets data

In this appendix, we describe details of the data used for the empirical analysis in Section 4, the details of the empirical estimations, the empirical robustness results, and the details of estimating the regressions (10) and (11) on model-generated data.

B.1 Definition of all variables used

In this subsection, we provide definitions of all SHIW variables that we use and that are not self-explanatory. Information regarding state variables, such as wealth, age, household size etc., refers to the end of the surveyed year. Information regarding flow variables, such as expenditures and income, refers to the sum of the flow over the past year.

Employment status. Category variable that indicates the employment status held for most part of that year.

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, Center and South-Islands.

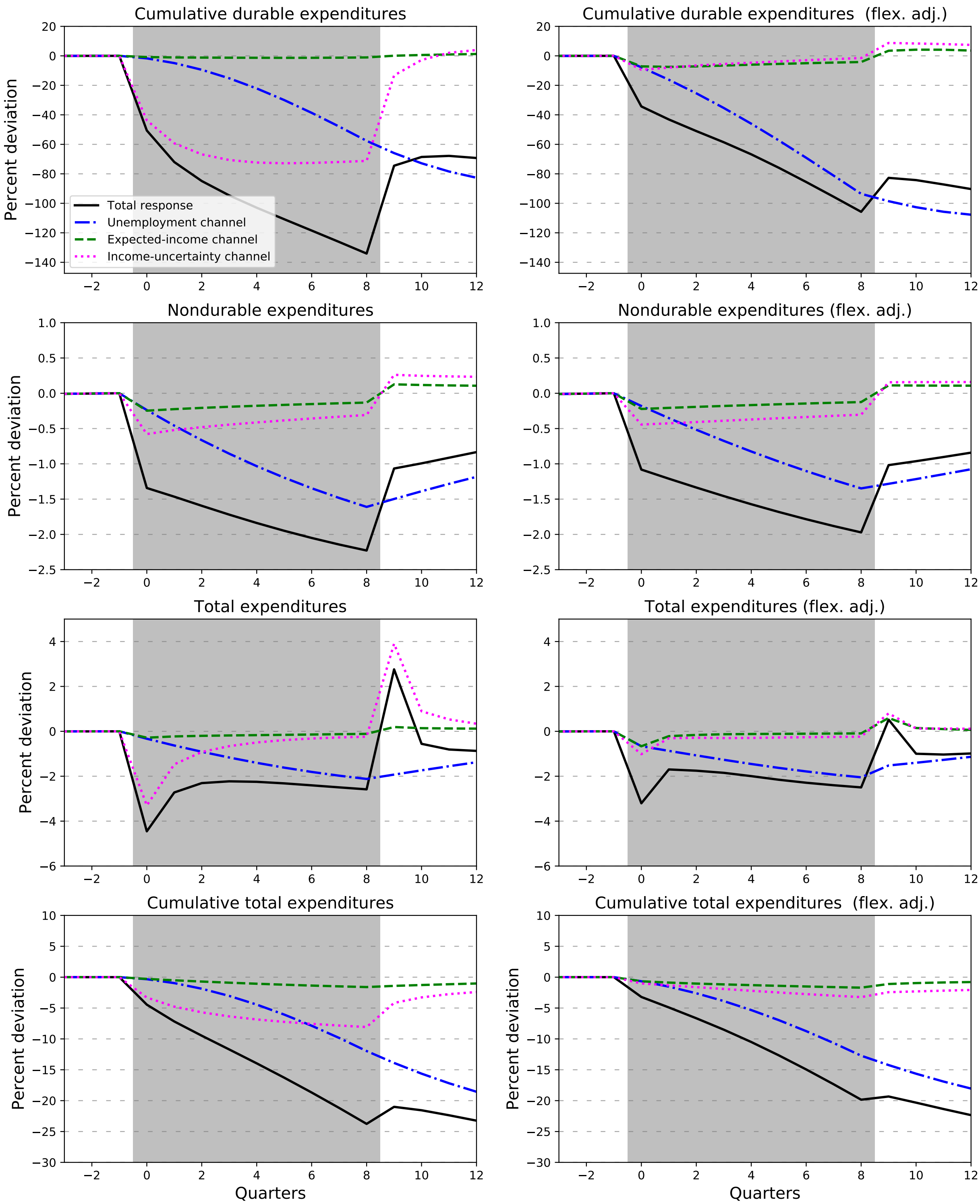

Figure 8: *Expenditure responses to a recession shock, comparing the baseline model to the counterfactual model with no adjustment cost and the collateral constraint* χ *set equal to its baseline value. The recession periods are indicated by the shaded area. The percentage deviation refers to the percentage deviation compared to the expenditure level in period* -1*, before the economy enters the recession.*

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/appliances stock. The self-estimated value of all household belongings of furniture/appliances (including electronics, furnishings 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/appliances and vehicle stock.

Net financial assets. The sum of all financial assets, e.g. deposit accounts, savings accounts, stocks, bonds, funds, shares in partnerships etc., net of debt owed to other households and debt for purchases of consumption goods, thus not including mortgage debt.

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

Nondurable expenditures. Self-estimated total spending less of expenditures on furniture, motor vehicles and jewellery. Does not include actual or imputed rents nor fringe benefits.

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

Vehicle purchase. A dummy variable that takes value 1 if vehicle expenditures in year $\mathtt{t}$ exceed 2/52 times the cross-sectional mean of household income in year $\mathtt{t}$, that is, it exceeds two weeks of average household income in that year.

Furniture/appliances expenditures. Net expenditures on furniture/appliances (including electronics, furnishings and sundry equipment).

Furniture/appliances purchase. A dummy variable that takes value 1 if furniture/appliances expenditures in year $\mathtt{t}$ exceed 2/52 times the cross-sectional mean of household income in year $\mathtt{t}$, that is, it exceeds two weeks of average household income in that year.

Durable expenditures. The sum of vehicle and furniture/appliances expenditures.

Durable purchase. A dummy variable that takes value 1 if either or both of the vehicle or furniture/appliances purchase variables take value 1.

B.2 Descriptive statistics

In Table 5, we provide descriptive statistics of the main variables that we use in the analysis, including the generated regressor $\mathsf{URISK}_{\mathtt{it+2|t}}$.

B.3 Estimation of factors and unemployment risk

Here, we describe how in detail how we estimate the factors and associated factor loadings used for the measurement of household unemployment risk, see Equation (12). We also report estimation results.

We retrieve the factors by multiple-correspondence analysis, which is analogous to principal-component analysis but adapted to suit categorical variables (Greenacre (2007); for a discussion, see also Ng (2015)). Let T denote the number of waves in the survey, N the number of households in the survey, K the number of observable characteristics and M the number of factors.[14] We perform multiple correspondence analysis on the matrix $\mathbf{X}$ in Equation (30),

[14]This notation is illustrative as we do not have a balanced panel, and the number of households in our

	Value/Mean	Std. Dev.	Minimum	Maximum
Share males	0.78	.	.	.
Age	44.4	6.6	25	54
Share with durable purchase	0.28	.	.	.
Share with vehicle purchase	0.15	.	.	.
Share with furniture/appliances purchase	0.16	.	.	.
Nondurable consumption/income	0.55	0.23	0.04	4.26
Net total assets/income	4.91	4.66	-1.65	46.35
Net financial assets/income	0.46	1.03	-3.16	34.12
Share denied/discouraged credit applicants	0.041	.	.	.
Estimated unemployment risk	0.030	0.035	-0.080	0.194
Estimated unemployment-risk growth	0.004	0.022	-0.117	0.12

Table 5: *Descriptive statistics of the sample used for estimating Equations* (10) *and* (11).

with rows consisting of all observations $j \in \{1, ..., NT\}$, and the columns consisting of the observable characteristics $k \in \{1, .., K\}$,

$$\underbrace{X}_{NT\times K} = \underbrace{\lambda'}_{NT\times M} \underbrace{F}_{M\times K} + \underbrace{\nu}_{NT\times K} . \tag{30}$$

In other words, we pool all the survey waves, and estimate time-invariant factors using the pooled sample. For each observation it, we retrieve a vector of factor loadings $\hat{\lambda}_{it}$ with dimension $M < K$. The first factor loads heavily on superregion, education, sex, marital status and household-size variables. The second factor loads heavily on superregion, industry and employment variables. The third factor loads almost exclusively on the regional variables. The loadings of the fourth to tenth factors are more mixed.

The results from estimating Equation (12) are reported in Table 6. We estimate the equation year by year and report R^2's, the sample size and F-statistics for each year. Note that, our sample contains, on average, 1218 observations per year (9740 observations in total). This is larger than the sample of 5095 observations used to estimate (10) and (11), since here, we only need to impose that households are part of two but not three consecutive

sample varies with each survey year.

waves of the survey. As seen from the table, there is substantial variation in several of the slope coefficients across time, which is the variation that we exploit for estimating Equations (10) and (11).

B.4 Robustness results

In Table 7, we show that results from estimating Equation (10) for motor vehicles and and furniture/appliances, separately. The point estimates for both durable-goods categories are close to the estimate for the combined measure. Unsurprisingly, the precision of the estimates are lower compared to the regression for total durables, especially so for furniture, as the number of households that purchase items from each category separately is significantly lower than the number of households that purchase items from any of the two categories; see the descriptive statistics in Table 5. In Figure 9, we show the corresponding specification curves, with the baseline specification indicated by the vertical lines. For motor vehicles, the baseline point estimate is at the lower end of the set of point estimates across the different specifications. The estimate increase as we increase the number of factors and winsorize a larger share of the data. For furniture, the baseline point estimate is in the middle of the set of different estimates, all of which are negative and sizable. We find lower estimates when restricting purchase sizes to be larger.

In Table 8, we show the regression results when estimating Equation (10) using a Probit model instead of OLS. Comparing to the results in Tables 4 and 7, the statistical significance of the estimates decrease when we use the Probit specification.

In Table 9, we show the regression results when estimating Equation (10) and (11) when including a control for the interaction between regional and time fixed effects. We provide this robustness check as as one can be worried that there is reverse causality between unemployment risk and spending even at the local level. Here, we cluster the standard errors on industry instead of region. Comparing to the results in Table 4, the statistical significance of the estimates are in general lower, but the overall pattern of the point estimates is the same.

	1998	2000	2002	2004	2006	2008	2010	2012
Intercept	0.020***	0.029***	0.025***	0.029***	0.024***	0.036***	0.039***	0.047***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)
Factor 1	0.058***	0.086***	0.080***	0.090***	0.100***	0.099***	0.107***	0.077***
	(0.016)	(0.020)	(0.018)	(0.019)	(0.016)	(0.019)	(0.020)	(0.023)
Factor 2	0.002	0.000	0.031	0.005	0.004	0.038*	0.014	0.013
	(0.017)	(0.021)	(0.020)	(0.021)	(0.019)	(0.023)	(0.024)	(0.028)
Factor 3	-0.056***	-0.055**	-0.017	0.011	-0.045**	-0.020	-0.043	-0.059*
	(0.018)	(0.023)	(0.021)	(0.024)	(0.021)	(0.026)	(0.026)	(0.030)
Factor 4	0.065***	0.048*	0.079***	0.057**	0.070***	0.136***	0.086***	0.081**
	(0.023)	(0.028)	(0.027)	(0.028)	(0.023)	(0.028)	(0.029)	(0.032)
Factor 5	-0.054**	-0.039	0.043	-0.033	-0.031	-0.043	-0.048	-0.043
	(0.026)	(0.034)	(0.032)	(0.034)	(0.028)	(0.035)	(0.029)	(0.035)
Factor 6	-0.032	-0.054	-0.041	-0.055	-0.042	-0.105***	-0.066*	-0.023
	(0.027)	(0.036)	(0.035)	(0.036)	(0.031)	(0.035)	(0.036)	(0.040)
Factor 7	-0.033	-0.094***	-0.058*	-0.110***	-0.034	-0.014	-0.032	-0.108***
	(0.027)	(0.035)	(0.033)	(0.034)	(0.029)	(0.036)	(0.036)	(0.041)
Factor 8	0.004	0.085**	0.003	0.014	0.056	-0.058	-0.023	-0.014
	(0.032)	(0.041)	(0.039)	(0.042)	(0.036)	(0.043)	(0.038)	(0.044)
Factor 9	-0.003	-0.026	0.066*	0.047	0.077**	0.092**	0.023	0.003
	(0.031)	(0.039)	(0.038)	(0.038)	(0.033)	(0.040)	(0.042)	(0.047)
Factor 10	-0.027	-0.027	-0.047	-0.027	0.030	0.014	0.004	-0.021
	(0.034)	(0.041)	(0.040)	(0.043)	(0.037)	(0.043)	(0.043)	(0.050)
N	1269	1156	1077	1152	1271	1339	1254	1222
R^2	0.035	0.043	0.040	0.037	0.048	0.053	0.036	0.024
F-stat	4.573	5.141	4.404	4.420	6.351	7.432	4.672	2.967

Table 6: *Results from estimating Equation (12). *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.*

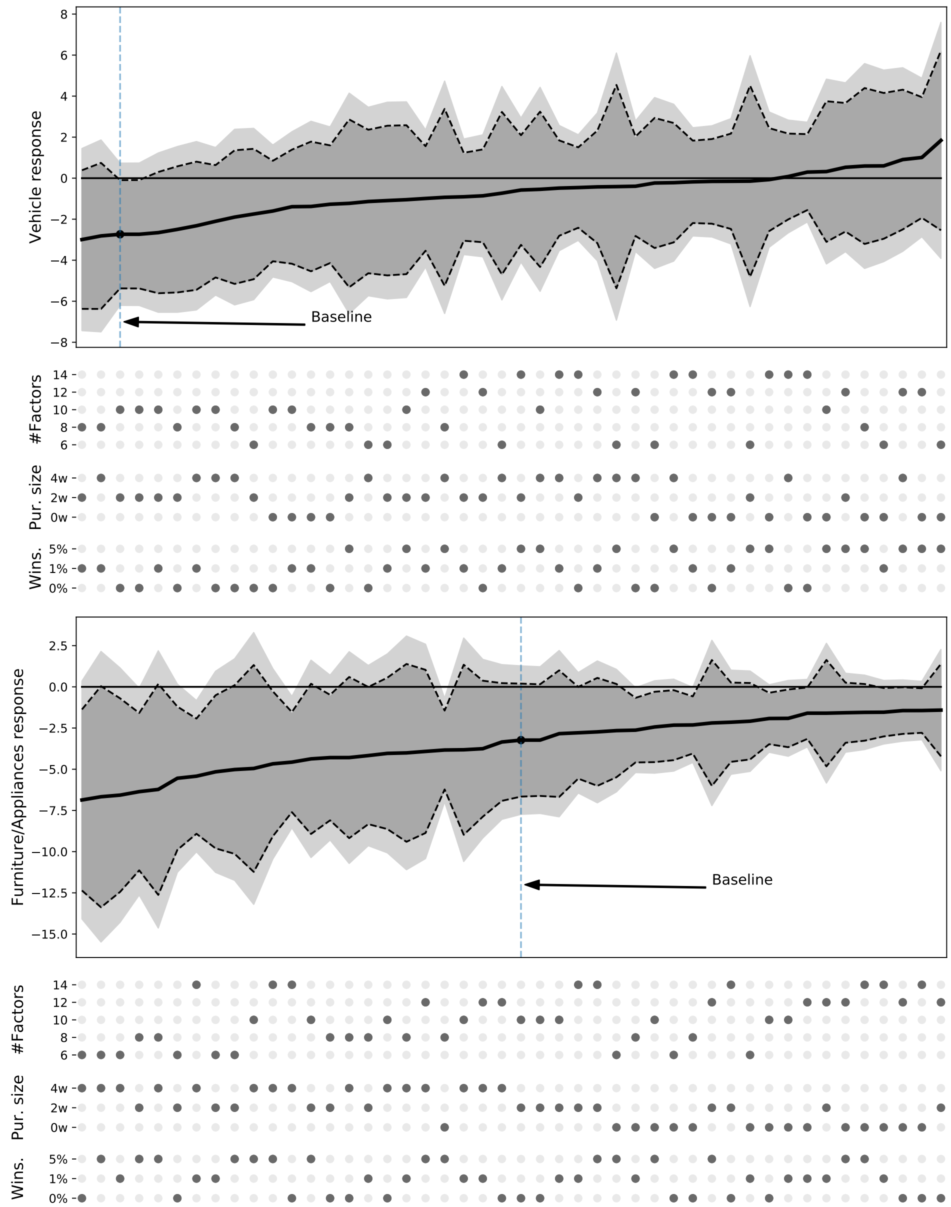

Figure 9: *Specification graphs for estimating Equation (10) for motor vehicles and furniture/appliances, respectively. The solid line indicate the point estimate. The shaded areas indicate 95% and 99% bootstrapped confidence intervals. The colored circles below each graph indicate the specification used when varying a) the number of factors in estimating Equation (12), b) the size cutoff for durable purchases (in terms of weekly household income) and c) the winsorization cutoffs for* $\Delta\mathsf{URISK}_{\mathtt{it}}$ *(0.01 means that we drop that 0.005 % highest and smallest values of* $\Delta\mathsf{URISK}_{\mathtt{it}}$*, respectively). The vertical line indicates the baseline empirical specification.*

	(1)	(2)	(3)
Durables	-2.84***	-3.38***	-2.84***
	(0.96)	(0.96)	(0.91)
R^2	0.01	0.01	0.08
Furniture/Appliances	-3.78**	-4.07**	-3.23*
	(1.72)	(1.76)	(1.66)
R^2	0.01	0.01	0.06
Vehicles	-2.17*	-3.30***	-2.73***
	(1.13)	(1.12)	(1.05)
R^2	0.01	0.01	0.07
Time fixed effects	Yes	Yes	Yes
Change in factor loadings	No	Yes	Yes
Household characteristics	No	No	Yes
Financial variables	No	No	Yes
N	5095	5095	5095

Table 7: *Regression results from estimating (10), for total durables and for both goods categories separately. The coefficients show the effect of a change in unemployment risk growth on the expenditure on nondurable goods and the purchase probability of durable goods, where the latter is normalized by the unconditional purchase probability. Standard errors are bootstrapped, clustered at the 2-digit regional level. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.*

B.5 Regressions on model-generated data

Here, we provide details on the estimation of Equation (10) and (11) using model-generated data.

Estimating cross-sectional variation in the unemployment risk process In the baseline model in Section 2, there is rich heterogeneity in the employment histories of the households, but since all household face the same job-separation and job-finding probability at each point in time, there is no cross-sectional variation in households' risk of becoming unemployed in the future. Moreover, having aggregate shocks to the job-separation probability in the model is redundant here, as our regression models only make use of cross-sectional

	(1)	(2)	(3)
Durables	-2.89***	-3.41***	-2.97***
	(1.03)	(1.19)	(1.15)
Pseudo-R^2	0.01	0.01	0.08
Furniture/Appliances	-3.89**	-4.15**	-3.22*
	(1.73)	(1.86)	(1.89)
Pseudo-R^2	0.01	0.01	0.07
Vehicles	-2.13	-3.29**	-2.95**
	(1.38)	(1.52)	(1.48)
Pseudo-R^2	0.01	0.01	0.08
Time fixed effects	Yes	Yes	Yes
Change in factor loadings	No	Yes	Yes
Household characteristics	No	No	Yes
Financial variables	No	No	Yes
N	5095	5095	5095

Table 8: *Regression results from estimating* (10), *using Probit instead of OLS. The coefficients show the average marginal effect normalized by the unconditional purchase probability. Standard errors are bootstrapped, clustered at the 2-digit regional level. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.*

variation in the data. We therefore replace the job-finding and job-separation probability processes in the baseline model with

$$\lambda_{it} = \lambda, \tag{31}$$

$$\log \zeta_{it} = \log \bar{\zeta} + \rho_\zeta \log \zeta_{it-1} + \sigma_\zeta \epsilon^\zeta_{it}, \qquad \epsilon^\zeta_{it} \sim N(0,1). \tag{32}$$

That is, we assume a constant job-finding probability λ and a time-varying job-separation probability ζ_{it}, which follows an $AR(1)$ in logs.[15]

We make the admittedly strong assumption of holding the job-finding probability constant. The SHIW data is not sufficiently rich to decompose the estimated fluctuations in

[15] Since ϵ^ζ_{it} 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.

	(1)	(2)	(3)
Nondurables	-0.15	-0.63	-0.45
	(0.34)	(0.41)	(0.47)
R^2	0.31	0.31	0.36
Durables	-2.30	-3.21*	-2.00
	(1.79)	(1.95)	(1.77)
R^2	0.01	0.01	0.08
Furniture/Appliances	-2.88	-3.12	-1.16
	(2.76)	(2.88)	(2.56)
R^2	0.01	0.01	0.06
Vehicles	-2.30	-4.37	-3.20
	(2.71)	(2.98)	(3.27)
R^2	0.01	0.01	0.07
Time-region fixed effects	Yes	Yes	Yes
Change in factor loadings	No	Yes	Yes
Household characteristics	No	No	Yes
Financial variables	No	No	Yes
N	5095	5095	5095

Table 9: *Regression results from estimating (10) and (11) including a time interacted with region fixed effect. The coefficients show the effect of a change in unemployment risk growth on the expenditure on nondurable goods and the purchase probability of durable goods, where the latter is normalized by the unconditional purchase probability. Standard errors are bootstrapped, clustered at the 2-digit industry level. *, **, *** indicate that the coefficients are significant at the 10%, 5% and 1% level, respectively.*

unemployment risk into the underlying fluctuations in the transition rates. By holding the cross-sectional job-finding probability 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 3.

As before, we calibrate these processes so that the average job-finding and job-separation probabilities, $\bar{\zeta}$ and λ, match the average job-separation probabilities and the average job-finding probabilities for Italy in the period 1998-2013, using aggregate labor market statistics from the OECD. We calibrate ρ_ζ and σ_ζ to match the variation in unemployment risk changes

Parameter	Value	Target moment	Value	Data
σ_ζ	0.22	$\mathsf{Sd}(\Delta \mathsf{URISK}_{it+2\|t})$	0.018	SHIW 1998-2014
ρ_ζ	0.87	$\mathsf{Corr}(\Delta \mathsf{URISK}_{it\|t-2}, \Delta \mathsf{URISK}_{it+2\|t})$	−0.34	SHIW 1998-2014

Table 10: *Calibrated parameter values for the job-separation probability process. Note that the time subscript here refers to a year, and not a quarter.*

that we have estimated in the data.[16] More specifically, we match the standard deviation and the autocorrelation of the estimated $\Delta \mathsf{URISK}_{i,t+2|t}$ with their model counterparts. The time subscript t denotes a year in the empirical analysis and a quarter in the model framework. For the empirical regressions, $\mathsf{URISK}_{i,t+2|t}$ is the conditional probability of being unemployed for "most part" of year $t+2$. In the model, we abuse notation, and define $\mathsf{URISK}_{i,t+2|t}$ as the probability of being unemployed for at least two quarters in any of the quarters between $t+5$ and $t+8$. The calibrated parameter values and the target moments are reported in Table 10.

Model-generated data We simulate the model to produce a sample of approximately the same size as the data sample. 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, defining variables in the same way as in the SHIW data. In the model-generated data, we define being employed in the last year as being employed at least two quarters of that year. In the SHIW data, being employed the last year is defined as being employed for "most part" of the last year. Unemployment risk in the model is the objective probability, given by the current idiosyncratic state, of being unemployed for most of the year two years into the future. A durable purchase in the model is simply a durable purchase while in the data the purchase must correspond to two weeks of mean household income. Similar to the empirical exercise, we exclude households that are currently unemployed in the final sample. We run regressions (10) and (11) on the sample, and repeat this exercise

[16] We only use the variation in $\Delta \mathsf{URISK}_{i,t+2|t}$ that stems from variation in factor-level exposure — the third term in Equation (14) — as it is only this variation that we exploit to estimate the effect of unemployment risk growth in the empirical regressions.

1,000 times. Similar to our preferred specifications of the empirical regressions, the set of control variables (see 3) includes log income growth, quartiles of net previous period net financial assets and current-period durable goods assets period prior to any purchase or sale, both of which are normalized by previous-period income.

The exact number of observations varies for each regression, as the number of realized unemployment spells is stochastic and we exclude the households that do become unemployed from the final samples. We set the number of households so that the samples, on average, are similar in size to the empirical sample.