Expenditure Risk and Household Wealth Dynamics*

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Abstract

This paper investigates the role of expenditure risk (ER)—persistent, unpredictable spending shocks—in shaping household wealth loss dynamics. Using PSID data (1999–2021), I document that, on average, 10% of U.S. households see their net worth drop to zero or negative levels between consecutive survey waves. While standard models attribute these transitions to income fluctuations, my empirical analysis finds that ER explains 6.73% of these wealth loss episodes, compared to 2.27% for transitory income risk, while permanent income risk plays no role. To rationalize these findings, I develop a heterogeneous-agent model in which ER enters as persistent shocks to the marginal utility of a fraction of the household consumption basket. The model shows that ER creates a wedge in the intertemporal Euler equation, altering optimal savings behavior and amplifying financial vulnerability. This mechanism generates wealth loss episodes consistent with the data and reveals how ER affects household wealth accumulation beyond income shocks alone. This paper highlights a previously overlooked driver of household dynamics by jointly identifying ER alongside imcome risk and explaining their differential impact on wealth loss.

Keywords: Income risk, Expenditure risk, Wealth dynamics, Precautionary savings
JEL Classification: D15, D31, D52, E21

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1 Introduction

What drives households into wealth loss? A substantial fraction of U.S. households live hand-to-mouth (H2M), consuming most of their income with little or no accumulated wealth to buffer against financial shocks. According to the Panel Study of Income Dynamics (PSID), around 20% of households hold zero or negative net worth, with 10% of households seeing their net worth drop to non-positive levels between consecutive survey waves. Standard economic theory attributes these transitions to transitory income fluctuations, implying that households experiencing wealth loss are those facing short-term income setbacks. However, the incidence of these episodes suggests that transitory income risk alone may not fully explain the observed wealth dynamics.

This paper argues that expenditure risk (ER)—persistent, unpredictable spending shocks—plays a critical role in wealth loss among H2M households. Using PSID data from 1999 to 2021, I estimate a flexible expenditure model and isolate expenditure risk as the residual component of household spending that cannot be explained by income risk, cash on hand, and demographic characteristics—key inputs in standard consumption-savings models. I then quantify its role in household wealth loss, finding that expenditure risk has significant predictive power, accounting for 6.73% of transitions into H2M status, compared to 2.27% explained by transitory income risk, while permanent income risk plays no role. These results suggest that wealth loss is not merely a reaction to income fluctuations but also a consequence of persistent, unpredictable expenditure shocks that standard models fail to capture. In particular, I find that transportation, education, and maintenance (house and car repairs) are the key consumption categories driving ER, creating sudden financial burdens that deplete household resources and force reductions in savings, ultimately increasing the likelihood of wealth loss.

While much of the literature focuses on the persistence of low wealth, my approach sheds light on what triggers transitions into H2M status. Existing models attribute the concentration of households at zero or negative net worth to time-preference heterogeneity, explaining why some remain persistently H2M. In contrast, I find that expenditure risk is a distinct driver of wealth loss episodes, complementing time-preference heterogeneity. To investigate this mechanism, I extend a standard heterogeneous-agent model with idiosyncratic income risk to include expenditure risk, modeled as persistent shocks to the marginal utility of part of the consumption basket. Unlike the standard model, which predicts no direct wealth response to permanent income shocks near the borrowing constraint, my framework generates a marginal wealth response to these shocks, consistent with the empirical findings. Moreover, the model replicates the observed predictive power of ER and transitory income risk for wealth loss episodes, while permanent income risk exhibits no explanatory power.

A standard model that relies on persistent household time-preference heterogeneity,[1] replicates the observed share and persistence of H2M households by attributing wealth loss episodes almost entirely to differences in discount factors. In this framework, households with low discount factors accumulate little wealth and are structurally vulnerable, with transitory income shocks acting as the proximate trigger for asset depletion, while permanent income shocks exert no direct effect near the borrowing constraint. However, the data tell a different story. Although time preferences play a key role, they do not fully account for the incidence of wealth loss; while both permanent and transitory income shocks exhibit significant marginal effects on wealth loss, only transitory income risk and expenditure risk retain predictive power for H2M transitions after controlling for household wealth and financial status. This suggests that financial vulnerability arises not only from fixed heterogeneity in time preferences but also from the dynamic interplay of income shocks and expenditure risk.

To better understand wealth transitions, I estimate an expenditure function that separates systematic spending patterns from unpredicted expenses. This approach measures expenditure risk as the persistent, unpredictable component of household spending unexplained by income risk, cash on hand, or demographics—key determinants in standard consumption-savings models. Using PSID data (1999–2021), I estimate a flexible machine-learning-based expenditure model that accommodates nonlinear relationships across all explanatory variables and consumption. Specifically, the random forest regression inputs include household income risk measures identified using income histories following Blundell et al. (2008), available resources, demographics, and household types inferred using grouped fixed effects following Bonhomme et al. (2022). The model predicts expenditure for each household-wave observation, and its residual—the gap between actual and predicted spending—captures unexpected expenses. I find these residuals exhibit significant persistence, which I exploit to identify ER. This approach disentangles transitory spending fluctuations from systematic expenditure shocks, highlighting ER's role in financial vulnerability.

The residual component of household expenditure exhibits persistence, which I leverage to identify expenditure risk. To separate its persistent and transitory components, I estimate an AR(1) process for household spending residuals and apply a first-difference transformation adjusted for the estimated persistence. This transformation enables the ap-

[1] Heterogeneity in time preferences is a central mechanism in models matching the household wealth distribution and financial behavior. Micro-data-driven studies on household savings and consumption dynamics, such as Aguiar et al. (2024), posit fixed heterogeneity in discount factors to generate heterogeneous target net worth. Similarly, structural models of the wealth distribution, starting with Krusell and Smith (1998), and more recently, heterogeneous-agent New Keynesian (HANK) models, have widely relied on this mechanism; see the recent survey by Kaplan and Violante (2022). Alternative wealth-distribution-focused modeling approaches include heterogeneity in rates of return, as in Hubmer et al. (2021), extreme income state realizations, as in Castaneda et al. (2003), or asset-based means-tested transfers, which can induce moral hazard over savings, as discussed in Hubbard et al. (1995).

plication of the variance-covariance identification strategy used in Blundell et al. (2008), allowing me to extract the innovations to the persistent component of household expenses. By construction, this approach ensures that ER captures systematic, long-lasting deviations from predicted expenditure, distinct from short-term fluctuations, which primarily reflect transitory shocks and survey-dependent noise. The resulting ER measure enables a precise assessment of how persistent expenditure shocks influence consumption growth, wealth accumulation, and transitions into H2M status.

To investigate the sources of ER, I analyze its relationship with household spending across non-durable consumption categories. Using cross-correlations between ER and expenditure shares, I find that ER is primarily driven by spending on education and essential maintenance costs, such as car and home repairs—categories that impose large, often unavoidable financial burdens. While education expenses reflect sustained commitments that adjust infrequently, maintenance shocks, such as car and home repairs, often require large, unavoidable payments that can disrupt household finances over multiple periods. In contrast, some spending categories exhibit little to no correlation with ER. Certain components of household consumption remain stable regardless of ER fluctuations, either due to consumption commitments, as in Chetty and Szeidl (2007), or because they are tightly linked to income and demographics. This heterogeneity highlights ER's distinct role: it captures financial stress arising from unpredictable yet persistent expenditure shocks that standard models struggle to accommodate.

Expenditure risk significantly affects household consumption growth, wealth accumulation, and transitions into H2M status.

Compared to PIR and TIR, ER explains a larger share of wealth loss episodes and plays a distinct role in household financial vulnerability.

These empirical findings highlight the key differences between ER and income risk, showing how expenditure risk operates through mechanisms unrelated to labor income fluctuations.

To rationalize these findings, I develop a heterogeneous-agent model where households face idiosyncratic income and expenditure risk under incomplete markets.

A key feature of the model is persistent shocks to the marginal utility of a fraction of the consumption basket, an approach that contrasts with alternative explanations based on means-tested transfers and moral hazard.

The model generates wealth loss episodes consistent with the data and shows that expenditure risk interacts with standard savings behavior, amplifying financial vulnerability.

This paper contributes to the literature on household consumption and income dynamics, building on seminal work by Hall and Mishkin (1982) and Blundell, Pistaferri, and Preston (2008).

It also relates to studies on the spending behavior and wealth dynamics of low-wealth households, such as Hubbard et al. (1995), Aguiar et al. (2024), and Hubmer et al. (2021).

Additionally, this paper connects to the literature on health shocks, which models stochastic variations in marginal utility (Palumbo (1999); French and Jones (2004); De Nardi et al. (2010)).

A closely related study is Miranda-Pinto et al. (2020), which explores stochastic consumption thresholds and saving constraints.

The rest of the paper is structured as follows. Section 2 examines the empirical evidence on income and expenditure risk in shaping household wealth transitions. Section 4 presents the theoretical framework and quantifies the impact of expenditure risk. Section 5 concludes.

2 Income Risk and Wealth Dynamics

The impact of income risk on wealth dynamics has been extensively explored in economic studies, particularly within the framework of consumption-saving theory under conditions of uncertainty and incomplete markets. According to the theory, to a first-degree approximation, economic agents adjust their consumption levels in response to permanent shifts in income. Conversely, in the face of transitory income fluctuations, they should utilize their financial assets to maintain steady consumption levels. In this section, I study how standard theoretical prescriptions hold up when confronted with the data, particularly in the case of transitions toward low-wealth status.

To account for Aguiar et al. (2024)'s recent developments in the theory of low-wealth holdings, I augment the standard consumption-saving framework under income risk and incomplete markets with fixed household types along the time-preference dimension. The model is able to generate transitions toward low-wealth in response to negative transitory income shocks but cannot deliver a significant relationship between zero-wealth transitions and permanent income risk realizations. The intuition is straightforward: particularly when approaching their borrowing constraint, households will cut down consumption expenditure when facing a permanent negative income shock.

On the other hand, in the data, I identify the differential effect of permanent and transitory income shocks on the binary outcome of transitioning into zero-wealth, exploiting the panel dimension of the PSID by following Blundell et al. (2008). I find that both types of income risk realizations, transitory and permanent, elicit zero-wealth transitions. The relationship holds true and significant for permanent income shocks after controlling for household head age or educational attainment, and the effects are larger in magnitude when observing households that are closer to the zero-wealth threshold.

2.1 Zero-Wealth Transitions in the Data

Table 1 shows the incidence and persistence of zero-wealth status in PSID data. Notably, there is a 10% unconditional probability of falling into low-net-worth status. Once there, two out of three family units will fail, in the following two years, to accumulate enough assets to achieve positive net worth. The outcome of these transition probabilities is the observed share of more than 20% zero-wealth households. Interestingly, the observed population share of zero-wealth households is very close to the unique stationary distribution[2] implied by the observed transition matrix, suggesting that average transition probabilities have not deviated much over the years from those measured in the data sample.

Table 1: Zero-Wealth Status Incidence & Persistence

	Transition Matrix		population share
	not-ZW$_{t+2}$	ZW$_{t+2}$	
not-ZW$_t$	.90	.10	78%
ZW$_t$	.34	.66	22%

Notes: ZW$_t$ is an indicator for households reporting non-positive net worth in a given survey wave t. Details on the definition of net worth can be found in section 2.1.1.

2.1.1 Data

The empirical analysis is conducted using the Panel Study of Income Dynamics (PSID) biennial surveys from 1999 to 2019. Since 1999, the PSID started measuring wealth and improved its expenditure data collection beyond food and housing. Specifically, my analysis centers on non-durable consumption expenditure, C, total household income, Y, and net worth, W. A set of controls X is used to partial out from the main interest variables the component explained by observable demographics. Flow variable values, although reported biennially, refer to their yearly realizations.

Consumption expenditure includes non-durable categories such as food, housing, childcare, healthcare, clothing, trips, recreation, house furnishing and repairs, utilities, vehicle payments and repairs, transportation, and schooling. As a measure of household income, I use the sum of all taxable income, transfer income, and social security income from the reference person, spouse (if present), and other family unit members (if present). For homeowners, housing costs are computed as 6 percent of the home value; on the other hand, I include the same value, subtracting associated mortgage interest and home insurance, as implicit rent.

[2] The stationary distribution for zero-wealth households, implied by Table 1 transition matrix, is: $\{.77, .23\}$

In this paper, I identify households being in a low-wealth status with those reporting non-positive net worth, which I label as Zero Wealth (ZW). Net worth is computed by subtracting liabilities from asset holdings. Assets include both liquid and non-liquid wealth, such as home equity, stocks, checking and savings balances, money market funds, certificates of deposit, treasury bills, and retirement accounts. Liabilities include mortgages, credit cards, medical and legal bills, and student loans. The net value of any business, farm, or vehicles is also added to net worth.

The choice of a measure of wealth status that is not relative to household income or earnings deviates from the hand-to-mouth-status approach, which represents a typical choice in the literature studying the spending behavior of low-wealth households. Classifying households as hand-to-mouth, according to either net worth or liquidity, is instrumental in addressing questions related to their response to fiscal stimuli or monetary shocks, thus related to their marginal propensity to consume. This paper focuses on wealth dynamics at the bottom of the household wealth distribution; therefore, I believe the use of the proposed zero-wealth definition to classify low-wealth status is more fitting.

The set of controls used throughout the whole empirical analysis, X, features a third-order polynomial in household age, household dummies for education, race, and residential region, household size, and number of children, plus calendar year dummies. Household age, education, and race refer to the household representative person.[3] The three continuous variables of interest – log consumption, log income, and wealth – are residuals obtained after partialling out the component explained by X. When estimating the consumption expenditure function, the household representative person's health status is added to X. Therefore, the measure of expenditure risk identified in this paper, as confirmed by the cross-correlation analysis in 3.2 with respect to non-durable expenditure sub-categories, does not include health risk.

To estimate the role of idiosyncratic risk realization in determining transitions toward zero wealth, I run a linear probability model with the dependent variable $\text{FALL}_{i,t}$, representing a transition from positive to non-positive net worth between $t-2$ and t. The binary regression model uses lagged wealth, changes in marital status, and home ownership together with ΔX, a first-difference transformation of X, as controls. I refer to this set of controls as ΔX^{FALL}.

My sample draws only on PSID's nationally representative sample. The household representative person's age is restricted to between 25 and 64. Following Aguiar et al. (2024), households with less than $2000 in income or reporting food or housing expenditure above 90% or below 5% of total expenditure are dropped. All nominal values are converted to CPI-deflated 2001-$ using the Federal Reserve Economic Data (FRED) Consumer Price Index for the United States series.

[3] In older PSID waves, the representative person was referred to as the household head.

2.1.2 Income risk identification

Income risk modeling, assumptions, and identification in this section closely follow Kaplan and Violante (2010), which builds on a simplified version of the seminal work by Blundell et al. (2008). Let y represent household income residuals, obtained after partialling out observable household characteristics[4] from observed log-income realizations $\tilde{y}$. Income residuals are then decomposed into a permanent component z^y and a transitory component ε^y. Given the sample timing characteristics, one period in the stochastic model corresponds to two years in the data.

$$
\begin{aligned}
\tilde{y}_{i,t} &= \Xi(X_{i,t}) + y_{i,t}, \quad y_{i,t} \perp\!\!\!\perp X_{i,t} \\
y_{i,t} &= z^y_{i,t} + \varepsilon^y_{i,t} \\
z^y_{i,t} &= z^y_{i,t-1} + \eta^y_{i,t} \\
\therefore \Delta y_{i,t} &= \eta^y_{i,t} + \Delta \varepsilon^y_{i,t} \\
\left(\varepsilon^y_{i,t}, \eta^y_{i,t}\right)' &\overset{\text{iid}}{\sim} \mathcal{N}\left(0_2, \ \ \text{diag}\left(\sigma^2_{\varepsilon^y}, \sigma^2_{\eta^y}\right)\right)
\end{aligned}
\tag{1}
$$

Given (1), income residual growth captures a noisy measure of income risk components and, under a pair of orthogonality conditions[5] on consumption growth $\Delta c_{i,t}$, there exists a set of measurable functions of income histories[6] $f_t^{\eta,\ \varepsilon}(y_i)$ with the following properties:

$$
\begin{aligned}
\text{cov}\left(\Delta c_{i,t}, \ \eta^y_{i,t}\right) &= \text{cov}\left(\Delta c_{i,t}, \ f_t^{\eta}(y_i)\right) \\
\text{var}\left(\eta^y_{i,t}\right) &= \text{cov}\left(\Delta y_{i,t}, \ f_t^{\eta}(y_i)\right) \\
\text{cov}\left(\Delta c_{i,t}, \ \varepsilon^y_{i,t}\right) &= \text{cov}\left(\Delta c_{i,t}, \ f_t^{\varepsilon}(y_i)\right) \\
\text{var}\left(\varepsilon^y_{i,t}\right) &= \text{cov}\left(\Delta y_{i,t}, \ f_t^{\varepsilon}(y_i)\right)
\end{aligned}
\tag{2}
$$

The objective of the empirical strategy in (2) is to identify the relationship between permanent $\eta^y_{i,t}$ and transitory $\varepsilon^y_{i,t}$ income innovations and consumption growth $\Delta c_{i,t}$; to assess the pass-through of stochastic income innovations on consumption dynamics. Therefore, using the appropriate functions of income residuals y_i, we can construct pass-through coefficients $\beta_{\Delta c|\bigstar^y}$, for $\bigstar \in \{\eta, \ \varepsilon\}$, as:

[4]The Ξ function is estimated using a linear regression model, following (Blundell et al., 2008); the vector of observables $X_{i,t}$ contains a third-order polynomial in household age, household dummies for education, race, and residential region, household size, and number of children, plus calendar year dummies.

[5]Consumption growth, $\Delta c_{i,t}$, must be orthogonal to given leads and lags of income stochastic component innovations. Given the income process detailed in (1), the following No-Foresight and Short-Memory conditions need to hold:

$$
\begin{aligned}
\text{(NF)}: &\qquad \text{cov}(\Delta c_{i,t}, \ \eta^y_{i,t+1}) = \text{cov}(\Delta c_{i,t}, \ \varepsilon^y_{i,t+1}) = 0 \\
\text{(SM)}: &\qquad \text{cov}(\Delta c_{i,t}, \ \eta^y_{i,t-1}) = \text{cov}(\Delta c_{i,t}, \ \varepsilon^y_{i,t-2}) = 0.
\end{aligned}
$$

[6]The set of measurable functions depends on the stochastic process specified for income residuals, given stated assumptions: $f_t^{\eta}(y_i) = \Delta y_{i,t+1} + \Delta y_{i,t} + \Delta y_{i,t-1}$ and $f_t^{\varepsilon}(y_i) = \Delta y_{i,t+1}$ deliver the desired result.

$$
\begin{aligned}
\beta_{\Delta c|\eta^y} &= \frac{\text{cov}\left(\Delta c_{i,t}, \sum_{j=-1}^{1}\Delta y_{i,t+j}\right)}{\text{cov}\left(\Delta y_{i,t},\ \sum_{j=-1}^{1}\Delta y_{i,t+j}\right)} \\
\beta_{\Delta c|\varepsilon^y} &= \frac{\text{cov}\left(\Delta c_{i,t}, \Delta y_{i,t+1}\right)}{\text{cov}\left(\Delta y_{i,t},\ \Delta y_{i,t+1}\right)}
\end{aligned}
\tag{3}
$$

Coefficients $\beta_{\Delta c|\bigstar^y}$ will identify how permanent or transitory income risk affects consumption dynamics $\Delta c_{i,t}$. The intuition for this empirical specificaiton follows a two-step instrumental variable framework where $f_t^{\bigstar^y}(y_i)$ are employed as instruments to extract, from observed (residual) income dynamics, the $\bigstar$ income-process-component effect on the dependent variable.

To measure the marginal effect of idiosyncratic risks on ZW transition probabilities, I run a linear probability model that uses the same two-step instrumental-variable framework from the pass-through coefficient identification analysis. Adding lagged wealth, changes in marital status, and changes in home ownership together with ΔX, a first-difference transformation of X, as controls. Therefore, for income risk, the regressors are the projections of income growth on the appropriate instrument for each component. The coefficients associated with these regressors are labeled as $\boldsymbol{\beta}_{\text{FALL}|\bigstar^y}$, for $\bigstar \in \{\eta,\ \varepsilon\}$.

2.1.3 Income risk and transitioning into zero-wealth

As predicted by the theory, income risk affects consumption dynamics. Table 2 reports estimated pass-through coefficients from (3). The difference in the number of observations that enter permanent versus transitory risk estimates depends on the different identification data requirements between the two risk sources. Results are in line with estimations from the literature.[7] As expected, permanent shocks pass through consumption expenditure more than transitory ones, and the explanatory power of permanent shocks, as measured by the reported R^2s, is ten-fold that of transitory ones.

Table 3 reports the pass-through coefficient estimates for both income risk components for the binary $\text{FALL}_{i,t}$ event. The causal relationship between income risk and fall events is present in the whole sample, as shown in the first column, and is robust to several cuts of the data aimed to isolate households who are more likely to experience a fall event.

2.2 Zero-Wealth Transitions in the Canonical Model

Here, I review some of the predictions of the canonical consumption-savings model under idiosyncratic income risk and incomplete markets augmented with ex-ante time-preferences heterogeneity, following Aguiar et al. (2024). Particularly, I focus on consumption dynamics

[7] See Crawley and Theloudis (2024) for a detailed summary of structural-methods estimates.

Table 2: Consumption Pass-Through Coefficients for Income Risk Components in PSID

	Δc	
	(1)	(2)
$\boldsymbol{\beta_{\Delta c\|\eta^y}}$	0.43***	
	(0.037)	
$\boldsymbol{\beta_{\Delta c\|\varepsilon^y}}$		0.06***
		(0.013)
R^2	0.0130	0.0014
households	3,543	4,323
hh waves	12,733	17,056

Notes: Column headers represent the variable of interest in the estimated pass-through coefficients as expressed by equations (3). Column (1) reports the pass-through estimates for permanent income risk, while column (2) reports the estimates for transitory income risk, as detailed in (1). Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

Table 3: Income Risk vis-à-vis Zero-Wealth Transitions in PSID

	FALL			
	all	$W_{i,t-1} \leq$ \$100K	$<$ college	age ≤ 45
$\beta_{\text{FALL}\|\eta^y}$	-0.11***	-0.14***	-0.11***	-0.11**
	(0.024)	(0.040)	(0.033)	(0.047)
$\beta_{\text{FALL}\|\varepsilon^y}$	-0.05***	-0.06***	-0.05***	-0.06**
	(0.010)	(0.016)	(0.013)	(0.019)
R^2	0.049	0.040	0.054	0.036
ΔX^{FALL}	Y	Y	Y	Y
households	3,524	2,531	2,304	1,917
hh waves	12,572	7,194	7,871	5,041

Notes: All columns report estimates of the linear probability model coefficient to the $\text{FALL}_{i,t}$ dummy. Each column header specifies eventual sample restrictions. Parameter η^y refers to permanent income innovations, ε^y to transitory ones, as detailed in (1). Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

and transitions towards zero-wealth status, extending the analysis in Kaplan and Violante (2010) to an economy with household types tied to preference heterogeneity.

The benchmark economy (BE) used to represent the predictions of the canonical model is detailed in Section 4.1. To summarize, BE features both ex-ante and ex-post heterogeneity among households. Ex-ante heterogeneity is represented by an independent bivariate distribution of income level fixed effects and discount factors. Ex-post heterogeneity is generated by idiosyncratic permanent and transitory income shock realizations and the consequently diverse income histories.

Table 4: Consumption Pass-Through Coefficients for Income Risk Components in BE

	Δc	
	(1)	(2)
$\beta_{\Delta c \mid \eta^y}$	0.45***	
	(0.003)	
$\beta_{\Delta c \mid \varepsilon^y}$		0.19***
		(0.002)
R^2	0.24	0.10
households	10,000	
hh waves	100,000	

Notes: Column (1) reports the pass-through estimates for permanent income risk, while column (2) reports the estimates for transitory income risk, as described in (1). Section 2.1.2, following Blundell et al. (2008), contains the description of pass-through coefficients identification. Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

As already shown by Kaplan and Violante (2010), the heterogeneous agent consumption-saving model with idiosyncratic income risk under incomplete markets can generate partial insurance levels, as measured by the pass-through coefficient introduced by Blundell et al. (2008), similar to the data when we allow for household borrowing. Results in Table 4 confirm their findings in an economy with ex-ante heterogeneity in time preferences. Moreover, as the permanent income hypothesis postulates, permanent shocks demand a larger pass-through to consumption than transitory ones.

What's the story the BE tells about falling into a low net worth position? The distribution of time-preference across households is calibrated to match the share of zero-wealth households in the economy. The mechanism acts by creating heterogeneous optimal wealth-to-income ratios; given the assigned time-preferences, some households are content with holding little-to-no wealth, as these target dynamics adjust along the life-cycle. Therefore, as shown by Table 5, ZW transitions are dominated by transitory income risk realizations. For those households with target wealth-to-income ratios close to the threshold, fluctuations in transitory income greatly influence which side of the threshold they stand, as pointed out by the last column of Table 5.

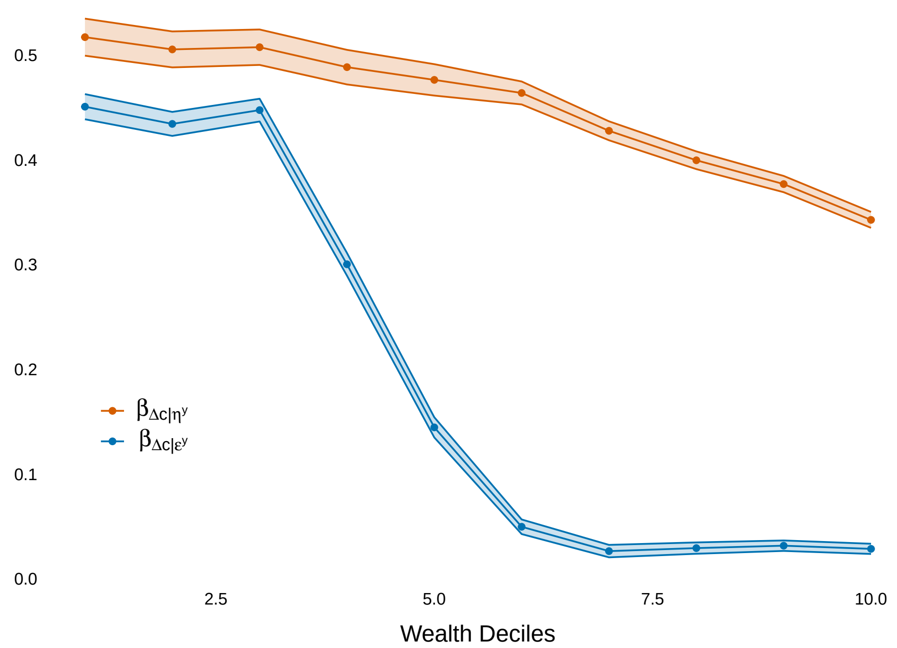
Summarizing, in the canonical framework, permanent income shocks do not significantly affect the financial vulnerability of households at the bottom of the wealth distribution. The optimal dynamic response dictated by the Euler equation demands an appropriate cut in household expenditure. This relationship between income risk pass-through and wealth can be seen clearly in Figure 1. As their wealth decreases, households' consumption responses to income shocks become larger. The effect is present in both components of income risk but is much stronger for transitory shocks, whose pass-through to consumption approaches the level of permanent shocks as household wealth decreases.

Table 5: Income Risk vis-à-vis Zero-Wealth Transitions in BE

	FALL			
	all	$W_{i,t-1} \leq \$100K$	$\beta_i \leq Q_{\beta_i,1/3}$	age ≤ 45
$\beta_{\text{FALL}\mid\eta^y}$	0.01	0.01	0.01	0.00
	(0.007)	(0.010)	(0.015)	(0.009)
$\beta_{\text{FALL}\mid\varepsilon^y}$	-0.10***	-0.14***	-0.12***	-0.11***
	(0.004)	(0.006)	(0.010)	(0.006)
R^2	0.02	0.01	0.10	0.02
$\Delta X^{\text{FALL}}_{\text{sim}}$	Y	Y	Y	Y
households	10,000	8,752	3,423	10,000
hh waves	100,000	69,520	34,230	59,767

Notes: All columns report estimates of the effect of permanent and transitory income risk on the $\text{FALL}_{i,t}$ event according to the empirical specification in section 2.1.2. Each column header specifies eventual sample restrictions, where $W_{i,t-1}$ is household asset holding at the beginning of the period and $Q_{\beta_i,1/3}$ represents the first tertile of the calibrated discount factor distribution, which equals 0.79 according to calibration in 4.1.1. Parameter η^y refers to permanent income innovations, ε^y to transitory ones, as described in (1). Beginning of period wealth, a second-order polynomial in age, and permanent income-level type have been added as $\Delta X^{\text{FALL}}_{\text{sim}}$ controls in all columns. Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

Figure 1: Income Pass-Through Coefficients by Wealth Decile in BE



Notes: Sample cuts are generated using deciles of the beginning-of-period net worth variable. The pass-through coefficients for permanent and transitory income shocks are then computed within each data cut.

3 Expenditure Risk

How do households deal with unexpected expenses? Is there any evidence of persistence across periods? What are the consequences for wealth dynamics? I use income risk measures for permanent and transitory shocks, identified using observed histories of income dynamics as detailed in Section 2.1.2, together with a measure of fixed income level and other observable demographics to estimate a flexible expenditure model. The arguments of the consumption function are modeled after the same canonical consumption-savings framework adopted in Section 2. I use histories of changes in the deviation of observed expenditure from its predicted counterpart to identify expenditure shocks.

To identify expenditure risk alongside income risk, I build a stochastic-process dependent identification strategy that hinges on two core assumptions: (i) mean independence between permanent income and expenditure shock innovations, and (ii) household preferences[8] consistent with a consumption policy function featuring multiplicative independent arguments with respect to income and expenditure shock realizations. This framework allows for a simple two-step procedure, where expenditure risk is measured using consumption residuals obtained by subtracting from observed expenditure its predictable component derived from income types, asset holdings, income shocks, and household demographics.

3.1 Empirical Consumption Model

Consider a consumption policy function $\tilde{G}(\cdot)$ featuring both income $(\eta^y,\ \varepsilon^y)$ and expenditure η^c risks alongside household income type τ, log available resources[9] z, and observable demographics X as arguments; expressed for log consumption as:

$$c_{i,t} = \tilde{G}\left(\tau_i, \eta^y_{i,t}, \varepsilon^y_{i,t}, \eta^c_{i,t}, z_{i,t}, X_{i,t}\right) + \epsilon_{i,t}, \quad \epsilon_{i,t} \perp\!\!\!\perp \eta^y_{i,t}, \eta^c_{i,t}, z_{i,t}, X_{i,t} \tag{4}$$

Assume household preferences allow for the decomposition of observed expenditure into two components: what can be predicted using the income risk framework $\hat{c}$ plus a residual part ξ.

$$c_{i,t} = G\left(\tau_i, \eta^y_{i,t}, \varepsilon^y_{i,t}, z_{i,t}, X_{i,t}\right) + h\left(\eta^c_{i,t}\right) + \epsilon_{i,t}, \quad \eta^y_{i,t} \perp\!\!\!\perp \eta^c_{i,t} \tag{5}$$

To estimate $G(\cdot)$, I run a supervised machine learning[10] algorithm allowing for unstructured non-linearity along and across all argument dimensions. Once $G(\cdot)$ is estimated using two-fold cross-validation, predicted expenditure $\hat{c}$ is computed using observed real-

[8] For instance, CRRA preferences with homogeneous curvature across consumption goods over time and states of the world would imply (5).

[9] Cash on hand $Z_{i,t}$ is measured as the sum of household predetermined net worth $W_{i,t-2}$ and current family income $Y_{i,t}$.

[10] The chosen random forest algorithm outperforms both a simple OLS linear framework and a penalized LASSO classifier with five-degree spline interactions among all function arguments.

izations of persistent income shocks, available cash on hand, and household demographics. Figure A.1 in Appendix A shows the marginal effect of cash on hand and permanent income risk on log consumption predictions, obtained by computing a partial dependence function.

The estimated log consumption function is concave over log available resources and increasing in permanent income innovations. Figure A.2 displays the contribution of each argument used in the random forest regression framework to predict log consumption. Household income types, cash on hand, family size, and income risk innovations are leading determinants of prediction accuracy, as measured by the decrease in node impurity. Node impurity quantifies the homogeneity of the target variable within the subsets created by a split during the creation of each decision tree. Lower impurity means that the subset is more homogeneous (i.e., the target variable values are more similar).

3.1.1 Unexpected expenses are not i.i.d.

Based on an income-risk driven theory of consumption and savings over the life cycle, any deviations from the household-policy-function's determined consumption expenditure are expected to be attributable solely to noise. However, I find that the residual component of log-consumption expenditure exhibits distinct patterns in both levels and its first difference.

$$\begin{aligned} c_{i,t} &= \hat{c}_{i,t} + \xi_{i,t} \\ \hat{c}_{i,t} &\equiv G\left(\tau_i, \eta^y_{i,t}, z_{i,t}, X^c_{i,t}\right) \\ \xi_{i,t} &\equiv h\left(\eta^c_{i,t}\right) + \epsilon_{i,t} \end{aligned} \tag{6}$$

Following (6), observed log-consumption expenditure, c, is decomposed into two components: one, $\hat{c}$, represents the best prediction we have of consumption expenditure based on household demographics and income dynamics, while the residual component ξ captures those expenses that go unpredicted using the model of idiosyncratic income risk from section 2.1.2.

Table 6: Stochastic Properties of log-Expenditure Components

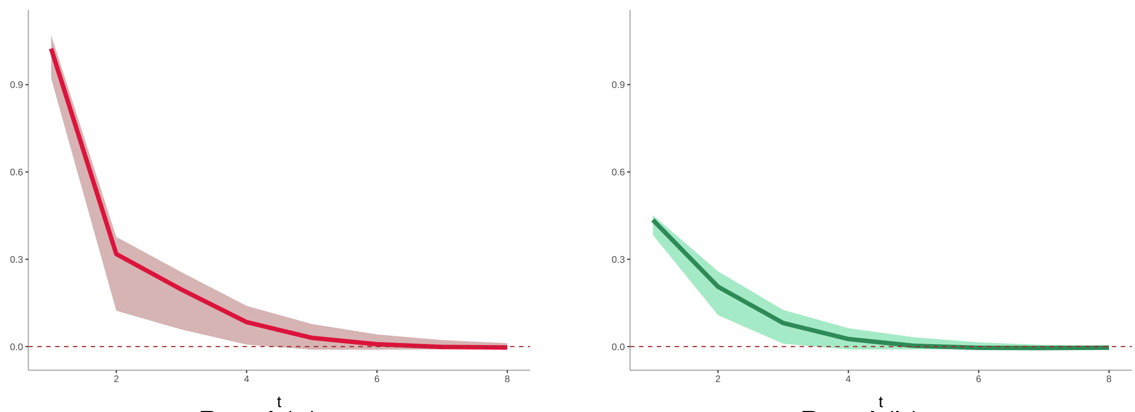
	(a) Levels			(b) Growth Rates	
	autocorr.	variance		autocorr.	variance
$c_{i,t}$	.80	.37	$\Delta c_{i,t}$	-.34	.25
$\hat{c}_{i,t}$	.86	.18	$\Delta \hat{c}_{i,t}$	-.24	.05
$\xi_{i,t}$	.55	.14	$\Delta \xi_{i,t}$	-.40	.13

Notes: Log expenditure is decomposed into two components, one predictable and one unpredicted, according to equations (6). Correlation with its first lag and variance are then computed for all three objects both in levels and in first differences.

Although predicted expenditure captures the observed autocorrelation in consumption, its residuals ξ display autocorrelation as well, indicating that a household identified as an over-spender in a particular wave is more likely to maintain the same status in the subsequent one. As already discussed in Fernández-Villaverde and Krueger (2007), and documented in the first row of panel (a) in Table 6, non-durable consumption expenditure is serially correlated across periods. Its predicted component $\hat{c}$ is serially correlated as well, consistent with serially correlated income risk series used as an estimation argument, but cannot capture all of it. In fact, after accounting for the degree of serial correlation we can expect based on household characteristics and permanent income risk realizations, the residual component ξ still exhibits a non-negligible level of autocorrelation. This hints at the presence of some persistent component in expenditure[11] that is missed by the standard income-risk model.

Furthermore, if we look at growth rates of consumption expenditure and its components, we can see in Table 6, panel (b), how consumption growth is negatively autocorrelated. Part of it can be explained by the standard income-risk driven framework, but the rest remains unexplained. Moreover, the growth rates of the unexplained component present higher volatility, pointing, as already postulated in (Blundell et al., 2008), again at the presence of some latent factor relevant for the household when formulating their optimal consumption-savings dynamic allocation.

Figure 2: Income and Consumption Residuals Impulse Response Functions



Panel (a)
income, corr$_{t,t+2}$ = 1

Panel (b)
consumption, corr$_{t,t+2}$ = 0.54

Notes: Side by side comparison of impulse response functions obtained by estimating a simultaneous panel-VAR regression of income and consumption residuals on its lags. One-period lags on the horizontal axis correspond to a two-year period in the survey data.

Finally, to complete the exploration of consumption residuals' stochastic properties, Fig-

[11] Hall and Mishkin (1982) estimate a moving average component to non-durable expenditure in order to fit the data.

ure 2 displays side-by-side the impulse response functions for income and consumption residuals computed by estimating a simultaneous Panel-VAR regression for both quantities. Autocorrelation estimates seem to exclude a random-walk modeling assumption for consumption residuals. Therefore, in the next section, I will estimate an autoregressive parameter for consumption residuals to be able to compute a persistence-adjusted first difference measure, as shown in equation set (7), necessary to identify persistent innovations to non-durable expenditure.

3.1.2 Expenditure risk identification

Based on their stochastic properties and generalizing on the income risk identification framework, consumption residuals ξ can be decomposed into a persistent component z^c and a transitory component ε^c. Following evidence about the stochastic properties of consumption residuals, an AR(1) assumption fits the data better than the martingale assumption used for income residuals. Therefore, to identify the relationship between consumption risk innovations η^c and any variable of interest, I will use a persistence-adjusted first-difference operator $\Delta_\rho x_t \equiv x_t - \rho^c x_{t-1}$.

$$
\begin{aligned}
\xi_{i,t} &= z^c_{i,t} + \varepsilon^c_{i,t} \\
z^c_{i,t} &= \rho^c \cdot z^c_{i,t-1} + \eta^c_{i,t} \\
\therefore \Delta_\rho \xi_{i,t} &= \eta^c_{i,t} + \Delta_\rho \varepsilon^c_{i,t} \\
\begin{pmatrix} \varepsilon^c_{i,t} \\ \eta^c_{i,t} \end{pmatrix} &\overset{\text{iid}}{\sim} \mathcal{N}\left(0_2, \ \ \text{diag}\left(\sigma^2_{\varepsilon^c}, \sigma^2_{\eta^c}\right)\right)
\end{aligned}
\tag{7}
$$

According to the stochastic modeling outlined in (7), the variance-covariance of persistent expenditure risk with respect to consumption growth is identified as:

$$
\begin{aligned}
\text{cov}\left(\Delta c_{i,t}, \ \eta^c_{i,t}\right) &= \text{cov}\left(\Delta c_{i,t}, \ g^\eta_t(\rho^c, \xi_i)\right) \\
\text{var}\left(\eta^c_{i,t}\right) &= \text{cov}\left(\Delta_\rho \xi_{i,t}, \ g^\eta_t(\rho^c, \xi_i)\right)
\end{aligned}
\tag{8}
$$

with $g^\eta_t(\rho^c, \xi_i) = \Delta_\rho \xi_{i,t+1} + \Delta_\rho \xi_{i,t} + \Delta_\rho \xi_{i,t-1}$. Therefore, we can construct the expenditure risk pass-through coefficient $\beta_{x|\eta^c}$ as:

$$
\beta_{\Delta c|\eta^c} = \frac{\text{cov}\left(\Delta c_{i,t}, \ \sum_{j=-1}^{1} \Delta_\rho \xi_{i,t+j}\right)}{\text{cov}\left(\Delta_\rho \xi_{i,t}, \ \sum_{j=-1}^{1} \Delta_\rho \xi_{i,t+j}\right)}
\tag{9}
$$

The $\beta_{\Delta c_{i,t}|\eta^c}$ parameter measures the effect of the persistent component of unexplained expenditure on consumption growth $\Delta c_{i,t}$, controlling for all arguments featured in the estimated consumption policy function, especially permanent and transitory income innovations, household income type, and net worth. Beyond the proposed measure of expenditure-risk pass-through, a test for randomness of consumption residuals can be performed by imposing a random-walk modeling assumption, which is rejected. Details of the random-walk-modeling pass-through coefficient and related estimates can be found in Appendix B.

Finally, following the linear probability regression framework used to assess the marginal effect of income risk on ZW transition probabilities, as described in section 2.1.2, I instrument persistence-adjusted consumption-residuals growth rates $\Delta_{\rho}\xi_{i,t}$ with the proposed $g_t^{\eta}\left(\rho^c,\ \xi_i\right)$ instrument. The parameter associated with the described IV regression for expenditure risk is labeled as $\beta_{\mathsf{FALL}|\eta^c}$.

3.2 Drivers of expenditure risk among non-durable categories

To investigate the drivers of expenditure risk, I look at the correlation between non-durable consumption sub-categories and measured persistent expenditure risk. The idea is to examine changes in expenditure shares in each consumption category and their comovement with expenditure risk; a positive correlation would indicate an expenditure-category which increases its expenditure share when expenditure risk hits. On the other hand, consumption categories that are not driving observed expenditure risk will mechanically show a weakly negative correlation between their expenditure shares and expenditure risk realizations.

Table 7 shows the results of this analysis based on the non-durable consumption categories available in the PSID. Only a subset of categories, together accounting on average for 23% of household expenditure, drive expenditure risk; it is expenditure in transportation, education, and maintenance (both house and car repairs) that drives measured expenditure risk.

The addition of household representative's health-status information controls, in a way, for healthcare expenditure. Thus, it is not surprising that the identified persistent expenditure risk measure does not correlate with healthcare spending. Moreover, among the spending categories with the strongest negative correlation, we can list food, housing, clothing, and utilities, which can be considered among those consumption commitments as theorized by Chetty and Szeidl (2007).

The analysis of the drivers of expenditure risk not only allows for a more precise understanding of the phenomenon, it also provides instructions for any framework aimed to model of expenditure risk. Households subjected to persistent shocks affecting a minor but relevant share of their consumption basket have two degrees of freedom to react to these shocks: adjusting their expenditure in the rest of their consumption basket or their savings.

Table 7: Consumption Categories Correlation with Expenditure Risk

			non-durable categories				
cross correlation	share	st.dev	negative corr.	positive corr.	cross correlation	share	st.dev
-0.07	0.13	0.06	food	transportation	0.03	0.15	0.08
-0.05	0.32	0.10	housing	school	0.06	0.03	0.07
-0.02	0.01	0.03	childcare	house repairs	0.03	0.02	0.04
-0.01	0.05	0.05	healthcare	car down pay	0.02	0.01	0.04
-0.05	0.02	0.02	clothing	car repairs	0.03	0.02	0.04
-0.02	0.03	0.04	trips				
-0.04	0.02	0.02	recreation				
-0.02	0.02	0.03	house furnish				
-0.06	0.08	0.04	all utilities				
-0.00	0.09	0.05	oth. car pay				
-0.06	0.77	0.77	c_1	c_2	0.06	0.23	0.27

Notes: Non-durable consumption categories have been split into c_1 and c_2 columns according to the sign of their cross-sectional correlation with expenditure shocks.

3.3 Empirical Results: Household Dynamics vis-à-vis Expenditure Risk

How "big" is expenditure risk? Expenditure risk, estimated as the projection of persistence-adjusted consumption-residuals growth between $t-2$ and t on its $t-4$ to $t+2$ counterpart, accounts for 35% of cross-sectional variability in observed log consumption, measured by the explained sum of squares of the dependent variable in a linear regression. A relative measure of expenditure risk can be produced by comparing its standard deviation with those of the other two sources of idiosyncratic risk identified in this paper. Expenditure risk volatility of 0.16 sits between permanent income shocks volatility, 0.10, and transitory shocks volatility, 0.25. All three quantities are measured in log deviations.

Unpredictable consumption deviations are not only non-iid, as shown in section 3.1.1, but their persistent component influences consumption dynamics and predicts zero-wealth episodes. Table 8 shows the consumption pass-through coefficients for all three different sources of risk analyzed in this paper, both individually and jointly.

Table 9 shifts the focus of the analysis towards household wealth dynamics around zero-wealth transition episodes. The estimated coefficients reported in the table measure the marginal effect on fall-event probabilities of each of the three sources of idiosyncratic risk present in this paper. The coefficient signs are unsurprising: negative income shocks and positive expenditure ones increase the probability of transitioning towards zero wealth. The magnitudes of the marginal effects are non-trivial. Given the unconditional 10% probability of falling into zero wealth (ZW) in the sample, a 10% permanent reduction in income

Table 8: Consumption Pass-Through Coefficients for Income Risk Components in PSID

	Δc			
	(1)	(2)	(3)	(4)
$\boldsymbol{\beta_{\Delta c\|\eta^y}}$	0.43***			0.57***
	(0.037)			(0.098)
$\boldsymbol{\beta_{\Delta c\|\varepsilon^y}}$		0.06***		0.20***
		(0.013)		(0.042)
$\boldsymbol{\beta_{\Delta c\|\eta^c}}$			0.17***	0.17***
			(0.061)	(0.060)
R^2	0.0130	0.0014	0.0048	0.0315
households	3,543	4,323	952	952
hh waves	12,733	17,056	2109	2109

Notes: Two columns are added to Table 2. Column (3) contains pass-through estimates for persistent expenditure risk, while column (4) shows estimates for all three risk sources jointly. Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

increases ZW transition probabilities by 5%. On the other hand, a 10% persistent increase in consumption expenditure increases ZW transition probabilities by 8.5%.

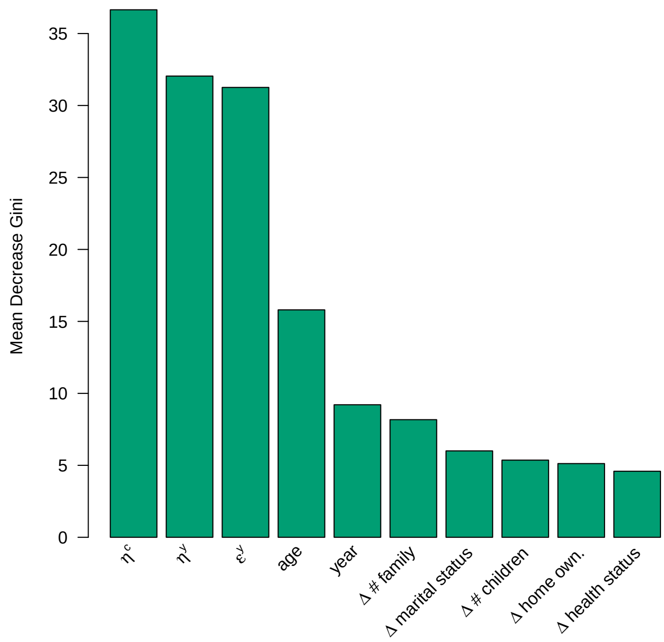
Table 9: Zero-Wealth Transitions and Idiosyncratic Risks in PSID

	FALL			
	(1)	(2)	(3)	(4)
$\beta_{\text{FALL}\|\eta^y}$	-0.057**			-0.064
	(0.0231)			(0.0396)
$\beta_{\text{FALL}\|\varepsilon^y}$		-0.026***		-0.017
		(0.0077)		(0.0158)
$\beta_{\text{FALL}\|\eta^c}$			0.085***	0.087***
			(0.0290)	(0.0290)
R^2	0.047	0.047	0.055	0.055
ΔX^{FALL}	Y	Y	Y	Y
households	3,524	4,296	949	949
hh waves	12,572	16,818	2,099	2,099

Notes: Marginal effects of all three sources of idiosyncratic expenditure risk on ZW transition probabilities measured via a linear probability model. Column (1) shows the marginal effect of permanent income shocks, column (2) that of transitory income innovations, column (3) reports expenditure risk marginal effect, while column (4) performs a joint estimate. Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

To assess the relative importance of each idiosyncratic risk source in predicting fall events alongside the used set of controls, I run a random-forest classification algorithm with the same set of predictors used in the linear probability model implemented to estimate the marginal effects reported in Table 9. Figure 3 reports the mean decrease in the Gini impurity index[12] for each predictor variable. The three idiosyncratic risk sources lead in importance over the set of controls, with expenditure risk leading among them. Running the same random forest classification algorithm on bootstrap samples, excluding two of the three risk sources each time, expenditure risk prediction success rate is 64%, permanent income risk is 60%, and transitory income risk is 58%. All pairwise differences in success rates are significant at the 1% level.

Figure 3: Fall-Event Prediction, Predictors Relative Importance



Notes: The bars measure the total decrease in node impurities from splitting on each variable, averaged over all trees, with respect to out-of-bag predictors classification. The node impurity is measured by the Gini impurity index, which measures the average misclassification probability.

Taking stock, I have jointly identified three distinct sources of risk shaping household consumption and wealth dynamics. The novel channel here, expenditure risk, explains 35% of the cross-sectional variability in observed log consumption. Additionally, the persistent component of unpredicted expenses significantly affects consumption dynamics and predicts zero-wealth episodes, outperforming income risk measures. These results underscore the critical role of expenditure risk in financial vulnerability and highlight the need to incorporate it into models of household wealth transitions.

[12]Gini impurity is calculated as: $GI = 1 - \sum_{i=1}^{n} p_i^2$, where p_i is the probability of a randomly chosen observation being correctly classified.

4 A Model of Income and Expenditure Risk with Time-Preference Heterogeneity Across Households

I will start with the description and calibration of the benchmark economy with idiosyncratic income risk and fixed preference heterogeneity to match the life cycle dynamics of asset accumulation. Aguiar et al. (2024) show how household heterogeneity in the discount factor can account for the observed fraction of households holding little wealth in the data, and I confirm it also delivers low-wealth status persistence across survey waves. Afterward, I will introduce the model ingredient for the expenditure-risk economy, which will be calibrated on the same set of targets as the benchmark economy plus those needed to discipline the added ingredient.

4.1 Benchmark Economy: Income Risk and Household Types

Since I focus on net worth, one asset is enough to characterize household wealth dynamics around the zero-wealth threshold. I will thus use a one-asset life-cycle adaptation of Aguiar et al. (2024) economy as the benchmark economy (henceforth BE) featuring preference heterogeneity by means of the discount factor. Households live $J^D = 60$ years, as workers until $J^R = 40$ and as retirees afterward. Agent i values their stream of non-durable consumption from age j onwards according to

$$\begin{aligned} V_{i,j}\left(x_{i,j}, \eta_{i,j}\right) &= \max_{a_{i,j+1} \in [-b,\ x_{i,j}]} u_j(x_{i,j} - a_{i,j+1}) + \beta_i \mathbb{E}_j V_{i,j+1}\left(x_{i,j+1}, \eta_{i,j+1}\right) \\ x_{i,j+1} &= R \cdot a_{i,j+1} + y_{i,j+1} \\ y_{i,j} &= \begin{cases} \exp\left(\mu_j + \tau_i + \eta_{i,j}\right), & j \leq J^R; \quad \text{at } j=1,\ \tau_i \overset{\text{iid}}{\underset{i}{\sim}} \mathcal{N}(0, \sigma_\tau^2) \\ rr_{y_{i,J^R}} \cdot y_{i,J^R}, & j > J^R \end{cases} \\ \eta_{i,j+1} &= \eta_{i,j} + \nu_{i,j}, \qquad \nu_{i,j} \overset{\text{iid}}{\underset{i,j}{\sim}} \mathcal{N}(0, \sigma_\nu^2) \\ u_j(x) &= n_j \frac{(x/n_j)^{1-\gamma} - 1}{1-\gamma} \end{aligned} \tag{10}$$

where x is net worth, η is the persistent income level, $b \geq 0$ is the borrowing limit, a is savings, β_i is the household-specific discount factor drawn from a Gaussian-mixture distribution discussed in the next section, R is the economy gross rate of return on savings, μ_j is a deterministic age income profile, τ_i is the household-specific income fixed effect, $rr_{y_{i,J^R}}$ are income-dependent replacement ratios, and $\nu_{i,j}$ are iid Gaussian innovations to persistent income. Flow utility exhibits constant relative risk aversion γ over per-person consumption computed with family number weights n_j estimated from the data.

4.1.1 Benchmark economy calibration

The benchmark economy features income risk, incomplete markets, and discount factor heterogeneity. Households draw their initial asset holdings, income fixed effect, and discount factor types from mutually independent distributions at the beginning of their working life; permanent income shocks are drawn every period until retirement.

In a life cycle model, target wealth-to-income ratios dynamically determine household asset holdings together with retirement preparation needs. Discount factor heterogeneity will be disciplined by a truncated discretized mixture of two Gaussian distributions, thus its distribution will be calibrated using 5 parameters.

$$F_{\beta} = \pi \cdot \mathcal{N}(\mu_{\beta,1}, \sigma^2_{\beta,1}) + (1-\pi) \cdot \mathcal{N}(\mu_{\beta,2}, \sigma^2_{\beta,2}) \tag{11}$$

Table 10: Externally Calibrated Parameters

parameter(s)	value	source
μ_j	match life cycle profile	PSID data sample
σ^2_τ	0.3764	Income risk identification
σ^2_η	0.0118	Income risk identification
σ^2_ε	0.0265	Income risk identification
R	1.03	
b	0.2 $\cdot\mathbb{E}$(discounted future income flow)	
γ	2	
rr vec	[.778, .591, .484, .422, .333]	IRS Tables

Notes: Externally calibrated parameters with their assigned value and data source. Missing data source indicates the parameter value has been arbitrarily set.

Table 10 shows the parameters that are determined outside the simulated-method-of-moments (SMM) calibration loop. The deterministic income profile μ_j is estimated from the data, income risk components variance parameters are computed using the observed variance of identified permanent and transitory income shocks from section 2.1.2, variance of the household-specific income fixed effect is calibrated to minimize the distance between simulated and observed income volatility at the beginning of the household working life, annual interest rate is fixed at 3%, households can borrow against 20% of their annualized expected discounted future income flow, the coefficient of relative risk aversion is set to 2, and the lifetime-income dependent replacement ratios are taken from US Internal Revenue Service (IRS) statistics.

Internal calibration of the discount factor distribution is obtained by matching the average zero-wealth share in the economy and the net worth holdings of the second and third

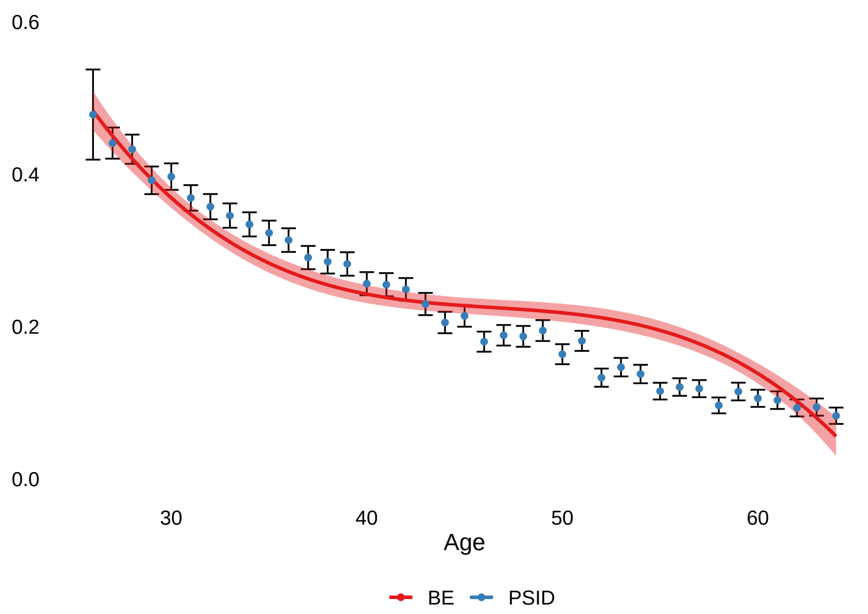
Table 11: Internal Calibration Benchmark Economy

$\mathcal{F}_\beta$ parameter	value	target	PSID	BE
$\mu_{\beta,1}$	0.96	share zero-wealth	0.23	0.24
$\sigma^2_{\beta,1}$	0.09	middle working life Q50	1.81	1.54
$\mu_{\beta,2}$	0.94	retirement Q50	5.26	4.87
$\sigma^2_{\beta,2}$	0.11	middle working life Q75	5.58	5.09
π_β	0.61	retirement Q75	14.68	15.74

Notes: Table shows parameter values determining the ex-ante time-preference heterogeneity in the BE. Data target values used for calibration and their model-simulated counterpart are provided.

quartiles of the wealth distribution[13] both in the middle of their working life and upon retirement. Table 11 shows the calibrated values and calibration data fit. The benchmark economy can deliver a wealth accumulation pattern compatible with the data on average and on both sides of the wealth distribution. Model predictions on consumption pass-through coefficients and zero-wealth transitions are discussed in detail in Section 2.2.

Figure 4: ZW Share Age Profile, Data vs BE



Notes: Zero-wealth age-specific shares are computed both in the PSID and in the Benchmark economy (BE). The age-specific share, together with 95% error bars, are plotted for the PSID. A third order polynomial projection over age, with 95% confidence bands, is plotted for the benchmark economy.

The benchmark economy effectively matches the share of zero-wealth households in the economy, both on average and across different ages, as illustrated in Figure 4. The

[13]Wealth is expressed in units of the sample median wealth measured in 2001$, approximately $33,000.

heterogeneity in time preferences, along with the retirement-saving incentives built into the life-cycle model, results in a distribution of the timing when these incentives become increasingly significant with respect to other optimal consumption-saving forces. This creates a smooth, decreasing age profile that aligns closely with the observed data.

4.2 A Theory of Expenditure Risk: Persistent Shocks to Marginal Utility

The empirical analysis in Section 3 overall highlights the role of expenditure risk in explaining wealth dynamics at the bottom of the distribution, specifically around the zero-wealth threshold. Moreover, Section 3.2 indicates there exists a subset of non-durable consumption categories whose expenditure shares respond positively to the identified measure of expenditure shocks. I thus model expenditure risk as persistent innovations to the marginal utility of a fraction of the household's non-durable basket of goods, as expressed in (12).

$$\begin{gathered} u_j\left(c_1, c_2, \xi, \phi_0\right) = n_j \left(\phi_0 \cdot \frac{(c_1/n_j)^{(1-\gamma)} - 1}{1-\gamma} + \exp(\xi) \cdot \frac{(c_2/n_j)^{(1-\gamma)} - 1}{1-\gamma}\right) \\ \xi_{i,j+1} = \rho^c \xi_{i,j} + \phi_{i,j+1}, \qquad \phi_{i,j+1} \underset{i,j}{\overset{\text{iid}}{\sim}} \mathcal{N}\left(0, \sigma_\phi^2\right) \end{gathered} \tag{12}$$

where ϕ_0 pins down the average relative expenditure size of the riskless portion of the consumption basket. Two parameters characterize the stochastic properties of the marginal utility shocks law of motion, the autocorrelation parameter ρ^c and the innovations variance σ_ϕ^2.

On average, the household spends a given fraction on the risky portion of the basket. As expenditure shocks hit, households will adjust relative consumption expenditure shares and savings as characterized by the intertemporal Euler equation and the intratemporal expenditure shares tradeoff:

$$\left(\frac{c_{1,j}}{n_j}\right)^{-\gamma} \leq R\beta_i \, \mathbb{E}_j \left(\frac{c_{1,j+1}}{n_{j+1}}\right)^{-\gamma} \tag{13}$$

$$\frac{c_{2,j}}{c_{1,j}} = \left(\frac{\exp(\xi_j)}{\phi_0}\right)^{1/\gamma} \tag{14}$$

The introduction of a second good in utility, subject to risky marginal utility realizations, delivers one extra degree of freedom to the household's dynamic optimal allocation problem together with one extra source of idiosyncratic risk to insure against.

4.2.1 Expenditure risk economy calibration

On top of calibrating discount factor distribution parameters, the expenditure risk economy simulation needs to pin down the parameters regulating the magnitude and stochastic properties of expenditure shocks. The average share of expenditure in each consumption basket category is regulated directly by ϕ_0 and can be computed given other preference parameters.[14] Expenditure shocks autocorrelation ρ^c and variance σ^2_ϕ are calibrated to match the serial correlation properties of observed log expenditure, both in levels and in first differences. As discussed in Section 3.1.1, log consumption autocorrelation properties can be explained by the assumed autoregressive expenditure risk stochastic process, thus representing an indirect calibration approach.

Table 12: Internal Calibration Expenditure Risk Economy

	parameter	BE	ER	target	PSID	BE	ER
	$\mu_{\beta,1}$	0.96	0.98	share zero-wealth	0.23	0.24	0.23
	$\sigma^2_{\beta,1}$	0.09	0.005	middle working life Q50	1.81	1.54	1.93
$\mathcal{F}_\beta$	$\mu_{\beta,2}$	0.94	0.28	retirement Q50	5.26	4.87	5.30
	$\sigma^2_{\beta,2}$	0.11	0.05	middle working life Q75	5.58	5.09	5.67
	π_β	0.61	0.80	retirement Q75	14.68	15.74	14.45
	ϕ_0		5.34	$\mathbb{E}c_2$ share	0.23		0.23
ξ	ρ^c		0.31	c autocorrelation	0.80		0.96
	σ^2_ϕ		0.14	Δc autocorrelation	-0.34		-0.27

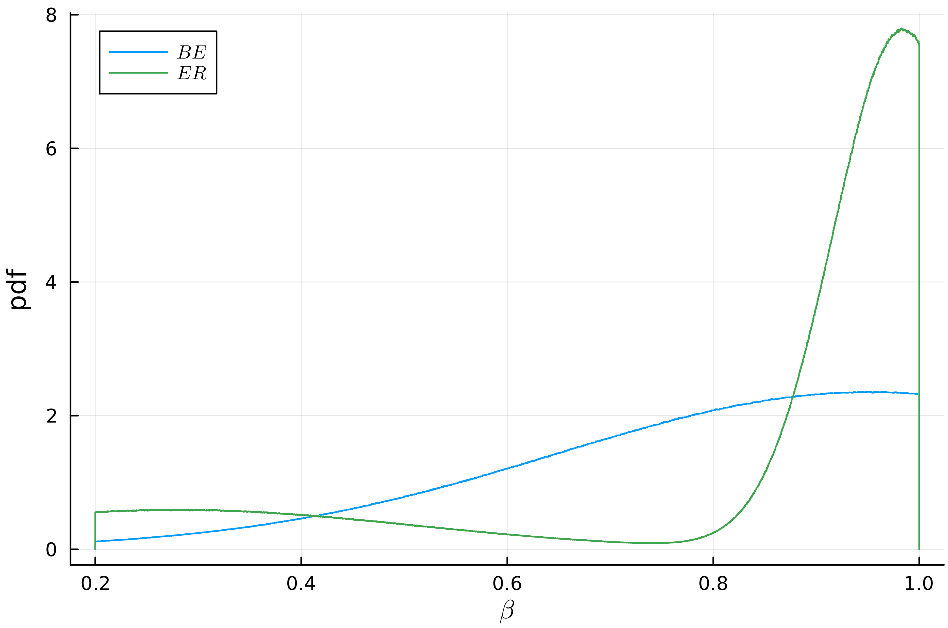
Notes: Parameter estimates for the ER economy are attached to the information displayed in Table 11. Beyond calibrating the parameters of the discount factor distribution $\mathcal{F}_\beta$, the ER economy needs to pin down marginal-utility-risk coefficients ξ.

In the top panel of Table 12, we can see how matching similar life cycle accumulation dynamics for the two economies generates quite different patterns of discount factor heterogeneity. Figure 5 and Table 13 help us visualize the differences in the discount factor distributions resulting from the calibrated truncated Gaussian mixture in each economy. Unlike the benchmark economy, the expenditure risk calibration generates a bimodal ex-ante household heterogeneity with a smaller fraction of households having a relatively low discount factor.

From the bottom panel of Table 12, the calibrated marginal utility shocks exhibit mild autocorrelation and strong variance. The resulting autocorrelation is sufficient to generate a negative autocorrelation in first differences, while the large variance is consistent with Section 3.2 results on the observed volatility of the risky expenditure share. The calibra-

[14] Taking expectation on the intra-temporal tradeoff from equation (14), we can solve for ϕ_0 as a function of the average expenditure share of good c_2, let's call it α, and of a geometric average of marginal-utility realization weighted by their unconditional probabilities: $\phi_0 = \left(\frac{1-\alpha}{\alpha}\right)^\gamma \cdot \left(\sum_{k=1}^{n_\xi} p_k \exp(\xi_k)^{1/\gamma}\right)^\gamma$ for ξ_k in the support of r.v. ξ pinned down by (12) and discretized using the Rouwenhorst method.

Figure 5: Discount Factor Probability Density Function



Notes: Using calibrated discount factor distributions $\mathcal{F}_\beta$ from Table 11, this figure compares the probability density function of the two continuous distributions.

Table 13: Discount Factor Quantiles

	quantiles				
	0.1	0.25	0.5	0.75	0.9
BE	0.48	0.63	0.78	0.89	0.96
ER	0.37	0.85	0.93	0.97	0.99

Notes: Using calibrated discount factor distributions $\mathcal{F}_\beta$ from Table 11, this table reports relevant quantiles of the populations of households used in the generation of the simulated economies.

tion thus results in an ER economy with a larger share of households displaying stronger intertemporal-savings motives, represented by the big hump in the $\mathcal{F}_\beta$ pdf close to one, while affected by fairly large marginal utility fluctuations.

4.3 Quantitative Results: ER Matters for ZW transitions

First, let's look at the ability of the expenditure risk economy to generate consumption dynamics in response to expenditure risk as seen in the data. Table 14 shows pass-through coefficients for the ER economy for all three sources of risk. Income risk estimates closely follow those from the data, available in Table 8. The pass-through effect of expenditure risk is larger in the simulated economy.

The question remains whether the introduction of expenditure risk has any effect on the household's optimal consumption-savings response to permanent income shocks. As

Table 14: Consumption Pass-Through Coefficients for Income Risk Components in ER

	Δc			
	(1)	(2)	(3)	(4)
$\boldsymbol{\beta_{\Delta c\|\eta^y}}$	0.42***			0.42***
	(0.003)			(0.003)
$\boldsymbol{\beta_{\Delta c\|\varepsilon^y}}$		0.14***		0.14***
		(0.002)		(0.002)
$\boldsymbol{\beta_{\Delta c\|\eta^c}}$			0.29***	0.29***
			(0.003)	(0.003)
R^2	0.213	0.0567	0.0527	0.3230
households	10,000			
hh waves	100,000			

Notes: The table replicates, for ER-simulated data, estimations reported in Table 8 for PSID. Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

Table 15 shows, relative to its benchmark counterpart in Table 5, expenditure risk affects the optimal response to permanent income risk around the ZW threshold. Without expenditure risk, households were able to cut down expenditure as needed when facing a negative permanent income shock. With the introduction of this extra source of risk, shocks to marginal utility together with intratemporal trade-offs in the two-goods economy generate a higher cost to adjust consumption expenditure when a persistent negative income shock hits.

Table 15: Income Risk vis-à-vis Zero-Wealth Transitions in ER

	FALL			
	all	$W_{i,t-1} \leq$ \$100K	$\beta_i \leq Q_{\beta_i,1/3}$	age ≤ 45
$\beta_{\text{FALL}\|\eta^y}$	-0.01**	-0.01**	-0.03**	-0.01
	(0.004)	(0.006)	(0.011)	(0.006)
$\beta_{\text{FALL}\|\varepsilon^y}$	-0.05***	-0.09***	-0.12***	-0.08***
	(0.003)	(0.004)	(0.007)	(0.004)
R^2	0.017	0.021	0.019	0.022
$\Delta X^{\text{FALL}}_{\text{sim}}$	Y	Y	Y	Y
households	10,000	8,334	3,353	10,000
hh waves	100,000	62,205	33,530	59,647

Notes: The table replicates, for ER-simulated data, estimation reported in Table 5 for BE-simulated data. $Q_{\beta_i,1/3}$ represents the first tertile of the ER discount factor distribution, which equals 0.91 according to calibration in Section 4.2.1. Household-level clustered standard errors are displayed in parentheses. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

To gain an intuition for the effects of expenditure risk on household response to permanent income shocks, it is useful to look at the Euler equation expressed in terms of the risky expenditure good c_2, obtained by combining equations (13) and (14):

$$\exp(\xi_j)\left(\frac{c_{2,j}}{n_j}\right)^{-\gamma} \leq R\beta_i\,\mathbb{E}_j\left[\exp(\xi_{j+1})\left(\frac{c_{2,j+1}}{n_{j+1}}\right)^{-\gamma}\right] \tag{15}$$

The multiplicative expectation term on the right-hand side of the equation implies a wedge in the household's abilities to adjust consumption to achieve income risk-dependent optimal consumption growth. It can be clearly seen by employing the marginal utility shocks law of motion from (12) and thus rewriting equation (15):

$$\mathbb{E}_j\left(\frac{c_{2,j+1}}{c_{2,j}}\right)^{-\gamma} - \frac{\exp\left\{(1-\rho^c)\,\xi_j\right\}}{R\beta_i} = -\mathsf{Cov}_j\left(\exp(\phi_{j+1}),\ \left(\frac{c_{2,j+1}}{c_{2,j}}\right)^{-\gamma}\right) \geq 0 \tag{16}$$

In the absence of shocks to marginal utility, the right-hand side of equation (16) is equal to zero, and we are back to the benchmark economy consumption growth behavior. Expenditure risk, as defined, implies a negative covariance between next period's marginal utility realization and risky expenditure. A positive shock to marginal utility tomorrow generates a higher need to consume the risky good, therefore implying a lower marginal utility growth rate. This positive wedge dampens optimal consumption growth with respect to its benchmark economy counterpart.

5 Conclusions

This paper investigates the empirical and theoretical role of income and expenditure risk together in explaining household wealth dynamics. The analysis is motivated by an intriguing phenomenon: despite economic theory suggesting the importance of precautionary savings, a significant proportion of U.S. households, 22%, hold zero or negative wealth, exposing themselves to consumption fluctuations. Surprisingly, more than half of these households maintain this zero-wealth position over multiple years, indicating a role for consumption dynamics.

Using the Panel Survey of Income Dynamics (PSID), I examine the joint dynamics of non-durable consumption expenditure, total household income, and wealth. To investigate the role of consumption fluctuations in the determination of wealth dynamics, I develop an econometric framework that allows for the identification of expenditure risk independently from income risk. The results demonstrate that both sources of risk matter for wealth dynamics and that, contrary to the standard theory of precautionary savings under idiosyncratic risk, permanent shocks to income can significantly lead to persistent depletion of family wealth and transition into non-positive net worth positions.

Expenditure risk, modeled as shocks to marginal utility hitting a fraction of the household consumption basket, is able to replicate household responses to permanent income variations by creating a wedge in the optimal intertemporal condition for consumption growth and savings dynamics. The covariance of marginal utility and future consumption choices hinders the household's ability to adjust expenditure when facing negative shocks to permanent income.

In summary, my study contributes to two strands of literature: the applied macroeconomic literature investigating consumption inequality and its relationship with income risk, and the theoretical literature on the spending behavior of low-wealth households. By refining empirical approaches and incorporating a flexible non-parametric consumption model, I provide insights into the dynamics of household wealth and the distinct role of consumption risk. The findings shed light on the nature of expenditure risk and its implications for household behavior, offering valuable insights for policymakers and researchers interested in understanding wealth dynamics and consumption inequality.

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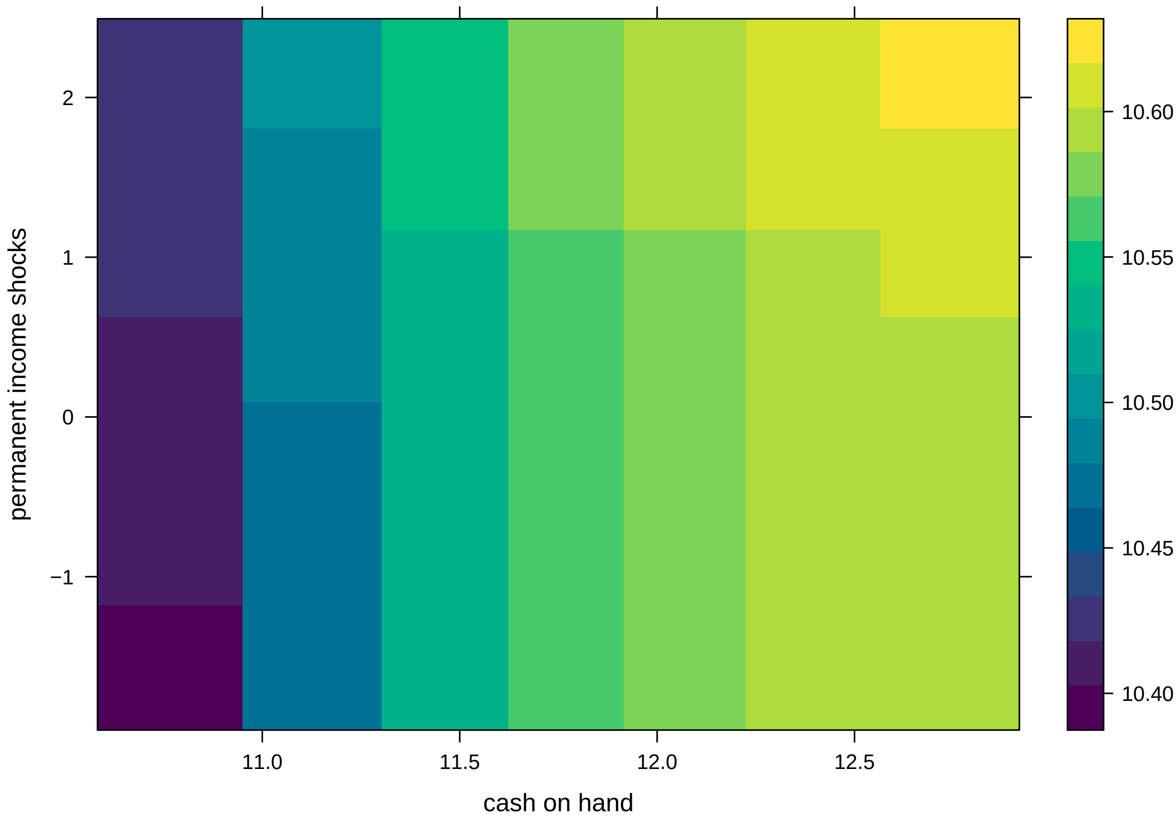
A Consumption Model Estimates

In this Appendic section, I report two measures informing on the estimated consumption function from Section 3.1. Figure A.1 shows the partial dependence function for two of the main arguments used in the expenditure function estimation, cash on hand and income shocks.

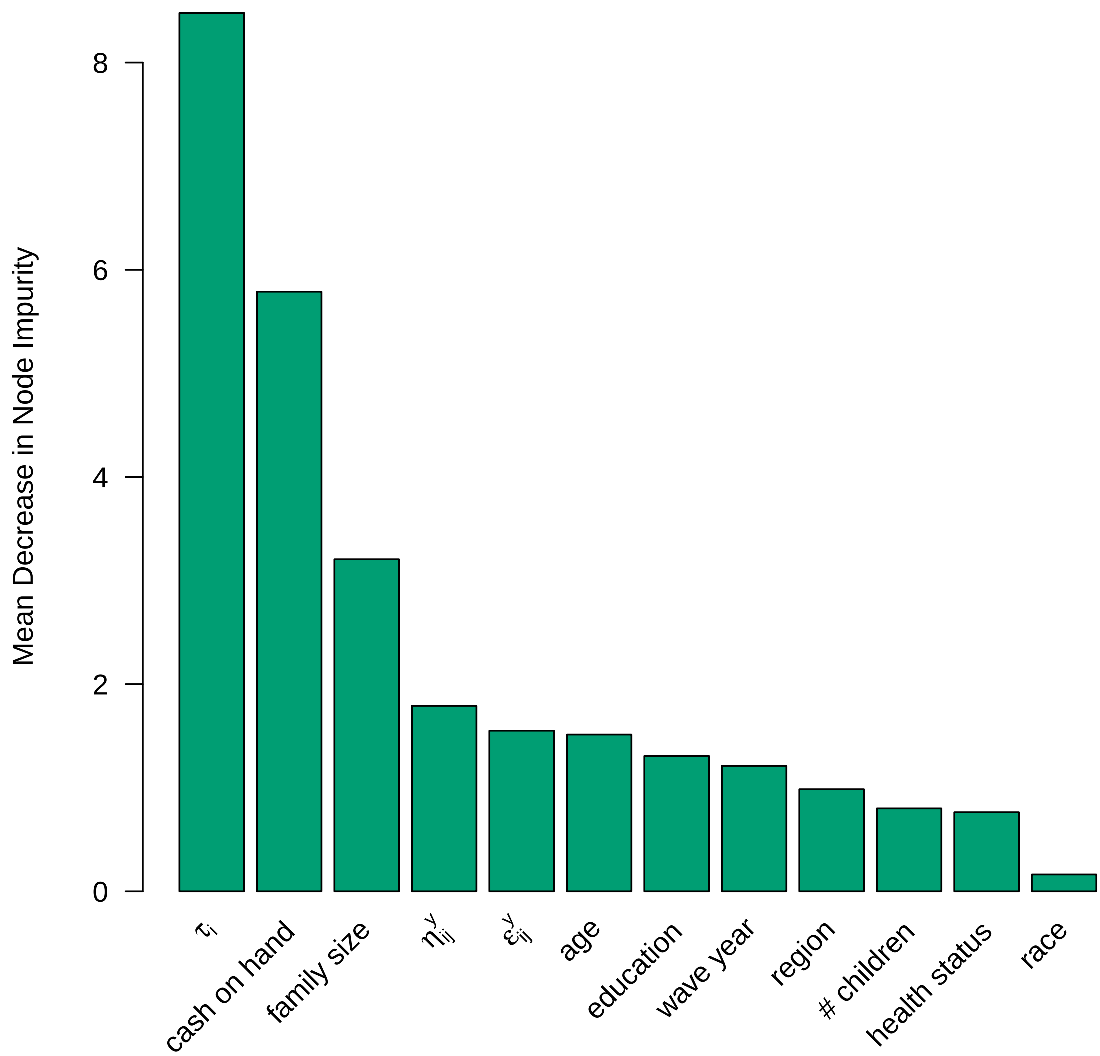
Figure A.1: Predicted Expenditure, Partial Dependence Function



Notes: Function $G(\cdot)$ from eq. (5) is estimated using the full set of regressors as detailed in Section 3.1. A partial dependence function is then computed and evaluated on a quantile grid to extract the marginal effect of log cash on hand and permanent income shocks on predicting log consumption. Permanent income shocks are measured in units of its standard deviation. The colorkey legend on the right of the plot represents levels of log consumption.

Figure A.2 reports the mean decrease in node impurity obtained by each argument of the estimated consumption function through the random forest algorithm. Node impurity quantifies the homogeneity of the target variable within the subsets created by a split measured in units of residual sum of squares of the dependent variable. Lower impurity means that the subset is more homogeneous.

Figure A.2: Arguments Contribution to Consumption Function Estimation Accuracy



Notes:The measure is the total decrease in node impurities from splitting on the variable, averaged over all trees. Node impurity quantifies the homogeneity of the target variable within the subsets created by a split. Lower impurity means that the subset is more homogeneous (i.e., the target variable values are more similar). It is measured in units of residual sum of squares of the dependent variable, in this case log consumption.

B Alternative Modeling of Consumption Residuals

In this Appendix Section, I propose an alternative modeling assumption for consumption residuals. As shown in detail in Section 3.1.1, there's no evidence indicating consumption residuals might follow a random walk. However a random walk modeling assumption can be convenient to pursue. The following simple derivations show how, using consumption residuals in first differences, the modified expenditure-risk pass-through parameter can be used to test the null hypothesis of no correlation betwen consumption growth and persistent changes in consumption residuals.

Under the random walk assumption, i.e. $\rho^c = 1$, the pass-through coefficient defined by (9) boils down to:

$$\beta^{\text{alt}}_{\Delta c_{i,t}|\eta^c} \overset{[\rho^c=1]}{=} \frac{\text{cov}\left(\Delta c_{i,t},\ \sum_{j=-1}^{1} \Delta\xi_{i,t+j}\right)}{\text{cov}\left(\Delta\xi_{i,t},\ \sum_{j=-1}^{1} \Delta\xi_{i,t+j}\right)} = \frac{\text{cov}\left(\Delta c_{i,t},\ \xi_{i,t+1} - \xi_{i,t-2}\right)}{\text{var}\left(\Delta\xi_{i,t}\right)} \tag{B.1}$$

Therefore, considering the time structure of the PSID, $\beta^{\text{alt}}_{\Delta c_{i,t}|\eta^c}$ measures the covariance of 2-years (observed) consumption growth with 6-years residual consumption growth. As Table B.1 clearly shows, we can reject the null hypothesis of no permanent component left in consumption residuals once we've controlled for household income-level type, income risk realizations, cash on hand, and other demographics as detailed in Section 2.1.

Table B.1: Consumption Pass-Through Coefficients in PSID, Alternative Expenditure Risk Modeling

	Δc			
	(1)	(2)	(3)	(4)
$\boldsymbol{\beta_{\Delta c\|\eta^y}}$	0.43***			0.53***
	(0.037)			(0.094)
$\boldsymbol{\beta_{\Delta c\|\varepsilon^y}}$		0.06***		0.19***
		(0.013)		(0.040)
$\boldsymbol{\beta^{\text{alt}}_{\Delta c\|\eta^c}}$			0.86***	0.85***
			(0.107)	(0.106)
R^2	0.0130	0.0014	0.0479	0.0692
households	3,543	4,323	949	949
hh waves	12,733	17,056	2,099	2,099

Notes: Estimates here replicates those expressed in Table 8 with the random walk assumption for expenditure risk permanent component as detailed in Appendix B. Household-level clustered standard errors are displayed in parenthesis. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

However, if we look at the ability to capture variability in log consumption, as expressed by explained sum of squares, this paper chosen AR(1)-specification expenditure risk measure explaines 35% of variability in log consumption, while the RW-specification can only account for about 1% of it.

C Full-Comparison ZW-Transitions Tables

In this appendix section, I report one ZW-transitions table for PSID data, with column restriction based on wealth holdings,x, and household head age. It is to be compared with

X and Y for BE and ER economy. I also report one ZW-transitions table for the ER economy, assessing the ability of the simulated economy with expenditure risk to generate fall events through expenditure shocks. It is to be compared with X for the PSID. Additionally, full coefficient comparison table are produced.

Table C.1: Income Risk vis-à-vis Zero-Wealth Transitions in PSID

	FALL			
	all	$\mathrm{W}_{i,t-1} \leq$ \$100K	$<$ college	age ≤ 45
$\beta_{\text{FALL}\mid\eta^y}$	-0.11***	-0.14***	-0.11***	-0.11**
	(0.024)	(0.040)	(0.033)	(0.047)
$\beta_{\text{FALL}\mid\varepsilon^y}$	-0.05***	-0.06***	-0.05***	-0.06***
	(0.010)	(0.016)	(0.013)	(0.019)
R^2	0.049	0.040	0.054	0.036
ΔX^{FALL}	Y	Y	Y	Y
households	3,524	2,531	2,304	1,917
hh waves	12,572	7,194	7,871	5,041

Notes: The Table reports marginal effect coeffcients, for permanent income risk η^y and transitory income risk ε^y, from linear probability model using fall events as dependent variable. A fall event realizes when an household is observed as ZW in period t but not in period $t-2$. Household-level clustered standard errors are displayed in parenthesis. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

Table C.2: Zero-Wealth Transitions and Idiosyncratic Risks in ER

	FALL			
	(1)	(2)	(3)	(4)
$\beta_{\text{FALL}\mid\eta^y}$	-0.01**			-0.01**
	(0.004)			(0.004)
$\beta_{\text{FALL}\mid\varepsilon^y}$		-0.05***		-0.05***
		(0.003)		(0.003)
$\beta_{\text{FALL}\mid\eta^c}$			0.04***	0.04***
			(0.006)	(0.006)
R^2	0.012	0.016	0.012	0.016
$\Delta X^{\text{FALL}}_{\text{sim}}$	Y	Y	Y	Y
households	10,000			
hh waves	100,000			

Notes: Marginal effects of all three sources of idiosyncratic expenditure risk on ZW transition probabilities measured via a linear probability model. Column (1) shows the marginal effect of permanent income shocks, column (2) that of transitory income innovations, column (3) reports expenditure risk marginal effect, while column (4) performs a joint estimate. Household-level clustered standard errors are displayed in parenthesis. ***, **, and * express significance at the 1%, 5%, and 10% level, respectively.

Table C.3: Consumption Dynamics Pass-Through, Full Estimates Comparison

	Δc		
	PSID	BE	ER
$\boldsymbol{\beta_{\Delta c \mid \eta^y}}$	0.57***	0.45***	0.42***
	(0.098)	(0.003)	(0.003)
$\boldsymbol{\beta_{\Delta c \mid \varepsilon^y}}$	0.20***	0.19***	0.14***
	(0.042)	(0.002)	(0.002)
$\boldsymbol{\beta_{\Delta c \mid \eta^c}}$	0.17***		0.29***
	(0.060)		(0.003)
R^2	0.03	0.24	0.32
households	952	10,000	10,000
hh waves	2109	100,000	100,000