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Taming the Zoo of Consumption Responses to Labour Income Changes

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Abstract

As policies aimed at enhancing household economic resilience routinely target labour income —the primary source of household income— understanding the consumption responses elicited by diverse labour income changes is essential for effective policy design. We study the heterogeneity in the consumption responses to labour income changes originating from the magnitude, sign, and dynamic nature of the income change (transient, recurrent, or permanent). While prior empirical research has explored how household characteristics shape consumption responses, the impact of different types of income changes has received little scholarly attention. The literature reports a wide range of often conflicting estimates — a "zoo" of responses — driven by variations in methodologies, definitions, datasets, and policy contexts. To tame this zoo, we propose a three-pronged approach. First, we establish a framework that categorizes income changes as recurrent, permanent, or transient, and develop an algorithm to identify these income changes in individual income time series at scale. Second, we use comprehensive administrative banking data, spanning twelve years and covering millions of households, to systematically estimate consumption responses to these different types of labour income changes. Third, we apply the COICOP consumption classification to disentangle how nondurable, semidurable, and durable consumption respond to each type of income change. We find that consumption responses to positive recurrent labour income changes are nearly twice as large as the responses to transient positive labour income changes. These consumption responses are primarily driven by changes in semidurable and durable consumption, rather than nondurable consumption.

Keywords income changes; consumption; excess sensitivity of consumption; liquid wealth

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1 Introduction

Recent economic crises have highlighted the vulnerability of many households to fluctuations in income and expenses, with even modest changes often leading to significant financial distress (Narayan et al. 2022). Governments play a crucial role in mitigating these effects through tax policies and income subsidies, which directly influence labour income. These interventions vary in their sign, magnitude, and dynamic nature—ranging from one-time stimulus checks (transient) to persistent tax adjustments (permanent). To understand the effectiveness of such policies, it is essential to estimate the macroeconomic spending multiplier, which is driven largely by the consumption responses to these policy-induced income changes.

While prior research has extensively studied the heterogeneity of consumption responses based on household characteristics such as liquidity constraints (Kaplan, Violante, and Weidner 2014; Jappelli and Pistaferri 2020), race (Ganong et al. 2020; Ganong and Noel 2019) and behavioural biases like perceptions of expectedness and myopia (Kőszegi and Rabin 2009), less attention has been given to how the characteristics of the income changes themselves, particularly their sign, magnitude, and dynamic nature (transient, recurrent, or permanent), affect consumption. Understanding these factors is crucial, as they are key determinants of the spending multiplier and thus the effectiveness of fiscal policy.

A few studies have examined the role of the sign and magnitude of income changes in shaping consumption responses. Christelis et al. (2019), Fuster, Kaplan, and Zafar (2021), and Mijakovic (2023) explored how the sign (positive or negative) and magnitude of income shocks affect consumption, using a "reported preference" approach. Their findings suggest that negative changes tend to elicit stronger consumption responses than positive ones. However, the "reported preference" method is known to poorly measure marginal propensities to consume (MPC) (Parker and Souleles 2019). In contrast, Baugh et al. (2021), using account-level data similar to ours, found that households, regardless of their liquid wealth, exhibit a stronger response to positive income changes while smoothing consumption following negative changes, leading to smaller overall consumption adjustments. Similarly, using a large transaction dataset from a US financial institution, Graham and McDowall (2024) find the same behaviour for the consumption response to tax refunds and bonuses, which represent positive transient and recurrent changes, across the liquid wealth distribution. These studies suggest that the sign of income changes play a crucial role in shaping consumption responses, but they do not provide a comprehensive taxonomy of income changes that captures the dynamic nature of these changes.

A limited number of earlier studies have explored the dynamic nature of income changes by directly estimating the consumption response to a single specific type of income change with panel data. Two notable cases are Browning and Collado (2001) and Hori and Shimizutani (2009), who studied institutionalized yearly labour income bonuses in Spain and Japan, respectively. Interestingly, the results from these studies are difficult to reconcile: Japanese households exhibited a significant consumption response to these recurrent income changes, while Spanish households did not. This discrepancy may be attributed to the use of survey data in both studies, which is vulnerable to recall bias and measurement errors (Moore, Stinson, and Welniak 2000). Similar limitations are found in the work of Hsieh (2003), who examined yearly payments from the Alaskan Permanent Fund and also found no reaction to this predictable, recurrent income change. Another strand of literature, led by Blundell, Pistaferri, and Preston (2008), uses the covariance restriction approach to separate the consumption response to permanent and transitory income changes. This approach, exemplified by the work of Attanasio, Kovacs, and Molnar (2020) and Kovacs, Rondinelli, and Trucchi (2021) uses survey data and subjective income expectations, which they map to Euler equations to estimate consumption responses. When estimating the pass-through of permanent and transitory shocks to consumption, they control for deterministic but time-dependent income components, which could be viewed as a precursor to capturing, among others, recurrent income changes. This approach has been fruitful, though it relies on strong assumptions about the income process and its covariance structure.

While these studies[1] offer valuable insights, they tend to focus on a single type of income change, in a specific context, using limited survey data. This makes it challenging to extrapolate findings to broader settings. As a result, estimates of the excess sensitivity of consumption vary wildly, ranging from implausible negative values to values greater than 1. This inconsistency stems from the diversity of datasets, definitions, and methods used across studies, leaving the literature in what we term a "zoo of responses", a chaotic collection of findings that are difficult to reconcile. This observation was first made by Browning and Lusardi (1996) and echoed by Havranek and Sokolova (2020), namely that "*It is frustrating in the extreme that we have very little idea of what gives rise to the different findings. (...) we still await a study which traces all of the sources of differences in conclusions to sample period; sample selection; functional form; variable definition; demographic controls; econometric technique; stochastic specification; instrument definition;*" This lack of robust evidence limits our ability to design optimal policy interventions that account for different types of income changes and how they impact households their consumption behaviour (Kaplan and Violante 2022).

1. An exhaustive overview of all previous estimates of excess sensitivity can be found in Jappelli and Pistaferri (2010)

To tame this "zoo" of consumption responses, we construct a framework that classifies income changes based on their magnitude, sign, and dynamic nature (transient, recurrent, or permanent) and developed an algorithm that identifies these changes in monthly labour income time series in a data-driven way. To this end, we leverage a large dataset of anonymized bank transactions from BNP Paribas Fortis Belgium to construct a granular panel dataset tracking monthly labour income and various kinds of consumption (nondurable, semidurable and durable) as defined by the UN's COICOP standard (UN 2018) of more than 1.4 million unique Belgian households across 12 years. This approach follows a recent trend to use individual financial data for this purpose (Gelman et al. 2014; Ganong et al. 2020; Baker and Kueng 2022; Buda et al. 2023). Our analysis also accounts for household characteristics, such as liquid wealth and socio demographics. These factors combined, enable us to systematically disentangle the heterogeneity in consumption responses across various household types, consumption types and types of income change for a large and representative sample of Belgian households within one unified framework.

Our findings show strong heterogeneity in the consumption response with respect to the different types of income changes. In line with the permanent income hypothesis (PIH), we find that households exhibit the strongest consumption responses to permanent income changes. However, contrary to the strict predictions of PIH, we also observe significant consumption responses to transitory income changes, with variations based on the predictability and sign of the change. Positive recurrent changes, such as annual bonuses, elicit small consumption responses, while negative recurrent changes prompt only modest reductions, suggesting that households largely smooth over these changes that are predictable due to their recurrent nature. In contrast, transient changes produce more pronounced consumption responses, with stronger reductions for negative shocks, likely due to liquidity constraints or precautionary motives. This pattern aligns with PIH when recurrent changes are viewed as anticipated and transient changes as unanticipated.

Our findings emphasize that the type of income change —whether it is transient, recurrent, or permanent— plays a more defining role in consumption behavior than the size of the change itself, a result confirmed by our sensitivity analysis. For both transient and recurrent changes, semidurable consumption shows the highest excess sensitivity, followed by durable and nondurable goods, a pattern that holds across all types of income changes. This sensitivity of semidurable and durable consumption may be linked to mental accounting, as households appear to reserve funds for specific types of expenditures, like hobby

and Crawley and Theloudis (2024).

items or durable goods, even when liquidity is available elsewhere. Low-liquidity households react more strongly to all types of income changes across all consumption categories, even to predictable positive recurrent changes, indicating they may lack the resources to fully smooth consumption. These findings provide a compelling case for policymakers: while interventions aimed at increasing labor income can positively impact spending across all categories, targeting low-wealth households and promoting sustained income changes may yield the most substantial economic effects, particularly in semidurable and durable spending.

2 Data

We use an anonymized dataset from BNP Paribas Fortis (BNPPF) that includes non-identifying client information and all transactions linked to their accounts. This allows us to create monthly individual panels with financial data including liquid wealth, spending via debit card, wire transfers and income by category, along with demographic details like age, gender, and marital status. Unlike previous studies that rely on third-party financial management applications (Baker and Yannelis 2017; Olafsson and Pagel 2018; Gelman et al. 2020), which avoid the reporting biases of surveys (Moore, Stinson, and Welniak 2000), our dataset additionally avoids issues like selection bias and the influence of platform usage on financial behaviour (Baker 2018). Participation in our sample is simply based on holding a current account at BNPPF, which captures a quarter of Belgium's commercial banking market and is widespread across all regions of Belgium[2]. The benefits of using commercial bank data have also been recognized by Ganong and Noel (2019) and Carvalho et al. (2021) whose data and approach to panel data construction resemble ours closely.

The main limitation of our data is that clients may have accounts at other institutions[3] and we do not capture in-kind transfers. Although we may not capture spending and saving in accounts outside BNPPF, this limitation likely primarily affects wealthier individuals who diversify savings across multiple banks to maximize the € 100 000 deposit insurance coverage per institution[4] (FOD Financiën 2024). To address these limitations, we restrict our analysis to active clients with adequate income and consumption levels,

2. Over 99 % of Belgians have a bank account, and more than 96 % of wage earners receive their salary via bank transfer (Demirgüç-Kunt et al. 2022). This high percentage is driven by legal requirements mandating that wages be paid through demand deposits, with only a few exceptions allowed for certain occupations (Belgische Federale Overheid 1965).

3. Anecdotally, only about 2 % of clients use BNPPF's Payment Services Directive (PSD2) functionality to consolidate accounts from multiple banks into their banking app, suggesting that most clients manage their finances primarily through BNPPF.

4. By applying an active client criterion, we reduce the proportion of individuals with total wealth exceeding the Guarantee Fund's protected threshold from 5 % in the entire sample to 1 % in the active client subset.

similar to the criterium used by Ganong and Noel (2019). In the following section, we detail the sample selection process and how the transaction-level data is aggregated into a household-level panel dataset.

2.1 Source data

The BNPPF dataset contains anonymized financial transactions from January 2012 to December 2023 for more than 1.4 unique million Belgian households and 2.2 million unique household members. It includes cash withdrawals and deposits, debit card purchases, end-of-month credit card payments and transfers. On average, there are around half a billion transactions per year, totalling nearly 3 trillion euros in volume. Beyond transaction data, the dataset also contains non-identifying individual level demographic information (age, gender, civil state, region of residence), household relationships and end-of-month account balances for all clients.

Each transaction record includes a timestamp, an anonymized counterparty identifier, the value in euros, the direction (debit/credit), and a label indicating the economic goal of the transaction, e.g. labour income or groceries[5]. A full list of the available labels is provided in the appendix A. These labels are determined by proprietary processes at the bank that analyse transaction patterns and metadata which is only available to the bank. Income categories such labour income, replacement income and pensions are identified based on legally mandated communication patterns (FOD Justitie 2006). This law, which predates the dataset, ensures the exceptionally high quality of income data. Consumption types are classified using transaction metadata, including Merchant Category Codes[6] (MCC) for both point-of-sale and online card transactions and NACE sector codes for transfers to company counterparties. Both Merchant Category Codes and NACE codes are mapped onto the United Nations' COICOP classification (UN 2018), which defines four consumption durability types: durables, semidurables, nondurables, and services. This results in 58 consumption categories, detailed in appendix A. For transactions in stores selling a wide variety of goods (e.g., hypermarkets selling both food and clothing) or end-of-month credit card bill payments, a "mixed" category is assigned, as the metadata cannot specify the exact content or durability type of the purchase.

5. 94.3 % of all transactions of the households in our dataset, representing 99.1 % of the total volume, are labelled.
6. A full list of MCC codes with their respective definitions can be found, for example, at https://usa.visa.com/content/dam/VCOM/download/merchants/visa-merchant-data-standards-manual.pdf.

2.2 Constructing monthly household panels

We begin by assigning each client to a household. Clients who either share a bank account or have reported a family relationship are grouped under the same household identifier. We correct for location on an aggregated neighbourhood level to account for households who still share accounts but no longer share the same domicile address. This identifier accounts for both traditional households (e.g. parents and children) and economic households (e.g. co-habiting individuals). The household identifier is dynamic, updating when members change their domicile address.

Once households are identified, we aggregate the data monthly. Labour income is summed per household for each calendar month. Consumption is aggregated by durability type, with total consumption defined as the sum of all types. End-of-month credit card bills are only included in the total definition. We consider the month when this payment is made as the moment when the consumption occurred, even if the goods were potentially received earlier. This approach avoids underestimating consumption by excluding debt-based smoothing effects[7].

In our analysis of consumption sensitivity by durability type, we focus only on categories classified under a single durability type. Mixed categories, which largely involve businesses selling goods of different durability types (e.g., hypermarkets), are assumed to follow the same consumption patterns as stores selling a single type such as for example clothing stores. I.e. we assume that the average change in consumption of goods of a certain durability (e.g. semidurables) is the same in stores that are labelled as that specific durability type (e.g. clothing stores) as in stores that are labelled as mixed (e.g. hypermarkets). As long as this assumption holds, our estimates will remain unbiased. The same applies across different payment methods—if consumers were to shift semi-durable purchases to cash, we would underestimate the actual consumption response for semi-durables. We assume a similar assumption for different payment methods. Finally, we construct a monthly measure of liquid financial wealth per household by summing the end-of-month balances across all accounts that can be liquidated on short notice with little to no financial penalty, which includes checking accounts and (term) savings accounts.

2.3 Analysis sample

Our analysis sample is based on the 1.4 million unique households or 2.2 million unique household members with accounts in the BNPPF dataset, using household-by-month observations from January

7. Debit cards are the most commonly used payment method in Belgium, with end-of-month credit card bills only accounting for 0.3 % of the total volume of consumption in our sample of active households.

2012 to May 2023. We restrict the sample to active households for two reasons mentioned in section 1. First, some households may have accounts at multiple banks, and we cannot track spending from non-BNPPF accounts. Second, while all clients have both current and savings accounts, this does not guarantee they use BNPPF for their daily expenditures. To address these concerns, we focus on households that use BNPPF as their primary bank. According to Belgian cost-of-living statistics (Storms, Van den Bosch, and Cantillon 2009), in 2009 a single-person household required a minimum monthly income of € 537 and nondurable consumption of € 140 for basic needs, including food and drinks.

We define a household as active in a given year if it exceeds the inflation-adjusted minimum income and consumption thresholds every month it is observed in that year. Households with any self-employed members are excluded because accurately labeling income for self-employed individuals is challenging due to the irregularity and variability of their earnings. The one-year window is chosen for both theoretical and practical reasons, as detailed in section 3. If we selected households across the entire 12-year period, we would exclude those that join or leave the bank in our 12-year window, biasing the sample toward older households with stable incomes. With our stepping window approach, we capture on average 500 000 active households per month between January 2012 and December 2023, retaining approximately 27 % of the original sample each month[8].

To assess representativeness of our sample, we construct a measure of fiscal income that closely aligns with the definition used by the Belgian statistics institute (Statbel 2019). When we compare the published distribution from StatBel with the fiscal income observed in the full BNPPF sample, as shown in table 1, the two distributions are largely similar.

3 Methodology

Life events and policy measures can lead to significant shifts in monthly income, which can take various forms. For example, a one-time bonus is a transient change, an end-of-year bonus is recurrent, and a pay rise is permanent. To examine how these income changes affect monthly consumption, we need a method to identify and classify them.

To this end, we construct a taxonomy of the different types of monthly income changes, and design a framework to automatically identify and classify the types of monthly income changes from income

8. In future work, we will test the robustness of this criterion by comparing it to other active household definitions used in the literature. Preliminary results, available on request, indicate that our active household criterion broadly selects the same households as Ganong and Noel (2019) criterion of at least 5 monthly outflows.

Table 1. Comparison of the fiscal income distribution from StatBel with our estimated fiscal income for individual clients in the BNPPF 2019 data. Our result includes regular labour income, unemployment benefits, other replacement incomes, and pensions.

Decile	Percentile	Statbel	Our results	Difference (%)
1		543.00	567.61	4.53
2		1227.67	1287.33	4.86
3		1470.00	1667.23	13.42
4		1771.08	1895.45	7.02
5		2122.92	2166.65	2.06
6		2563.58	2532.32	−1.22
7		3126.00	3076.98	−1.57
8		4008.75	3912.22	−2.41
9		5651.75	5403.65	−4.39
	91	5901.67	5664.68	−4.02
	92	6180.00	5974.14	−3.33
	93	6493.00	6311.64	−2.79
	94	6866.42	6761.84	−1.52
	95	7319.58	7315.00	−0.07
	96	7893.50	8016.60	1.56
	97	8687.75	9059.51	4.28
	98	9945.17	10 688.72	7.47
	99	12 669.58	14 241.69	12.41

time series. Finally, we apply this approach to our household panel data of Belgian households, and our results are validated by comparing the classifications with known patterns in the Belgian labour market.

Our classification extends the idea of Ganong and Noel (2019) who distinguished between typical and atypical income changes. Typical changes, i.e. changes in labour income (Brown et al. 2014) are our focus. Atypical changes, such as receiving an inheritance or winning the lottery, are excluded. Our analysis further classifies changes in labour income into three categories: transient, recurrent, and permanent. This taxonomy allows for a more detailed analysis of household income dynamics.

3.1 Taxonomy of monthly income changes

Our taxonomy follows Blundell, Pistaferri, and Preston (2008) and Jappelli and Pistaferri (2010) in decomposing log-labour income $I_{i,t}$ of a household i in month t into two components: a permanent component $P_{i,t}$, and a transitory component $\nu_{i,t}$ which captures the deviations from this stable permanent component.

$$I_{i,t} = P_{i,t} + \nu_{i,t} \tag{1}$$

To avoid that monthly income changes driven by stable seasonal patterns (e.g. end-of-year bonus) are misclassified as transitory, we need to take seasonality into account. We therefore subdivide the transitory component $\nu_{i,t}$ into a transient component with no seasonality $T_{i,t}$, and a recurrent component $R_{i,t}$ with seasonality as follows:

$$\nu_{i,t} = T_{i,t} + R_{i,t}. \tag{2}$$

To the best of our knowledge, we are the first to explicitly separate these two types in the income classification, despite Brown et al. (2014) reporting that recurrent bonuses are one of the most frequent reasons for changes in the income of US households. By taking the first difference of components (1) and (2) and assuming that the transitory components $T_{i,t}$ and $R_{i,t}$ are non-persistent shocks affecting only period t[9], we derive our final taxonomy of labour income changes:

$$\Delta I_{i,t} = \Delta P_{i,t} + T_{i,t} + R_{i,t}, \tag{3}$$

with $\Delta I_{i,t}$ monthly log-labour income changes, subdivided into month-on-month permanent changes $\Delta P_{i,t}$ (e.g. pay rise) and transitory deviations $\nu_{i,t}$ from the permanent income component. These transitory changes are further subdivided in to transient changes $T_{i,t}$ (e.g. varying working hours) and recurrent changes $R_{i,t}$ (e.g. end-of-year bonus). Within this taxonomy we can further separate each type into positive and negative changes, allowing us to study the asymmetric consumption responses to different types of income variations.

9. This assumption implies that $T_{i,t-1} = 0$ and $R_{i,t-1} = 0$, so the changes in the transitory components are $\Delta T_{i,t} = T_{i,t}$ and $\Delta R_{i,t} = R_{i,t}$.

3.2 Identifying monthly income changes

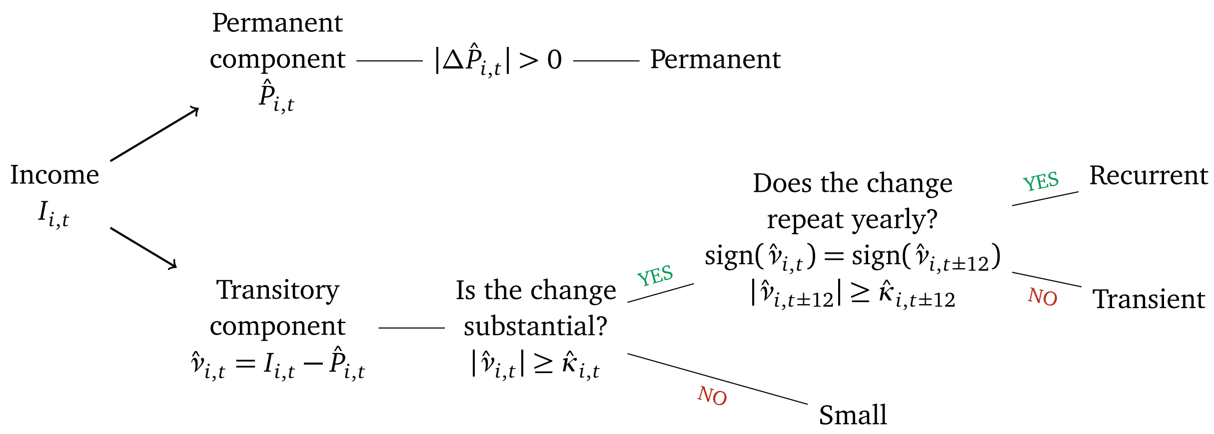


Figure 1. Flowchart of our income change identification and classification framework. The income time series $I_{i,t}$ is first decomposed into a permanent component $\hat{P}_{i,t}$ and a transitory component $\hat{\nu}_{i,t}$. Changes in the permanent component $\Delta\hat{P}_{i,t}$ are classified as permanent if they are non-zero. Substantial changes in the transitory component $\hat{\nu}_{i,t}$, which exceed the household and time dependent threshold $\kappa_{i,t}$, are classified as transient. Changes below are classified as small. Transient changes are further categorized as recurrent if a transient change of the same sign occurs the next year $t+12$, or in the previous year $t-12$ if no observation of next year is available. These two options are denoted with the $\pm$ sign, depending on the availability of the future or past observations.

Figure 1 outlines the methodology for empirically decomposing monthly income time series into its permanent component $\hat{P}_{i,t}$ and transitory component $\hat{\nu}_{i,t}$, and classifying changes in these components into permanent changes and small, transient or recurrent changes respectively. We further distinguish between positive and negative changes for each type of change except for the small changes. The permanent component of the income time series $\hat{P}_{i,t}$ is estimated with a double rolling median, resulting in a nearly piecewise constant time series. As such, any change in this estimated permanent component is classified as a permanent change. The transitory component $\hat{\nu}_{i,t}$ is calculated as the difference of the original income time series and this estimated permanent component. Within the transitory component, we only classify substantial changes, defined as those that exceed a time- and household-specific threshold. This threshold accounts both for differences across households incomes (e.g. different working hours and regimes), as well as for changes within a household their income (e.g. changing jobs). We do not explicitly separate the transitory component into a transient $T_{i,t}$ and recurrent component $R_{i,t}$. Instead, we apply a simple rule to the transitory component $\hat{\nu}_{i,t}$ to divide the substantial changes into transient changes and recurrent changes. If a substantial change is followed by another substantial change of the same sign at a future date, the change is classified as recurrent. Otherwise, the change is classified as transient.

The permanent income component $\hat{P}_{i,t}$ is estimated with a double rolling median:

$$
\begin{aligned}
\hat{S}_{i,t} &= \text{median}(I_{i,t-n}, \ldots, I_{i,t}, \ldots, I_{i,t+n}) \\
\hat{P}_{i,t} &= \text{median}(\hat{S}_{i,t-n}, \ldots, \hat{S}_{i,t}, \ldots, \hat{S}_{i,t+n}).
\end{aligned} \tag{4}
$$

Permanent income changes, such as a reduction in working hours or a raise, appear as level shifts in the income time series. The rolling median $\hat{S}_{i,t}$ in (4) identifies these level shifts, while removing noise (Tukey 1970). The second application reduces the estimation error of the permanent component $\hat{P}_{i,t}$, while retaining level shifts (Frieden 1984). More specifically, $\hat{P}_{i,t}$ approximates a step function whose standard deviation is 0, when robustly estimated with the median absolute deviation (MAD) (Maronna et al. 2019), motivating our decision not to apply a threshold to classify changes in the permanent component, unlike in the transitory component. Any change in $\hat{P}_{i,t}$ is classified as a positive or negative permanent change depending on the sign of the change.

The window length $n = 6$ is used for both applications of the rolling median for a total window length of 13 observations. This means that we classify a change as permanent if it persists during the next 6 months. This choice is consistent with research by Benartzi and Thaler (1995), which suggests that the financial horizon for most people is about one year. Increasing the window size, e.g. to $n = 12$, would reduce our sample the number of households in our sample and limit our ability to estimate the permanent component near the end of our observation period. Setting $n = 6$ strikes a balance between a timely sensitivity to a change in the income level and efficient estimation when income remains stable.

The transitory component $\hat{\nu}_{i,t}$ is estimated by subtracting $\hat{P}_{i,t}$ from the original labour income time series $I_{i,t}$. The transistory component reflects the deviations from the permanent income. We then distinguish between substantial and small changes within this transitory component. The distinction is based on three main considerations. First, small income changes may not be noticeable, while more salient changes are more likely to affect consumption behaviour (Jappelli and Pistaferri 2010, p. 488). Second, failing to smooth small income changes only has small second-order utility and welfare costs for a household (Cochrane 1988; Kueng 2018). Finally, the economic significance of an income change is directly tied to its magnitude—small changes and their consumption responses are often economically negligible.

A change in the transitory component $\hat{\nu}_{i,t}$ is considered substantial if it exceeds a household-specific and time-varying threshold $\kappa_{i,t}$:

$$\hat{\nu}_{i,t}^{\text{substantial}} = \hat{\nu}_{i,t} \quad \text{if} \quad |\hat{\nu}_{i,t}| \geq \kappa_{i,t} = c \cdot \sigma_{i,t}. \tag{5}$$

with c a constant, and $\sigma_{i,t}$ the conditional standard deviation of the change in income around its permanent component at time t when no substantial income change occurred. We discuss the estimation of $\sigma_{i,t}$ and the calibration of this threshold in section 3.3. The constant c is a parameter that controls how restrictive $\kappa_{i,t}$ is in defining substantial income changes[10]. Any change in the transitory income component $\hat{\nu}_{i,t}$ that does not exceed the threshold of (5) is not further classified and is labelled as small.

Within the substantial changes, we distinguish between transient and recurrent changes. Every substantial change, as defined by (5), is transient. We separate recurrent changes from transient changes by employing the one-year horizon of Benartzi and Thaler (1995). A substantial change $\hat{\nu}_{i,t}^{\text{substantial}}$ is recurrent if $\hat{\nu}_{i,t+12}$ also is a substantial change[11]. If data for $t+12$ is unavailable (e.g. at the end of the observation window), we use the observation from the previous year, $t-12$, to ensure that both the first and last instances of a recurring change can be identified. While some events may occur more frequently, as 12 is divisible by 2, 3, 4, and 6, our one-year horizon will also capture recurrent changes with these shorter periodicities, provided they occur consistently within the year and at least once in the following year.

3.3 Calibration

The framework above, summarized in table 2, classifies income changes into 8 distinct categories. Concrete implementation requires calibration of the time series of thresholds $\kappa_{i,t}$ used in the classification rules of the changes in the transitory component. In our large-scale setup, we recommend a data-driven calibration of this threshold aimed at controlling the number of false positives and achieving power to detect income changes. Our approach is inspired by the literature on robust outlier detection (see e.g. Maronna et al. (2019)) and is designed to be robust to time variation in the income process. We

10. In line with the characteristics view in Gelman 2021 the parameter c could also be interpreted as a characteristic of households. What one household might experience as a substantial income change and react in one way, another might perceive as a small income change and react to in another way. Estimating this value per household from the data would, however, require at least one identifying assumption about consumption response to either type of income change. Since we do not want to make any prior assumptions about the consumption response, we leave the exploration of this avenue to future work.

11. We apply simple rules similar to those used in technical trading analysis. Although more complex procedures could be valuable for analyzing a single time series in detail, we prioritize simple, transparent rules for our large-scale setup, which involves analyzing hundreds of thousands of time series.

calibrate the threshold $\kappa_{i,t}$ based on the standard deviation of the monthly income changes around the permanent component. To this end, we estimate this standard deviation of $\hat{\nu}_{i,t}$ in a robust fashion with the median absolute deviation (MAD)[12].

We calibrate $\kappa_{i,t}$ to separate the substantial observations from the small observations in $\hat{\nu}_{i,t}$ under the assumption that the small transitory observations of log-income are locally normally distributed with variance $\sigma^2_{i,t}$ and without autocorrelation: $\nu_{i,t} \sim N(0, \sigma^2_{i,t})$. Under this assumption, it suffices to have a reliable estimate of $\sigma^2_{i,t}$ to control for false positives in the detection of income changes. There are several challenges in accurately estimating $\sigma_{i,t}$. First, we need an estimation window of approximately constant variance. The larger the estimation window length n, the less accurate the approximation becomes. Second, in estimation windows with a comparatively large proportion of substantial income changes (outliers) the classical standard deviation estimate is inflated, which may lead to an underdetection of income changes. To avoid such outlier masking, a robust estimator is needed, such as the MAD (Leys et al. 2013). We estimate $\sigma_{i,t}$ with the MAD for each household using a backward-looking rolling window of size $n = 12$ to account for time variation in the transitory component. The local scale estimate $\hat{\sigma}_{i,t}$ is then given by

$$\hat{\sigma}_{i,t} = \max\Big(\mathrm{MAD}(\hat{\nu}_{i,t-n}, \ldots, \hat{\nu}_{i,t}), \varepsilon\Big), \tag{6}$$

where $\varepsilon = 0.5\,\%$ prevents the scale estimate from collapsing to zero. This choice is motivated similarly to the choice not to differentiate between small income changes, namely that anything below ε will be of low economic significance. The threshold for distinguishing small from substantial changes is defined as a multiple c of the local scale estimate:

$$\hat{\kappa}_{i,t} = c \cdot \hat{\sigma}_{i,t}. \tag{7}$$

This threshold specification can be interpreted as an estimate of the quantile of the estimated transitory component $\hat{\nu}_{i,t}$. The constant c determines the statistical power of the detection method. Lower values of c lead to many income changes being detected as substantial income changes, and vice versa. The constant c must be large enough to avoid spurious detections but small enough to maintain the sensitivity needed for identifying relevant changes. We calibrated c by drawing on the critical values from a one-sided test, setting $c = 1.645$, which corresponds to the 95th percentile of the standard

12. Several other robust scale estimates can be considered see e.g. Gelper et al. (2009).

normal distribution. Sensitivity analysis in appendix C confirms that our results are robust to variations in this threshold, and our conclusions remain unchanged.

3.4 Classifying monthly income changes

The classification of income changes is based on the taxonomy of income changes in (3) and the identification of income changes in section 3.2. We categorize income changes $\Delta I_{i,t}$ into 8 distinct categories: small changes, positive and negative transient changes, positive and negative recurrent changes in the transitory component $\hat{\nu}_{i,t}$, and positive, negative, or no changes in the permanent component $\Delta\hat{P}_{i,t}$. Each change is classified into one exclusive type within its respective component. Since changes in the transitory and permanent components are classified separately, our framework can capture composite changes. A summary of all categories and their identification strategy and classification rules is provided in table 2. The centred rolling window used to estimate the permanent

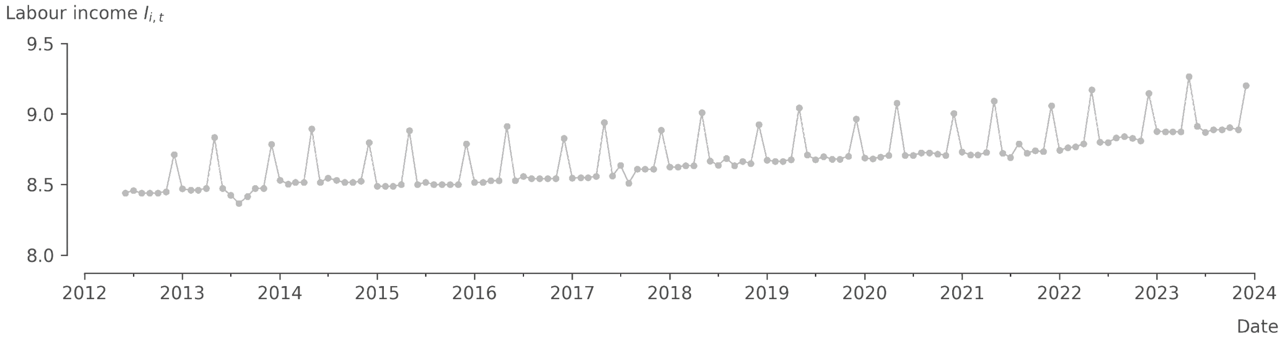
Table 2. List of all categories of the income change taxonomy of section 3.1, how they are identified with the identification criteria as defined in section 3.2 and how they relate to the income change classification of section 3.4.

Taxonomy	Component	Change type	Abbreviation	Criterion
$\Delta P_{i,t}$	$\Delta\hat{P}_{i,t}$	Positive permanent	PP	$\Delta\hat{P}_{i,t} > 0$
$\Delta P_{i,t}$	$\Delta\hat{P}_{i,t}$	No change	NC	$\Delta\hat{P}_{i,t} = 0$
$\Delta P_{i,t}$	$\Delta\hat{P}_{i,t}$	Negative permanent	NP	$\Delta\hat{P}_{i,t} < 0$
$\nu_{i,t}$	$\hat{\nu}_{i,t}$	Small	S	$\lvert\hat{\nu}_{i,t}\rvert < \hat{\kappa}_{i,t}$
$T_{i,t}$	$\hat{\nu}_{i,t}$	Positive transient	PT	$\hat{\nu}_{i,t} \geq \hat{\kappa}_{i,t}$
$T_{i,t}$	$\hat{\nu}_{i,t}$	Negative transient	NT	$\hat{\nu}_{i,t} \leq -\hat{\kappa}_{i,t}$
$R_{i,t}$	$\hat{\nu}_{i,t}$	Positive recurrent	PR	$\hat{\nu}_{i,t\pm12} \geq \hat{\kappa}_{i,t\pm12}$ and $\text{sign}(\hat{\nu}_{i,t}) = \text{sign}(\hat{\nu}_{i,t\pm12})$
$R_{i,t}$	$\hat{\nu}_{i,t}$	Negative recurrent	NR	$\hat{\nu}_{i,t\pm12} \leq -\hat{\kappa}_{i,t\pm12}$ and $\text{sign}(\hat{\nu}_{i,t}) = \text{sign}(\hat{\nu}_{i,t\pm12})$

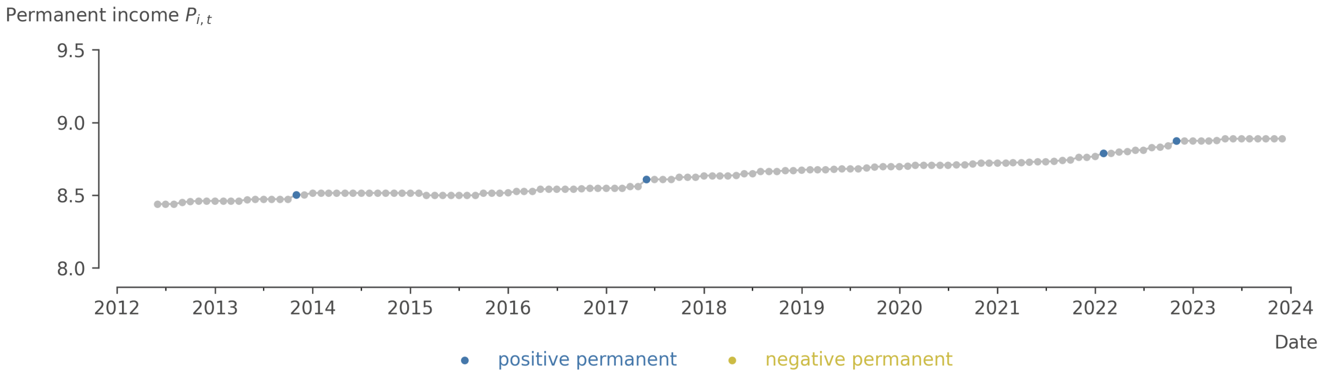
component $\hat{P}_{i,t}$ (4) has a window size of 13, while the backward-looking rolling median for $\hat{\sigma}_{i,t}$ (6) uses a window size of 12. This creates edge effects, preventing us from estimating $\hat{P}_{i,t}$ in the first and last 6 months, and the MAD in the first 12 months of observations. To reduce the loss of data, we dynamically adjust the window sizes near the edges. The minimum window sizes are 5 for $\hat{P}_{i,t}$ and 6 for the MAD, allowing us to classify income changes from the seventh month of the first year of observations through the third-to-last month of observations.

3.5 Application of the income change classification

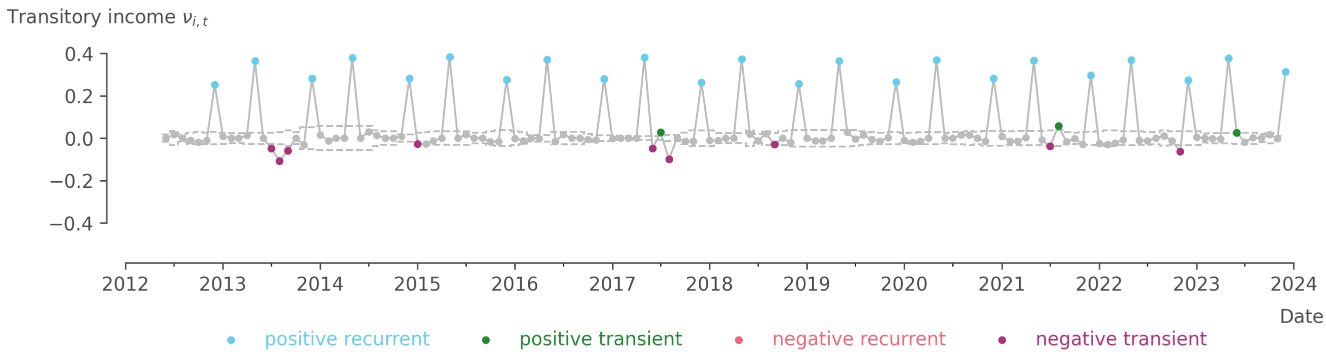
Figure 2 shows the classified income series for a typical household. Our method successfully separates the permanent component, detects level shifts, and captures substantial changes in the transitory component. The classification of changes as transient or recurrent matches the observed time series patterns.



(a) Monthly log-labour income series $I_{i,t}$ of a typical Belgian household.



(b) The permanent component $\hat{P}_{i,t}$ of the labour income of fig. 2a. Classified changes in the permanent component are highlighted in colour.



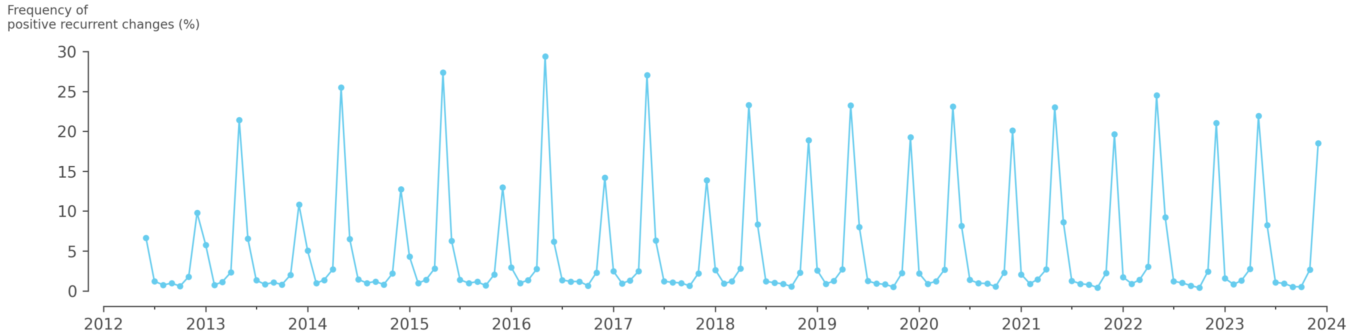
(c) The transitory component $\hat{\nu}_{i,t}$ of the labour income of fig. 2a. Classified changes, those exceeding the substantial change threshold $\hat{\kappa}_{i,t}$ represented as a dashed line, are highlighted in colour.

Figure 2. Monthly income time series of a typical Belgian household, showing the estimated permanent and transitory components. Months with classified changes in either component are highlighted in colour. This household consistently receives a holiday bonus in May and an end-of-year bonus in December, both marked as positive recurrent changes. They experienced raises, classified as positive permanent changes, in 2013, 2017, and twice in 2022, likely due to Belgium's automatic wage indexation mechanism. Additionally, income volatility in 2013, 2017, and 2021 led to classifications of positive or negative transient changes. Although no threshold is used for permanent changes in our main analysis, a minimum 2 % change is applied here, reflecting the raise from automatic indexation in Belgium. This threshold aids in visualization, and our results are robust to the choice of any threshold or its absence, as shown in the sensitivity analysis in appendix C.

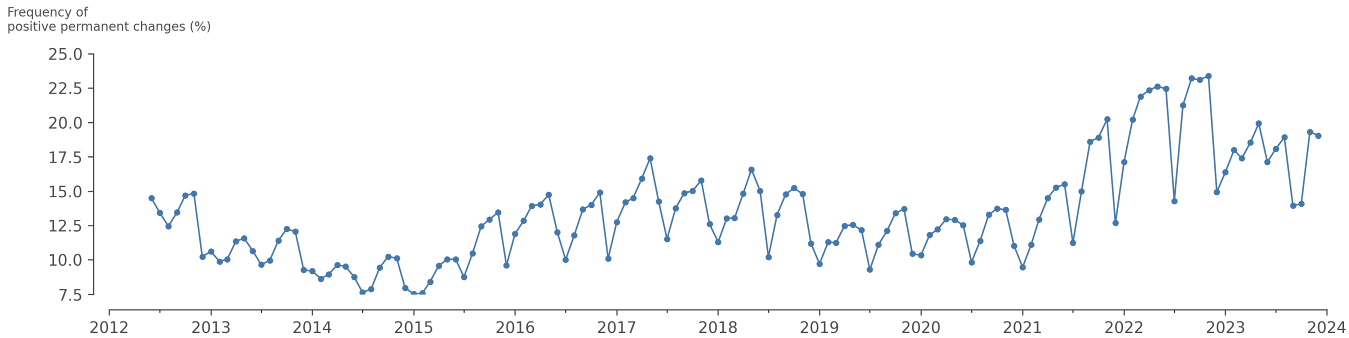
4 Results

4.1 Income change occurrence patterns

Section 3.5 demonstrated how the classification framework works for an individual household. Building on that, we now extend our analysis to cover all households in the sample. Figure 3 shows the relative frequency of a specific type of income change across all months from January 2012 to December 2024. As seen in fig. 3a, positive recurrent changes are most common in May and December, reflecting the timing of holiday pay and end-of-year bonuses in Belgium. Meanwhile, fig. 3b highlights that positive permanent changes peak in January, coinciding with wage indexation for many Belgian workers. The time series for all other types of income changes are provided in appendix D.



(a) Relative frequency of positive recurrent income changes over time. Nearly all recurrent changes occur in May and December, and to a lesser extent in June. Most Belgian households receive holiday pay in May or June, depending on which sector they are employed in. Similarly, many Belgian households receive an end-of-year bonus in December. Outside these months, almost no positive recurrent changes are observed.



(b) Relative frequency of positive permanent income changes over time. In Belgium, the wages of nearly all private and public sector workers are automatically indexed when the harmonized consumer price index (CPI) exceeds a 2 % threshold (European Central Bank 2008, p.51). The timing of these wage adjustments is determined by the relevant paritair comité (PC) representing employees. Most PCs adjust wages in the month the threshold is exceeded, while others do so annually. Notably, one of the largest PCs, representing white-collar workers, indexes wages every January (Sergio Santoro 2012). This explains the recurring spikes at the start of each year. However, as many households receive end-of-year bonuses, our estimated permanent component often shifts in December, leading to the observed peaks in December rather than January. Additionally, the period of high inflation in 2022 caused the CPI threshold to be exceeded multiple times in the same year, contributing to the surge in positive permanent income changes during that time.

Figure 3. The relative frequency of positive recurrent and positive permanent changes in income across all months from January 2012 until December 2024. The time series for all other types of income changes can be found in appendix D.

A limitation of our data-driven approach is illustrated in fig. 3b, where permanent changes are sometimes detected a month earlier if preceded by a transient or recurrent change of similar sign and magnitude. This highlights the core philosophy of our framework: rather than classifying every income change based on detailed household-level information, which is unavailable at scale as the information set of the econometrician is limited compared to that of the household, we apply simple, transparent rules to classify changes directly from the household labour income time series. In this case, while the true reason for the positive permanent change is wage indexation in January, the labour income of the household already increases to a comparable level in December and remains there, leading to an earlier detection of the level shift in our estimation. Figure 1 illustrates how our framework consists of steps that can be independently adapted or extended as needed, such as using a different method to estimate the permanent component or applying more complex classification rules. However, given the scale of our analysis, we prioritize the simplicity and interpretability of our current approach.

4.2 Summary statistics on consumption changes versus income changes

Summary statistics for income, consumption, and liquid wealth (in euros), along with key variables in our analysis (in log euros), are presented in table 3, unconditional on the type of income change. The mean household income is € 3503, of which an average of € 2653 is spent, indicating that households typically save a portion of their income each month. This is further supported by the high average liquid wealth of € 34 420, with nearly 75 % of households holding at least one month's worth of labour income in liquid assets. Semidurable and durable purchases are infrequent but substantial when they do occur, as shown by the low median, higher mean, and large standard deviation, suggesting a skewed distribution with occasional, larger expenditures.

Income changes for Belgian households appear symmetric, as both the mean and median changes are zero, and the first and third quartiles are of similar magnitude, approximately ±12 % but in opposite directions. This symmetry is reinforced when comparing quartiles for positive and negative income changes: the first quartile of positive changes aligns closely with the third quartile of negative changes, and vice versa. The permanent component closely follows log income, being slightly lower by construction. The transitory deviations around this permanent component average 5.2 % in magnitude. These deviations exhibit asymmetry, with the third quartile (8.6 %) being larger than the first quartile (−3.2 %), suggesting a tendency toward larger positive fluctuations. Our time- and household-specific threshold, estimated using the outlier-robust MAD, averages 11.6 %, which is smaller than the standard deviation of 28.0 % in the transitory component, underscoring the presence of considerable transitory fluctuations, as discussed in section 3.3.

In contrast, permanent changes are more stable, with a mean of 0.3 % and a standard deviation of 2.8 %.

The average positive permanent change is 1.8 %, which aligns with Belgium's wage indexation threshold of 2.0 %, after accounting for taxation. Consumption changes display slight asymmetry across all types of consumption (nondurable, semidurable, and durable) and are significantly more volatile than income changes, as reflected by their larger standard deviations.

Table 3. Descriptive statistics for the main variables in the dataset, unconditional on the type of income change. The table shows the mean, first quartile (Q1), median, third quartile (Q3), and standard deviation. The first panel displays variables in euros to provide context for the data, while all subsequent panels report variables in log euros, consistent with their use in our analysis and regression speficiations.

Description	Variable	Mean	Q1	Median	Q3	Std. dev
Income (€)		3503.7	1897.0	2762.7	4341.6	4602.4
Nondurable consumption (€)		635.0	279.0	511.9	848.2	1653.2
Durable consumption (€)		104.3	0.0	0.0	33.0	1229.4
Semidurable consumption (€)		142.5	0.0	55.1	177.0	380.1
Total consumption (€)		2653.4	1305.5	1969.8	2963.6	14 976.9
Liquid wealth at the start of the month (€)		34 420.7	2549.1	11 879.6	38 881.7	81 622.9
Log income	$I_{i,t}$	7.972	7.549	7.924	8.376	0.585
Income changes	$\Delta I_{i,t}$	0.000	−0.121	0.000	0.124	0.413
Positive income changes	$\Delta I^+_{i,t}$	0.267	0.036	0.141	0.406	0.325
Negative income changes	$\Delta I^-_{i,t}$	−0.278	−0.419	−0.154	−0.039	0.332
Permanent income component	$\hat{P}_{i,t}$	7.920	7.546	7.878	8.295	0.515
Permanent income changes	$\Delta\hat{P}_{i,t}$	0.003	0.000	0.000	0.000	0.028
Positive permanent income changes	$\Delta\hat{P}^+_{i,t}$	0.018	0.002	0.007	0.018	0.038
Negative permanent income changes	$\Delta\hat{P}^-_{i,t}$	−0.027	−0.026	−0.009	−0.003	0.058
Transitory income component	$\hat{\nu}_{i,t}$	0.052	−0.032	0.000	0.086	0.280
Substantial change threshold	$\hat{\sigma}_{i,t}$	0.116	0.031	0.074	0.158	0.125
Log liquid wealth at the start of month	$W_{i,t-1}$	8.773	7.844	9.383	10.568	3.216
Change in nondurable consumption	$\Delta C^{\mathrm{ND}}_{i,t}$	0.008	−0.338	0.000	0.352	0.937
Change in durable consumption	$\Delta C^{\mathrm{D}}_{i,t}$	0.009	−0.023	0.000	0.063	2.524
Change in semidurable consumption	$\Delta C^{\mathrm{SD}}_{i,t}$	0.006	−0.904	0.000	0.912	2.492
Change in total consumption	$\Delta C^{\mathrm{total}}_{i,t}$	0.003	−0.272	0.004	0.280	0.574

Table 4 presents the distribution of income, income changes, and consumption changes for all households in the sample. The data reveals that 75 % of transitory changes are small, while 65 % of the time, the permanent component remains unchanged, reflecting its stepwise nature. Across all income change types, positive changes occur more frequently and tend to be larger than negative changes. Although our framework allows for the classification of changes in both income components independently, the mean change in one component is close to zero when the other component changes, indicating that composite income changes are relatively rare. Consistent with expectations, positive income changes lead to increased consumption across all consumption categories, while negative income changes result in smaller consumption reductions. This asymmetry is evident in the transitory component across all durability types, but is not observed for permanent changes. Notably, positive recurrent changes are, on average, larger than positive transient changes and are associated with disproportionately higher increases in durable and semidurable consumption.

Table 4. Summary statistics for income and consumption changes by type of classified income change. The table presents the average frequency, as well as the average income and consumption change, for each type. Frequency is expressed as a percentage of the total number of observations in its respective component, as changes in the permanent and transitory components can occur simultaneously.

Change type	Component	Freq. (%)	$\overline{I_{i,t}}$	$\overline{\Delta I_{i,t}}$	$\overline{\nu_{i,t}}$	$\overline{\Delta P_{i,t}}$	$\overline{\Delta C^{\text{ND}}_{i,t}}$	$\overline{\Delta C^{\text{D}}_{i,t}}$	$\overline{\Delta C^{\text{SD}}_{i,t}}$	$\overline{\Delta C^{\text{total}}_{i,t}}$
Small	$\hat{\nu}_{i,t}$	74.81	7.91	−0.06	0.00	0.00	−0.01	−0.02	−0.04	−0.01
Pos. transient	$\hat{\nu}_{i,t}$	8.57	8.21	0.34	0.37	0.00	0.07	0.09	0.16	0.06
Neg. transient	$\hat{\nu}_{i,t}$	5.22	7.59	−0.40	−0.34	0.01	−0.05	−0.07	−0.14	−0.06
Pos. recurrent	$\hat{\nu}_{i,t}$	9.85	8.47	0.47	0.48	0.00	0.11	0.18	0.31	0.10
Neg. recurrent	$\hat{\nu}_{i,t}$	1.55	7.55	−0.48	−0.42	0.01	−0.02	−0.05	−0.12	−0.04
No change	$\Delta\hat{P}_{i,t}$	65.63	7.96	0.00	0.05	0.00	0.01	0.01	0.01	0.00
Pos. permanent	$\Delta\hat{P}_{i,t}$	26.41	8.03	0.04	0.06	0.02	0.01	0.02	0.02	0.01
Neg. permanent	$\Delta\hat{P}_{i,t}$	7.96	7.93	−0.08	0.01	−0.03	−0.01	−0.02	−0.03	−0.01

4.3 Panel regression specifications

We estimate the excess sensitivity of consumption following the approach of Havranek and Sokolova (2020), which builds on the organizing framework from Jappelli and Pistaferri (2010, eq. 14). To analyse how various types of income changes impact the consumption response to labour income fluctuations, we employ multiple panel regressions. Our base specification follows the approach of Ganong et al. (2020), but we estimate it on the household rather than the individual level. The specification is

$$\Delta C^{\text{ND}}_{i,t} = \beta \Delta I_{i,t} + \varepsilon_{i,t}, \tag{8}$$

where $\Delta I_{i,t}$ represents the change in the household's log labour income in month t, $\Delta C^{\text{ND}}_{i,t}$ is the change in log nondurable consumption, and $\varepsilon_{i,t}$ is the error term. We extend (8) in multiple ways. Firstly, using our labelled data, we also estimate the consumption response for durable $\Delta C^{\text{D}}_{i,t}$, semidurable $\Delta C^{\text{SD}}_{i,t}$ and total consumption $\Delta C^{\text{total}}_{i,t}$. Secondly, we include a vector of demographic control variables $X_{i,t}$ with the mean age of the household members who are at least 20 years old[13] and the type of household, household-fixed effects α_i, and time-fixed effects λ_t. The extended specification, without specifying a type of consumption, is

$$\Delta C_{i,t} = \beta \Delta I_{i,t} + \theta X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \tag{9}$$

13. We calculate the median age of a household by considering only members aged 20 and above, as these are the individuals likely to contribute to the household's income. This choice is informed by European labour statistics, which define the working-age population as those between 20 and 64 years old. Individuals younger than 20 are typically still in full-time education or not yet fully participating in the labour market, making them less likely to contribute financially to the household.

Thirdly, we modify (9) to allow for asymmetry in the consumption response to positive $\Delta I^{+}_{i,t}$ and negative income changes $\Delta I^{-}_{i,t}$. To this end, we estimate the following regression:

$$\Delta C_{i,t} = \beta^{+}\Delta I^{+}_{i,t} + \beta^{-}\Delta I^{-}_{i,t} + \theta X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}. \tag{10}$$

Finally, we incorporate our classified income changes. For each household and income change type we construct a time series of dummies $S^{\text{type}}_{i,t}$ that indicates when the income change is of the given type. The final specification includes interaction terms between these dummies and their respective income components, allowing us to estimate the consumption response for each type of change separately. Using the abbreviations of table 2, the final model is

$$\begin{aligned}\Delta C_{i,t} = {} & \Delta \hat{P}_{i,t} \cdot \left(\beta^{\text{PP}} S^{\text{PP}}_{i,t} + \beta^{\text{NP}} S^{\text{NP}}_{i,t}\right) \\ & + \hat{\nu}_{i,t} \cdot \left(\beta^{\text{S}} + \beta^{\text{PT}} S^{\text{PT}}_{i,t} + \beta^{\text{NT}} S^{\text{NT}}_{i,t} + \beta^{\text{PR}} S^{\text{PR}}_{i,t} + \beta^{\text{NR}} S^{\text{NR}}_{i,t}\right) \\ & + \theta X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t},\end{aligned} \tag{11}$$

where small changes in the transitory component serve as the reference category for the transient and recurrent changes. Note that the coefficients β in (11) can be interpreted as the excess sensitivity of the consumption response to an income change. In case of a transient or recurrent change, the full sensitivity is the sum of the elasticity of the reference category and the interaction, e.g. for positive transient change the excess sensitivity is $\beta^{S} + \beta^{\text{PT}}$. The excess sensitivity for a positive permanent change is β^{PP} as every change different from 0 is classified. Finally, we extend the specification to allow for a differential consumption response to income changes by low-wealth households. We introduce a dummy variable $S^{\text{LW}}_{i,t}$ that is equal to 1 if the liquid wealth of the household is in the lowest quartile of the liquid wealth distribution of that month. To address potential endogeneity and capture the liquid wealth available at the start of the month, we incorporate a lagged version of this dummy. This approach allows us to estimate how limited liquid wealth amplifies or dampens consumption responses across different types of income changes. The extended regression is

$$
\begin{aligned}
\Delta C_{i,t} = {} & \Delta\hat{P}_{i,t} \cdot \left(\beta^{\mathrm{PP}} S^{\mathrm{PP}}_{i,t} + \beta^{\mathrm{NP}} S^{\mathrm{NP}}_{i,t}\right) \\
& + \hat{\nu}_{i,t} \cdot \left(\beta^{\mathrm{S}} + \beta^{\mathrm{PT}} S^{\mathrm{PT}}_{i,t} + \beta^{\mathrm{NT}} S^{\mathrm{NT}}_{i,t} + \beta^{\mathrm{PR}} S^{\mathrm{PR}}_{i,t} + \beta^{\mathrm{NR}} S^{\mathrm{NR}}_{i,t}\right) \\
& + \beta^{\mathrm{LW}} S^{\mathrm{LW}}_{i,t-2} \\
& + S^{\mathrm{LW}}_{i,t-2} \cdot \left[\Delta\hat{P}_{i,t} \cdot \left(\beta^{\mathrm{PP,LW}} S^{\mathrm{PP}}_{i,t} + \beta^{\mathrm{NP,LW}} S^{\mathrm{NP}}_{i,t}\right)\right] \\
& + S^{\mathrm{LW}}_{i,t-2} \cdot \left[\hat{\nu}_{i,t} \cdot \left(\beta^{\mathrm{S,LW}} + \beta^{\mathrm{PT,LW}} S^{\mathrm{PT}}_{i,t} + \beta^{\mathrm{NT,LW}} S^{\mathrm{NT}}_{i,t} + \beta^{\mathrm{PR,LW}} S^{\mathrm{PR}}_{i,t} + \beta^{\mathrm{NR,LW}} S^{\mathrm{NR}}_{i,t}\right)\right] \\
& + \theta X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}
\end{aligned}
\tag{12}
$$

The excess sensitivity for a low-wealth household is then the sum of the base excess sensitivity and that of the low-wealth interaction. For example, the excess sensitivity for a positive transient change for a low-wealth household is given by $\beta^{\mathrm{S}} + \beta^{\mathrm{PT}} + \left(\beta^{\mathrm{LW}} + \beta^{\mathrm{S,LW}} + \beta^{\mathrm{PT,LW}}\right)$.

4.4 Panel regression estimates

The results in columns 1 to 3 of table 5 show that the inclusion of household-level control variables (such as the type of household and the median age of household members) and household-fixed effects, which account for household-specific trends in income or consumption growth, does not alter the excess sensitivity estimate in either the base model (8) or the extended model (9). However, adding time-fixed effects reduces the coefficient, indicating that some consumption responses are influenced by time-specific factors. These patterns hold across all consumption types and for the other regression specifications discussed in section 4.3. In all remaining results, household control variables, household-fixed effects, and time-fixed effects are always included. Our elasticity estimate of 0.123 in columns 1 to 3 is comparable to the findings of Ganong et al. (2020), who reported an elasticity of 0.075 using a similar specification at the individual level. Our estimate aligns more closely with their instrumental variable estimate of 0.176, which accounts for potential endogeneity in labour supply decisions. Since our sample excludes households with self-employed individuals, it is reasonable to assume that the households in our analysis have limited flexibility to adjust their labour supply, explaining why our results alings more closely with the instrumental variable estimate.

The first row in columns 4 to 8 of table 5 shows significant heterogeneity in the consumption elasticity to income changes across different types of consumption. The elasticity is particularly pronounced for semidurable consumption, which is twice as large as that of nondurable consumption. The total

Table 5. Columns 1 to 4 show the step-by-step extension of the excess sensitivity specification in (8) for nondurable (ND) consumption, culminating in the fully extended specification in (9). The inclusion of household-level control variables and fixed effects, which account for unobserved household-specific factors such as risk aversion, does not significantly alter the excess sensitivity estimate. However, the addition of time-fixed effects lowers the coefficient, indicating that some consumption response is driven by time-specific factors. For example, many Belgian households receive end-of-year bonuses, often used for holiday and Christmas spending. Columns 4 to 8 present the fully extended specification of (9), as well as the asymmetric income changes specification of (10), applied to nondurable (ND), semidurable (SD), durable (D), and total consumption. Total consumption includes nondurable, semidurable, durable, services, and mixed consumption. The total number of observations for all specifications is 50 277 887.

	$\Delta C^{\text{ND}}_{i,t}$	$\Delta C^{\text{ND}}_{i,t}$	$\Delta C^{\text{ND}}_{i,t}$	$\Delta C^{\text{ND}}_{i,t}$	$\Delta C^{\text{SD}}_{i,t}$	$\Delta C^{\text{D}}_{i,t}$	$\Delta C^{\text{total}}_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta I_{i,t}$	0.123***	0.123***	0.123***	0.074***	0.165***	0.095***	0.081***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
R^2	0.003	0.003	0.006	0.019	0.022	0.005	0.028
$\Delta I^+_{i,t}$	0.146***	0.143***	0.146***	0.099***	0.217***	0.126***	0.102***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)
$\Delta I^-_{i,t}$	0.100***	0.104***	0.101***	0.050***	0.114***	0.066***	0.059***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)
R^2	0.003	0.003	0.006	0.019	0.022	0.005	0.028
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Household FE			Yes	Yes	Yes	Yes	Yes
Time FE				Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

consumption response, which averages the heterogeneity across consumption types, is similar to that of nondurable consumption. The second and third rows indicate that the consumption response is consistently stronger to positive income changes than to negative income changes across all consumption types, while maintaining the same relative patterns. This asymmetry —where positive changes elicit a stronger response than negative changes— supports the findings of Baugh et al. (2021), who used similar transaction-level data to ours. In contrast, studies using survey data, such as Fuster, Kaplan, and Zafar (2021) and Christelis et al. (2019), report the opposite pattern.

Table 6 presents our primary results, estimating the consumption responses for each type of income change across different consumption categories. In this table, the total effect for transient and recurrent changes can be derived by summing the base term with the corresponding interaction term. A detailed explanation of the coefficients is provided in table 2. Figure 4 visualizes these total effects, by summing up the different components, illustrating the consumption response to each income change type across all categories.

Table 6. Regression results of our main specification (11) where we study the consumption response to the classified income changes listed in table 2. The coefficients for the transient and recurrent changes are relative to the reference category of small changes. The specification is estimated for nondurable (ND), semidurable (SD), durable (D) and total consumption. Total consumption includes nondurable, semidurable, durable, services, and mixed consumption.

	$\Delta C^{\text{ND}}_{i,t}$	$\Delta C^{\text{SD}}_{i,t}$	$\Delta C^{\text{D}}_{i,t}$	$\Delta C^{\text{total}}_{i,t}$
	(1)	(2)	(3)	(4)
$\hat{\nu}_{i,t}$	0.118***	0.296***	0.175***	0.129***
	(0.001)	(0.003)	(0.004)	(0.001)
$\hat{\nu}_{i,t} \cdot S^{\text{PT}}_{i,t}$	−0.011***	−0.053***	−0.026***	−0.002*
	(0.002)	(0.004)	(0.004)	(0.001)
$\hat{\nu}_{i,t} \cdot S^{\text{NT}}_{i,t}$	−0.033***	−0.087***	−0.055***	−0.029***
	(0.002)	(0.005)	(0.005)	(0.001)
$\hat{\nu}_{i,t} \cdot S^{\text{PR}}_{i,t}$	−0.003*	−0.002	0.007	0.000
	(0.001)	(0.004)	(0.004)	(0.001)
$\hat{\nu}_{i,t} \cdot S^{\text{NR}}_{i,t}$	−0.072***	−0.142***	−0.094***	−0.050***
	(0.003)	(0.007)	(0.007)	(0.002)
$\Delta\hat{P}_{i,t} \cdot S^{\text{PP}}_{i,t}$	0.210***	0.471***	0.305***	0.230***
	(0.005)	(0.016)	(0.017)	(0.004)
$\Delta\hat{P}_{i,t} \cdot S^{\text{NP}}_{i,t}$	0.189***	0.311***	0.293***	0.198***
	(0.007)	(0.019)	(0.021)	(0.005)
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	50 277 887	50 277 887	50 277 887	50 277 887
R^2	0.019	0.022	0.005	0.028

Standard errors in parentheses
$^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$

Our findings provide mixed evidence for the permanent income hypothesis (PIH). In line with PIH predictions, we observe that permanent income changes elicit the strongest consumption responses, surpassing the reactions to transient or recurrent changes (Hall 1978). However, contrary to PIH, statistically significant consumption adjustments also occur in response to all types of transitory changes, suggesting that households do not fully smooth consumption when faced with temporary income fluctuations. This pattern is consistent with the literature, where many studies also find departures from strict PIH predictions (Crawley and Theloudis 2024). The results further reveal that asymmetric consumption responses found in table 5 also hold for the permanent and transitory components separately. Positive permanent changes lead to a larger consumption increase compared to negative permanent changes, indicating that households may moderate consumption reductions in response to permanent income declines.

For transient and recurrent income changes, distinct consumption behaviors emerge. Positive transient changes contribute a modest increase on top of the base response, whereas negative transient changes generate a notably larger consumption reduction, producing a smaller overall effect. This suggests a degree of consumption smoothing when households face transient income reductions. The smoothing behavior is even more pronounced for recurrent changes. Positive recurrent changes show minimal, statistically insignificant, additional impact on consumption, while negative recurrent changes, though more significant, remain substantially smaller than their transient counterparts. These results suggest that predictable, recurring income changes allow households to anticipate and smooth consumption, reducing fluctuations in response to both positive and negative recurrent changes. This behavior aligns with the permanent income hypothesis (PIH), which posits that households adjust less to expected income changes, treating them as part of a stable financial pattern rather than as disruptions. Recurrent changes, by nature, are regular and expected, like annual bonuses or holiday pay, enabling households to incorporate them into their budgeting and moderate any immediate consumption adjustments.

If we interpret transient changes as primarily unanticipated—such as unexpected adjustments in working hours or sporadic bonuses—the results further align with PIH predictions. Under PIH, unanticipated changes would prompt stronger responses, as they are not integrated into long-term financial plans. This is indeed what we observe: positive transient changes lead to modest consumption increases, while negative transient changes result in more marked reductions, likely due to precautionary motives or liquidity constraints. Households respond most strongly to positive permanent changes, enabling them to adjust their living standards accordingly. Thus, our findings suggest that households manage consumption based on the perceived stability and predictability of income changes, aligning with the core PIH predictions when interpreting recurrent changes as anticipated and transient changes as unanticipated.

Because we classify only transitory changes that exceed a household-specific threshold as transient or recurrent, the small but statistically significant additional effects suggest that the size of the income change has limited additional influence on the consumption response. Our sensitivity analysis in appendix C confirms that this finding is robust across different threshold levels, reinforcing the idea that the type of income change — whether transient, recurrent, or permanent — plays a more crucial role in shaping consumption behavior than the magnitude of the change.

For transient and recurrent changes, we observe the highest excess sensitivity for semidurable consumption, distantly followed by durable and then nondurable goods. We find the same order for permanent changes, though the durable consumption response increase compared to the transient changes. The results imply that households are more likely to adjust spending on semidurable items, such as clothing and hobby items, even when time-fixed effects control for seasonal factors. There is some evidence to suggest that mental accounting can account for higher consumption responses to durable consumption than nondurable consumption (Zhang and Sussman 2018). Mental accounting states that households often maintain separate (mental) accounts for different types of goods. This could explain why they may be more inclined to allocate funds to durable goods following a positive income shock, even if they already have sufficient liquidity in other accounts to cover such purchases. This compartmentalized budgeting approach could help explain the relatively high sensitivity of durable consumption to income changes, as seen in our findings and those of Souleles (1999, p.954). As the majority component of (changes in) consumption, nondurable goods primarily drive the total consumption response across all income change types, underscoring the value of analyzing consumption by durability category to uncover the distinct behaviors in the other types of consumption.

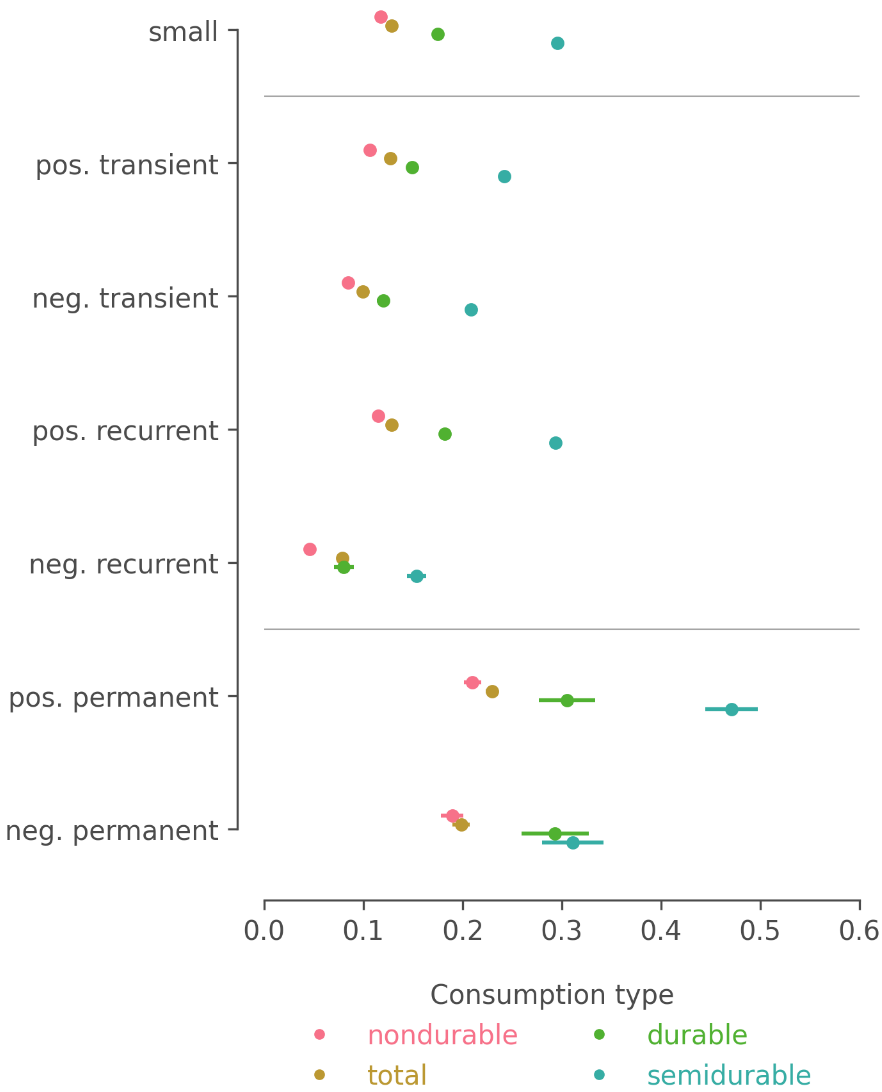


Figure 4. Coefficient plot of our main specification (11) showing the consumption response to classified income changes listed in table 2. Significant consumption responses are observed even for small transitory changes, counter to the strict predictions of the permanent income hypothesis (PIH). Permanent income changes consistently yield the highest coefficients, indicating stronger adjustments for lasting income shifts. The notably small response to negative recurrent changes suggests households smooth their consumption over predictable, recurring income reductions. Across income change types, semidurable consumption exhibits the highest sensitivity, followed by durable, total, and nondurable consumption. The total consumption response aligns closely with nondurable consumption, reflecting the stability of essential expenditures. The error bars show the 95 % confidence intervals, with standard errors calculated using the delta method.

In table 7, we examine how liquid wealth moderates the consumption response to income changes. Households are classified as low-wealth if their liquid assets in a given month are in the lowest quartile of the liquid wealth distribution. Our findings indicate that low-wealth households demonstrate a stronger consumption response to income changes compared to their wealthier counterparts. Specifically, the interaction coefficients between low-wealth status and both small transitory changes and positive permanent changes are significant, suggesting that low-wealth households are more likely to increase spending following positive income shocks and reduce consumption more sharply in response to transitory income declines.

Interestingly, low-wealth households respond more to both positive and negative recurrent changes, while high wealth households show minimal additional response to positive recurrent changes. This suggests that low-wealth households may lack the means to fully smooth these anticipated, repeated changes as wealthier households do. While the additional effects for transient and recurrent changes are modest compared to the main interaction effects, low-wealth households exhibit consumption patterns in line with liquidity constraints. For instance, although their responses to negative permanent changes in durable and semidurable consumption are similar to those of high wealth households, they sharply reduce durable purchases, likely due to the need for prior savings to finance these larger expenditures. Positive recurrent changes have a particularly pronounced effect on the consumption of low-wealth households, with responses exceeding 0.6 for semidurable goods and nearly 0.4 for durable goods, again indicating that they require these recurrent changes to finance larger semidurable and durable goods. This suggests that positive recurrent income changes create substantial consumption boosts among low-wealth households, potentially amplifying macroeconomic multiplier effects.

Table 7. Regression results of our main specification, extended with an interaction with a low-wealth dummy. This dummy is for a household if their liquid assets in a given month fall within the first quartile of the liquid wealth distribution of that month. The excess sensitivity for a low-wealth household is given by the sum of the base excess sensitivity and that of the low-wealth interaction. The specification is estimated for nondurable (ND), semidurable (SD), durable (D) and total consumption. Total consumption includes nondurable, semidurable, durable, services, and mixed consumption.

	$\Delta C_{i,t}^{\text{ND}}$	$\Delta C_{i,t}^{\text{SD}}$	$\Delta C_{i,t}^{\text{D}}$	$\Delta C_{i,t}^{\text{total}}$
	(1)	(2)	(3)	(4)
$\hat{\nu}_{i,t}$	0.075***	0.216***	0.141***	0.095***
	(0.001)	(0.004)	(0.004)	(0.001)
$\hat{\nu}_{i,t} \cdot S_{i,t}^{\text{PT}}$	−0.009***	−0.056***	−0.033***	−0.002*
	(0.002)	(0.005)	(0.005)	(0.001)
$\hat{\nu}_{i,t} \cdot S_{i,t}^{\text{NT}}$	−0.024***	−0.056***	−0.041***	−0.023***
	(0.002)	(0.006)	(0.006)	(0.001)
$\hat{\nu}_{i,t} \cdot S_{i,t}^{\text{PR}}$	−0.004**	−0.027***	−0.010*	−0.005***
	(0.002)	(0.005)	(0.005)	(0.001)
$\hat{\nu}_{i,t} \cdot S_{i,t}^{\text{NR}}$	−0.056***	−0.090***	−0.081***	−0.039***
	(0.003)	(0.008)	(0.008)	(0.002)
$\Delta\hat{P}_{i,t} \cdot S_{i,t}^{\text{PP}}$	0.159***	0.375***	0.252***	0.180***
	(0.006)	(0.019)	(0.021)	(0.005)
$\Delta\hat{P}_{i,t} \cdot S_{i,t}^{\text{NP}}$	0.193***	0.316***	0.328***	0.208***
	(0.007)	(0.022)	(0.024)	(0.006)
$S_{i,t}^{\text{LW}}$	−0.012***	−0.016***	−0.022***	−0.028***
	(0.000)	(0.001)	(0.001)	(0.000)
$S_{i,t}^{\text{LW}} \cdot \hat{\nu}_{i,t}$	0.178***	0.333***	0.143***	0.143***
	(0.003)	(0.008)	(0.008)	(0.002)
$S_{i,t}^{\text{LW}} \cdot \hat{\nu}_{i,t} \cdot S_{i,t}^{\text{PT}}$	0.003	0.038***	0.045***	0.012***
	(0.004)	(0.010)	(0.010)	(0.002)
$S_{i,t}^{\text{LW}} \cdot \hat{\nu}_{i,t} \cdot S_{i,t}^{\text{NT}}$	−0.047***	−0.149***	−0.067***	−0.038***
	(0.004)	(0.011)	(0.011)	(0.002)
$S_{i,t}^{\text{LW}} \cdot \hat{\nu}_{i,t} \cdot S_{i,t}^{\text{PR}}$	0.014***	0.123***	0.084***	0.028***
	(0.003)	(0.010)	(0.009)	(0.002)
$S_{i,t}^{\text{LW}} \cdot \hat{\nu}_{i,t} \cdot S_{i,t}^{\text{NR}}$	−0.061***	−0.211***	−0.054***	−0.039***
	(0.006)	(0.016)	(0.015)	(0.004)
$S_{i,t}^{\text{LW}} \cdot \Delta\hat{P}_{i,t} \cdot S_{i,t}^{\text{PP}}$	0.183***	0.334***	0.193***	0.191***
	(0.013)	(0.036)	(0.037)	(0.009)
$S_{i,t}^{\text{LW}} \cdot \Delta\hat{P}_{i,t} \cdot S_{i,t}^{\text{NP}}$	−0.009	−0.013	−0.153***	−0.035***
	(0.017)	(0.046)	(0.045)	(0.011)
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	50 277 887	50 277 887	50 277 887	50 277 887
R^2	0.019	0.022	0.005	0.029

Standard errors in parentheses
$^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$

5 Conclusion

Our analysis provides a comprehensive three-pronged approach for understanding consumption responses to income changes. First, we establish a systematic framework that categorizes income changes into transient, recurrent, and permanent types. Second, we leverage a large transaction dataset comprising twelve years of daily transaction data for millions of households, offering unprecedented granularity. Third, the dataset is enhanced by labelling transactions according to the UN's Classification of Individual Consumption According to Purpose (COICOP) standard. This standardized approach ensures consistent definitions across studies, facilitating comparisons and minimizing the inconsistencies that arise from varying methodologies, definitions, and data sources. Together, these three components enable us to estimate consumption responses within a unified framework, effectively taming the "zoo" of conflicting estimates found in the literature.

Our results clearly demonstrate the heterogeneity in consumption responses to different types of income changes. Permanent income changes elicit the strongest consumption responses. However, we also find significant reactions to transient and recurrent changes, which challenge the strict predictions of PIH that suggest households should completely smooth consumption in response to temporary income fluctuations. An exception is the case of negative recurrent changes, where the consumption responses are notably subdued. This indicates that households anticipate and smooth their consumption over predictable, recurring reductions in labour income. The recurrent nature of income changes has received limited attention in previous research, despite clearly eliciting different consumption behaviors compared to transient or permanent changes. Among the various consumption categories, semidurable goods exhibit the highest sensitivity to income changes, followed by durable and nondurable goods. The response of total consumption, which encompasses all durability categories, is largely driven by the behavior of nondurable goods consumption, underscoring the need to analyze consumption by durability category to reveal distinct responses among the other types.

These findings have significant implications for both research and policy design. Our framework provides a consistent method for studying all types of income changes, allowing for better cross-study and cross-context comparisons. Understanding the heterogeneous impacts of income changes can help policymakers design more targeted interventions. For example, while permanent income increases may result in widespread boosts across different types of consumption, transient income changes primarily drive increased spending on semidurable and durable goods. Future research will explore the effects of specific government policies aimed at stabilizing income fluctuations, offering insights into policy effectiveness through a series of policy assessment exercises. Additionally, we intend to investigate how consumption responds to changes in non-labor income, an increasingly important policy question given the rising share of capital income and the growing aging population relying on such income for their consumption needs.

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A Consumption labels

Table 8 presents the consumption labels available in our dataset, categorized by their durability type. These labels are derived from the United Nations' COICOP classification (UN 2018), which was adopted wherever possible. Deviations from COICOP occur in two cases, firstly for categories that are out of scope for COICOP (e.g., cash withdrawals) but relevant to consumption, secondly when transaction data only allow for the identification of a subset or superset of COICOP categories. When a superset includes items of different durability types, the Mixed durability type was assigned.

The durability types are as follows:

- Durables (D)

  Goods designed for long-term use, typically lasting over a year. Examples include vehicles and household appliances.

- Semidurables (SD)

  Goods with an expected lifespan longer than a year but shorter than durables, often less expensive. Examples include clothing and small appliances.

- Nondurables (ND)

  Goods primarily intended for single or short-term use. Examples include food, beverages, and toiletries.

- Services (S)

  Non-physical goods provided to individuals, such as assistance or professional advice.

- Mixed (M)

  Purchases that encompass goods with different durability types, such as transactions from hypermarkets, where a variety of goods are sold.

Table 8. Consumption labels provided by BNP Paribas Fortis (BNPPF), categorized by the COICOP classification scheme and assigned durability types. Durability types include D (Durable), SD (Semi-Durable), ND (Non-Durable), S (Services), and M (Mixed). If a label is derived from COICOP, the corresponding code is provided; otherwise, labels constructed by BNPPF are noted. Deviations from COICOP arise when categories are out of scope (e.g., cash withdrawals) or when the data cannot fully differentiate COICOP subcategories.

Source	COICOP Code	Label	Durability	Comment
COICOP	11.2	Accommodation Services	S	
BNPPF	–	Alcoholic Beverages and Tobacco	ND	Only includes specialty stores, excludes narcotics (COICOP 2.0).
COICOP	6.1.3	Assistive Products	D	
BNPPF	–	Cash Withdrawals	M	Not in scope of COICOP.
COICOP	3.0	Clothing and Footwear	SD	
BNPPF	–	Credit Card Payments	M	End-of-month payments. Not in scope of COICOP.
BNPPF	9.1, 9.5	Cultural and Recreational Durables	D	Combines COICOP recreational and cultural durable goods.
BNPPF	9.4, 9.6	Cultural and Recreational Services	S	Combines COICOP cultural and recreational services.
COICOP	5.6.2	Domestic and Household Services	S	
BNPPF	10.1, 10.2, 10.3	Education - Mandatory	S	Includes all levels of mandatory education in Belgium.
BNPPF	10.5	Education - Other	S	
COICOP	10.4	Education - Tertiary	S	
COICOP	12.2	Financial Services	S	
BNPPF	–	Fines	ND	Not in scope of COICOP.
COICOP	11.1	Food and Beverage Serving Services	S	
COICOP	1.0	Food and Non-alcoholic Beverages	ND	
COICOP	7.2.2	Fuels and Lubricants for Personal Transport Equipment	ND	
COICOP	5.1	Furniture, Furnishings, Loose Carpets	D	Excludes repair, installation, and hire services.
COICOP	9.3	Garden Products and Pets	ND	
BNPPF	–	Groceries	ND	Combines grocery and specialty stores (e.g., bakeries, supermarkets).
BNPPF	6.2, 6.3, 6.4	Health Services	S	
COICOP	5.3	Household Appliances	M	Mixed durability for stores where appliance type (large/small) is unclear.

Table 8 continued from previous page

BNPPF	5.2, 5.3.2, 5.4	Household Textiles, Tableware, Small Appliances	SD	Excludes repair and hire services.
COICOP	8.1	Information and Communication Equipment	D	Excludes unrecorded media, which are semi-durable.
COICOP	8.3	Information and Communication Services	S	
COICOP	12.1	Insurance	S	
BNPPF	–	Luxury Goods	D	Bundles COICOP 13.2.1 with other luxury goods.
COICOP	6.1	Medicines and Health Products	ND	Excludes assistive products.
BNPPF	–	M Retail - Building Materials	M	Purchases at DIY and home improvement stores.
BNPPF	–	M Retail - Personal Use	M	
COICOP	9.2	Other Cultural and Recreational Goods	SD	Includes books and similar items.
BNPPF	–	Other Durable Goods	D	Other durable goods not elsewhere classified.
BNPPF	–	Other Non-Durable Goods	ND	Includes office supplies, newspapers, etc.
BNPPF	–	Other Semi-Durable Goods	SD	Other semi-durable goods not elsewhere classified.
BNPPF	–	Other Services	S	Based on COICOP 13.9, broader scope.
COICOP	4.4.4	Other Services Relating to NEC	S	
COICOP	9.8	Package Holidays	S	
COICOP	7.2.1	Parts and Accessories for Personal Transport Equipment	SD	
BNPPF	7.3.3	Passenger Transport Services - Air	S	
BNPPF	7.3.1	Passenger Transport Services - Public	S	
BNPPF	7.3.2	Passenger Transport Services - Road	S	
BNPPF	7.3.4	Passenger Transport Services - Water	S	
BNPPF	–	Personal Care Products	ND	Corresponds to COICOP 13.1.
BNPPF	–	Personal Care Services	S	Corresponds to COICOP 13.1.
COICOP	7.1	Purchase of Vehicles	D	
BNPPF	–	Second-Hand Retail	M	Includes second-hand stores, mostly selling semi-durable or durable goods.

Table 8 continued from previous page

COICOP	4.3.1	Security Equipment and Materials	ND	Excludes major repair and construction materials.
COICOP	4.3.2	Services for Maintenance and Repair of Dwellings	S	Excludes materials for repairs.
BNPPF	7.2.3, 7.2.4	Services for Personal Transport Equipment	S	
COICOP	4.4.3	Sewage Collection	S	
COICOP	13.3	Social Protection	S	
COICOP	7.4	Transport Services of Goods	S	
BNPPF	–	Utilities	ND	Includes utilities not classified into specific subcategories.
COICOP	4.5.1	Utilities - Electricity	ND	
COICOP	4.5.2	Utilities - Gas	ND	
COICOP	4.5.3	Utilities - Liquid Fuels	ND	
COICOP	4.5.5	Utilities - Other Energy for Heating/Cooling	ND	
COICOP	4.5.4	Utilities - Solid Fuels	ND	
COICOP	4.4.1	Utilities - Water Supply	ND	

B Identification of labour income and replacement income

A detailed description of these symbols can be found in Dirix (2018, p.142–147) and FOD Justitie (2006). Below is an English translation of the bill in Dutch outlining the communication codes required for different types of income payments in Belgium.

B.1 Labour Income

The symbol "*/A/*" must be included in the communication for transactions related to the following payments:

- employment contracts
- apprenticeship or learning agreements
- statutes or official regulations
- subscriptions
- wages for work performed under the authority of another person, even outside a formal employment contract
- holiday pay under annual leave legislation

B.2 Replacement Income

The symbol "*/B/*" must be included in the communication for transactions related to the following types of replacement income:

- income from activities outside those listed under /A/
- maintenance benefits, whether provisional or otherwise, as awarded by the court, including benefits for spouses post-divorce
- pensions, adjustment benefits, transition benefits, annuities, interest contributions, and pension benefits paid under any applicable law, statute, or agreement
- holiday pay and supplementary retirement allowance under the retirement and survivor's pension legislation for employees
- unemployment benefits and benefits disbursed by social security funds

- incapacity benefits and invalidity benefits under sickness and invalidity insurance legislation or the law of 16 June 1960, which also applies to former employees of the Belgian Congo and Ruanda-Urundi, as well as overseas social security legislation
- benefits, annuities, and allowances under legislation on compensation for workplace accidents or occupational diseases, the law of 16 June 1960, or insurance contracts under overseas social security, except as specified in § 2, 4° of this article
- militia allowances as referred to in the law of 9 July 1951
- benefits provided for interruptions in professional careers

Additionally, institutions that pay out unemployment benefits include specific identifiers in their communications, which can be used to distinguish these payments from other types of replacement income.

B.3 Social Security Income

The symbol "*/C/*" must be included in the communication for transactions related to the following social security payments:

- family benefits, including those for wage-earning soldiers
- orphan pensions or annuities granted under any law, statute, or agreement
- disability allowances
- compensation for severe mutilation requiring assistance, paid under workplace accident compensation laws, as well as allowances under the Compulsory Health Insurance and Benefits Act of 14 July 1994
- disbursements for:
  - medical benefits to eligible individuals, covered by health insurance or under the law of 16 June 1960, or overseas social security legislation
  - medical, surgical, pharmaceutical, and nursing expenses, as well as prosthetics and orthopaedic devices, for those affected by workplace accidents or occupational diseases under relevant legislation
- guaranteed income for the elderly or income support for the elderly

- subsistence allowances
- social services disbursements by public welfare centers
- benefits provided under the law of 22 December 2016 for self-employed persons under the bridging right
- provisional or other reimbursements for prosthetics, medical aids, and implants
- amounts specified in Article 120 of the Program Law (I) of December 27, 2006, paid through the Asbestos Victims Compensation Fund
- expense allowances under Article 10 of the Act of 3 July 2005 on volunteer rights
- intervention payments from the Compensation Fund for COVID-19 victims, as outlined in Articles 15 and 16 of Royal Decree no. 22 of 4 June 2020

Institutions responsible for paying pensions also include additional identifiers in their communications, which can be used to distinguish pension payments from other social security income.

C Sensitivity analysis

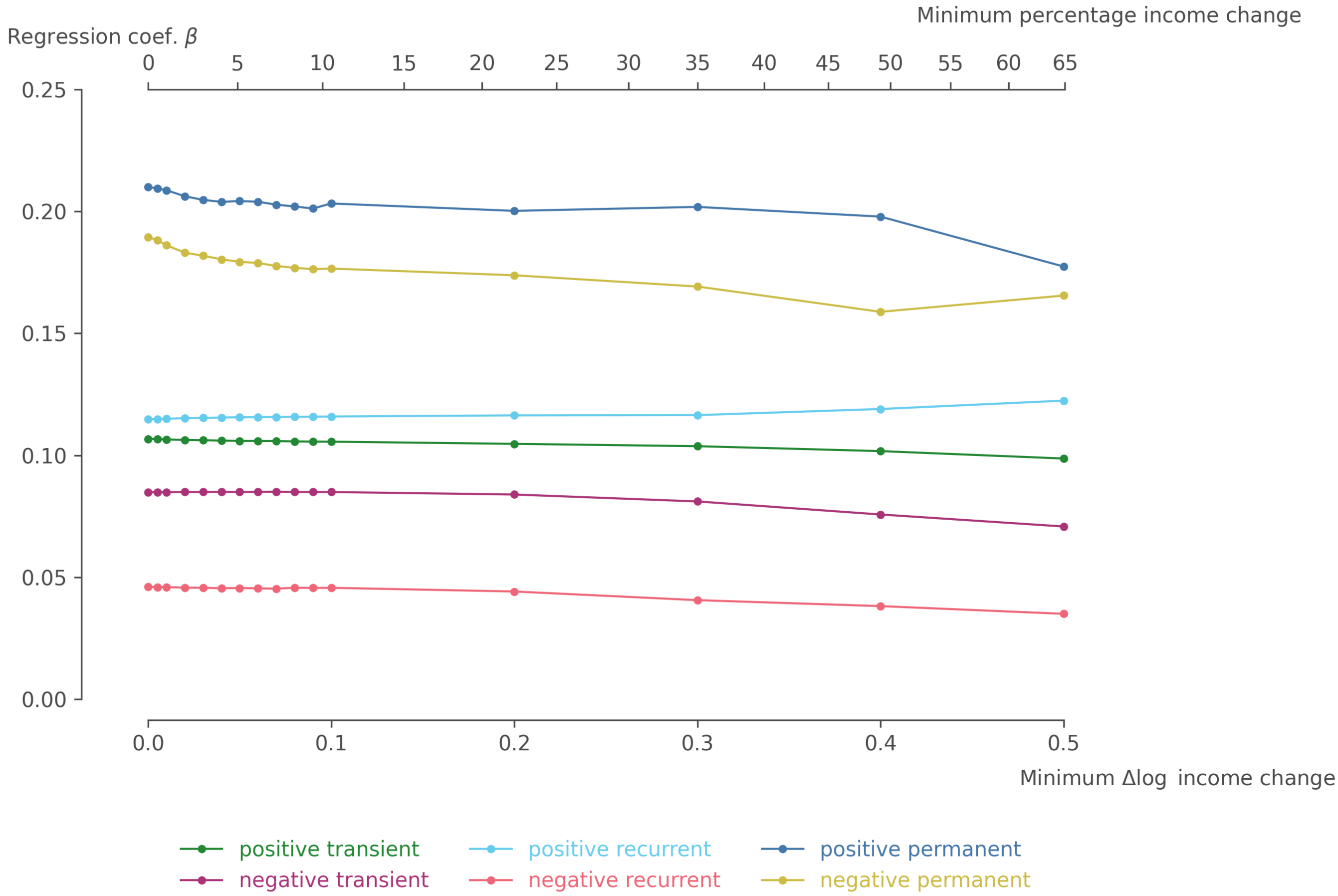

Figure 5. The lines in the figure represent the regression coefficients for each type of income change across different threshold values. We classify changes in the transitory component $\hat{\nu}_{i,t}$ only when they exceed the threshold defined in (5). To assess the sensitivity of our results to the chosen threshold, as determined by (6), we estimate the main specification (11) while varying the threshold in log income from 0, classifying all changes, to 0.5, classifying only changes that alter income by more than 50 %. Although no threshold is applied to the permanent component $\hat{P}_{i,t}$ we conduct a similar sensitivity test. The nearly horizontal lines indicate that the choice of threshold has minimal impact, suggesting that excess sensitivity is largely independent of the magnitude of the income change.

D Income change frequency plots

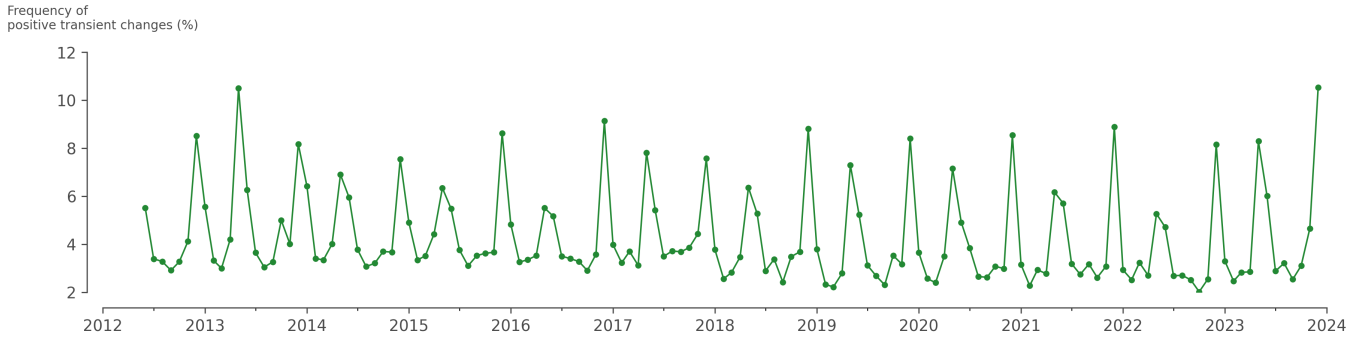

Figure 6. Relative frequency of positive transient income changes over time. The time series resembles that of positive recurrent changes in fig. 3a, but with a higher average baseline of approximately 4 %. Peaks in May and December, typically associated with holiday pay and end-of-year bonuses, are classified as transient if the household does not receive a similar payment in the following year, such as when a job change occurs after the payment.

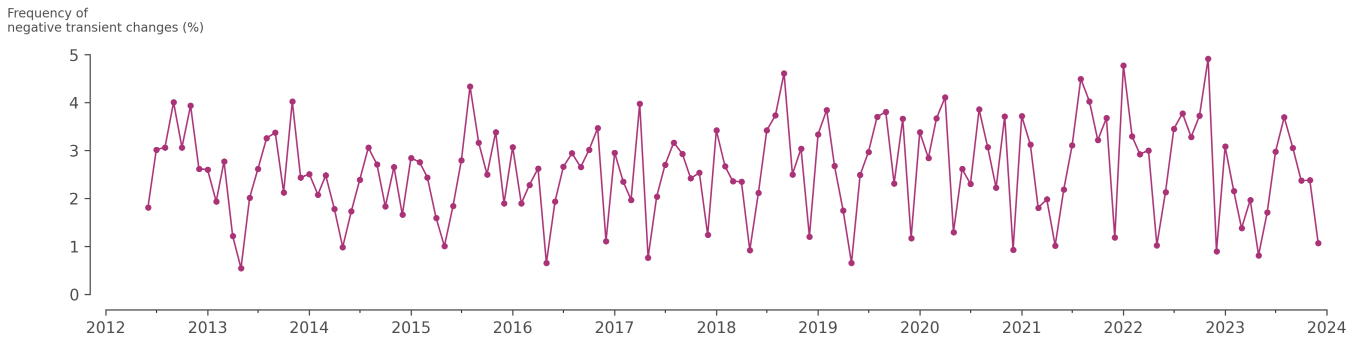

Figure 7. Relative frequency of negative transient income changes over time. The absence of a clear pattern suggests that these temporary negative income changes are primarily driven by household-specific events, rather than broader trends in the Belgian labour market.

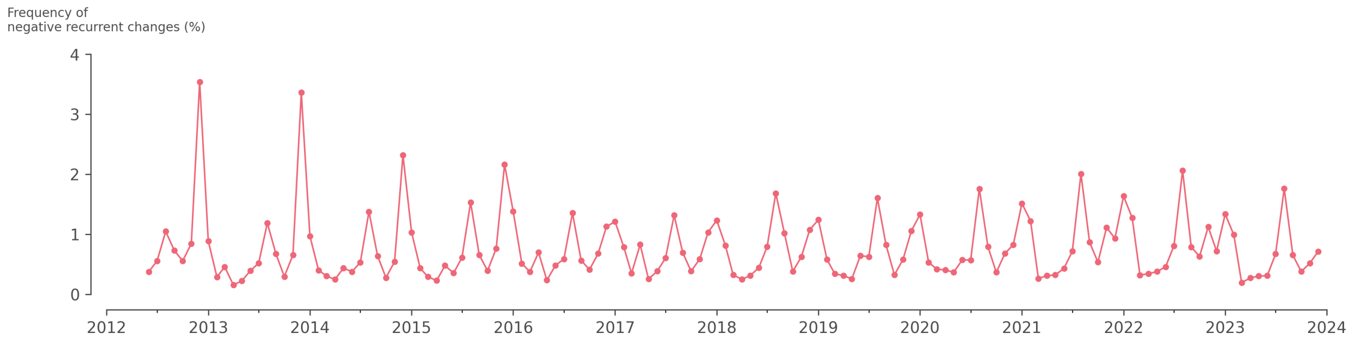

Figure 8. Relative frequency of negative transient income changes over time. Negative recurrent changes are rare in the Belgian labour market, accounting for only about 1 % of the observations. The small peaks observed near the winter and summer months suggest that seasonal employment may be a key driver of these events.

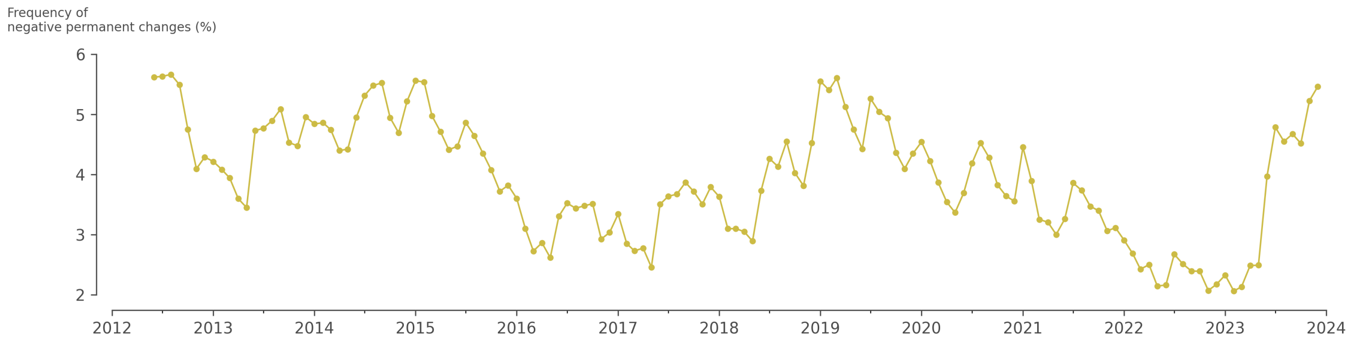

Figure 9. Relative frequency of negative permanent income changes over time. Three key periods stand out where these changes, including layoffs, job transitions, and reduced working hours, became more frequent. The spike in 2013–2014 likely reflects the aftermath of the Eurozone debt crisis, which prompted cost-cutting measures across Europe, impacting both public and private sector employment. The increase in late 2018 coincides with a global economic slowdown fueled by trade tensions and Brexit uncertainties, leading companies in Belgium to adjust workforce hours and roles. Finally, the rise from May 2023 onward likely responds to the energy crisis and high inflation in 2022–2023, as firms faced elevated operational costs and sought to stabilize finances by reducing staff costs.