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The Consumption Response to Labour Income Changes

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Abstract

We develop an income shock classification taxonomy that classifies income changes into 9 categories based on the magnitude, direction and permamency of the income change. Using 01/2017 – 06/2022 bank transaction data of Belgian employees and workers, we apply this classification on labour income changes to find that the elasticity to a positive recurrent labour income shocks is almost double that of a regular labour income change and a transient positive labour income shock. The effect significantly varies among different consumption durability types and is amplified in case of low levels of liquid wealth. Accounting for the heterogeneity in types of income changes is therefore important to understanding the multiplier effect of fiscal policy aimed at increasing available income.

Keywords: Income changes; consumption; liquid wealth; marginal propensity to consume

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1 Introduction

Recent economic crises have brought to the foreground that many households are ill-equipped to withstand even modest amounts of income and expense volatility (Narayan et al., 2022). Through tax policy and income subsidies, governments can have a large impact on labour income that vary in both magnitude, recurrency, and permanence (e.g. a one-time stimulus vs a persistent tax shift). Cost-benefit analysis of such policies requires the estimation of their total economic impact, which to a considerable extent depends on the consumption response to the policy-induced income change and the precise nature of the income shock (transient, level shift or recurrent).

Previous work has uncovered large heterogeneities in consumption responses to income changes driven by, among others, liquidity (Ganong et al., 2020; Jappelli and Pistaferri, 2020; Kaplan et al., 2014), perception on the expected versus unexpected nature of the income (Jappelli and Pistaferri, 2010), the sign and magnitude of the shock (Christelis et al., 2019), myopia or present-bias (Kőszegi and Rabin, 2009; Ganong and Noel, 2019), and the individual's wealth and age (Jappelli and Pistaferri, 2020).

Due to the fact that results in the literature originate from a vast amount of different research approaches and contexts, many questions however still remain unanswered. Do transient income changes yield a consumption response? How does consumption respond to predictable or anticipated income changes? Does the size of the consumption response depend on the sign of the income change, or is the effect symmetric? As noted by Gelman et al. (2020), the study of the consumption response to labour income changes is notoriously difficult as it depends, among other things, on the consumer's perception of the duration and severity of the income shock. Survey studies have been popular in the literature, because they allow researchers to formulate precise questions in the hope of identifying the consumption response to a specific type of income change. Though surveys allow for such specificity, they also tend to focus strongly on a singular type of change often of fixed sign, type, and magnitude. The literature also provides a large number of event studies that treat a specific income policy intervention as a quasi-experiment. While this alleviates the concerns about recollection bias and misreporting characteristic to surveys C. Moore et al. (2000), the specificity and atypical nature of the evaluated policy experiments should make researchers hesitant to extrapolate their findings to other comparable income changes[1]. This scientific caution against undue extrapolation is only reinforced by the fact that estimates often vary in orders of magnitudes across event studies of the same income change type (Havranek and Sokolova, 2020). There is thus a clear need for an framework that enables researchers to study multiple types of income changes at the same time and within the same sample. In this work, we seek to fill the gap.

In this paper, we use bank transaction data to study all monthly income changes of workers and employees. These income changes can originate from a multitude of reasons such as flexible working schedules, public policy interventions or life events. An exhaustive enumeration is elusive. Instead we take a data-driven approach and structure income change heterogeneity based on their magnitude, sign, and dynamic nature. This leads to a taxonomy of nine possible income changes: no shock, a positive/negative transient shock, a positive/negative level shift, a positive/negative recurrent shock, and positive/negative bounce back shock. Public policymakers have a direct impact on these income shocks, either by inducing certain shocks themselves or by amplifying or dampening them through e.g. taxation, income subsidies and other government policies. Understanding the consumption response to these income shocks is important for the evaluation of the macroeconomic multiplier of government intervention in response to these shocks and thus for assessing the government intervention's aggregate economic effects.

Policy interventions affecting the labour income distribution have been a powerful tool for governments to support their population, and the economy. Policies such as tax and labour market reforms, and income support policies, enable policymakers to directly affect

[1] Ganong et al. (2020) motivates this hesitancy by referring to the first stimulus checks that were sent out in 2001 in the US. At first sight, this event presents a perfect quasi-expertiment. However, Time Magazine reported that House cabinet members urged the public to use the stimulus to go on a national spending spree, which undoubtedly decreases the validity of any analysis results beyond that specific event.

the incomes of individuals. However, the net cost of such policies, and the effect on the population and the economy at large, critically depends on the consumption reactions to the income changes, also called Marginal Propensity to Consume (MPC). If people transfer the additional income to illiquid saving or investment products, this would reduce the macro-economic multiplier of the policy and thus increase its net cost. Inversely, if they react by increasing their consumption, this would lead to a higher GDP, an increase in tax revenues, a reduction of government debt, and thus a lowering of the net cost of the policy. Recent evidence shows that these government spending multipliers are influenced by the characteristics of the population and can be much larger than 1, even reaching values of up to 4 (Bernardini et al., 2020).

Designing (or evaluating) adequate policies thus requires a careful understanding of the micro-mechanisms at play. In this project, we leverage a unique, individual-level, panel dataset of bank transactions to study the drivers of heterogeneity in the consumption response to income changes. A key feature of our data set is that we can distinguish between consumption types (non-durable, semi-durable and durable) and account for a number of individual characteristics (age, marital status and wealth) when estimating the consumption response to income. This more granular approach is instrumental for targeted policy intervention. In particular, we expect a higher consumption response for permanent and recurrent income shocks than for transient shocks. We also hypothesize that the consumption response to income shocks is higher for individuals with low levels of wealth and for semi-durable consumption such as clothing.

We test these hypotheses using the monthly changes in labour income and consumption expenditures for employees and workers in Belgium over the period January 2016 – June 2022. Our approach involves analysing an anonymized dataset containing (non-identifying) personal characteristics and financial transactions of millions of clients of BNP Paribas Fortis in Belgium. For every client, we have, for each transaction, a record of the transaction time, the amount, and a label identifying the economic goal of the payment. Thanks to these labels, we are able to disentangle labour income from other incoming payments, and separate expenditures for consumption of goods from consumption of services and other outgoing transactions. We use the transaction labels to further decompose the consumption expenditures into expenditures for durable goods (*e.g.* a car), semi-durables (*e.g.* clothing) and non-durables (*e.g* food). We develop a decision tree that only uses the labour income data to classify labour income changes into one out of 9 income change categories. We then employ panel data regression models to these individual-level data on income and consumption to uncover the heterogeneity of consumption responses to different types of income changes.

Our main findings are as follows. Income shocks are very heterogeneous. Our study highlights 3 dimensions in which shocks exhibit strong heterogeneity. Firstly, the type of consumption matters. People react to both negative and positive shocks more strongly by respectively reducing or increasing their consumption of semi-durables rather than that of non-durables or durables. Secondly, there is a much stronger reaction to recurrent shocks and level shifts than to transient shocks. Finally, people with little liquid wealth react more strongly to income, regardless of the type of shock.

We contribute to the literature in a number of ways. Due to data restrictions and challenges in differentiating between different types of changes, the literature either looks very broadly at responses to changes in income, or very narrowly to one specific type of change (e.g. unemployment, tax rebate), often based on survey data with small sample sizes (Jappelli and Pistaferri, 2010). In this paper we follow a recent trend to use individual financial data for this purpose (Gelman et al., 2014; Baker, 2018; Ganong et al., 2020). We present a methodology to filter several types of income changes from these individual transaction-based income timeseries and analyse how consumption responses differ across different types of shocks. Finally we verify how these consumption responses are moderated by individual wealth and delve deeper into the nature of these consumption responses by separating durable and semi-durable from non-durable consumption.

Our results are relevant and important for policy makers as they provide insights on the conditionality in the effect of additional income (support) on consumption. In particular, our results suggest that policy measures aiming at increasing labour income may be especially beneficial for the sector of semi-durables, and that the consumption elasticity to income shocks is most pronounced when the measure is permanent or recurrent and targeted to the individuals with a low wealth.

2 Data

In this paper, we study the consumption responses to different types of income changes. To this end, we leverage an anonymized bank dataset from BNP Paribas Fortis (BNPPF) containing both non-identifying account details as well as all transactions involving these accounts. This anonymized dataset has several advantages over existing data sources: it allows us to construct monthly individual panels containing financial information such as liquid wealth, spending and income by category, as well as non-identifying personal characteristic such as age, gender, and civil state. Selection into the sample is only dependent on having a bank account at BNPPF, which holds a quarter of the commercial banking market in Belgium and is active across all regions in Belgium. The transactions dataset is enriched with transaction-level economic labels enabling differentiation of categories of income (e.g. labour income and pensions) and spending (e.g. durable consumption). This is in stark contrast to the often used small-sample surveys which can only cover a limited amount of topics, are often cross-sectional, and suffer from measurement error and recollection bias (C. Moore et al., 2000).

While the recent trend in leveraging third-party financial management and aggregator apps (Baker and Yannelis, 2017; Olafsson and Pagel, 2018; Gelman et al., 2020) eliminates the reporting shortcomings of surveys, concerns have been raised about selection bias and the salience effect of platform usage on financial behaviour (Baker, 2018). The benefits of commercial bank data have also been recognised by Ganong and Noel (2019), whose data and empirical approach to panel construction most resembles ours. The main limitations of our data are that clients might have bank accounts at other financial institutions, and that in-kind transfers are not observed. We assume most Belgians hold accounts at only one financial institution.[2]. This might not be the case for higher wealth individuals. They might spread their wealth across savings accounts from multiple banks in order to benefit from

[2]Anecdotally BNPPF has opened PSD2 mechanisms according to the open banking directive to allow clients to import bank accounts from other banks into one banking app or a third party financial aggregator. Less than 2 % of the clients that the bank considers active however use the functionality actively. There thus either seems to be a lack of people wanting to aggregate bank accounts in a single place, or there is simply no need to. Either way, the low numbers (weakly) support that consumption likely occurs from a single bank.

the Bank Guarantee Funds that protects 100 000€ per person per establishment. In this scenario, the bank accounts at different banks are savings accounts, which would not violate our assumption that most Belgians receive income and pay for expenditures with a single current account. If a person has current accounts at multiple banks that are all actively used to both receive income and finance their consumption, we might underestimate spending and as a result underestimate their sensitivity to labour income changes. In the remainder of this section, we explain how the analysis sample is selected and how the transaction-level data is aggregated into an individual-level panel dataset.

2.1 Source data

The BNPPF dataset contains an anonymized version of all financial transactions executed within the bank from January 2016 until June 2022 for more than 4.4 million Belgian retail clients. These transactions cover cash withdrawals, debit card purchases, and wire or SEPA transfers. For the card transactions, this results, on average, to about 65 million transactions per month totalling over 2 billion euro in volume. Beyond financial transaction data, non-identifying individual level data is also available for all clients. More specifically this covers monthly balances for every account, and demographic information including, age, gender, civil state and region of residence.

For every transaction, we observe the timestamp, an anonymized identifier of the counterparty, the value (in euro), the direction (debit/credit), and a label indicating the economic goal of the transaction. The augmentation of the data with the labels was done by proprietary processes at the bank leveraging both patterns in the communication and the metadata that accompanies every transaction and is only available to the bank. Below we outline which information these processes leverage to assign the labels relevant to our analysis.

For the identification of our income categories, namely *labour income*, *replacement income*, and *social security income*, the processes rely solely on patterns in the communication of a transaction. In Belgium, these sources of income are (partly) protected by law from debt confiscation. For this reason, organisations and institutions are obligated to include fixed patterns in the communication of these transactions such that these protections can be upheld[3]. Full details on which symbols must accompany which income types can be found in Appendix A. Since this law predates the start of our data, the quality of the income labels we use in this work is exceptionally high over our entire time frame.

For the identification of (different types of) consumption, the metadata of the transaction is used. This metadata includes a Merchant Category Code (MCC)[4] if the transactions occurred at a Point Of Sale (POS), the NACE sector code of the counterparty if said counterparty is a company, and a category code that indicates the technical type of transaction (e.g. ATM cash withdrawal).

The bank mapped these codes to the best of her abilities onto the Classification of Individual Consumption According to Purpose (COICOP) of the United Nations UN (2018) which also includes a durability type for every category. The different durability types in COICOP are:

- *Durables* (D): goods that can be used repeatedly or continuously over long periods of times that are significantly longer than one year and are often expensive. Examples include cars and refrigerators.
- *Semi-durables* (SD): goods that differ from durable goods in that their expected lifetime of use, though more than one year, is often significantly shorter and their purchase prices are substantially less. Examples include clothing, small household appliances and sports equipement.
- *Non-durables* (ND): mostly one-time-use goods. Examples include food, alcoholic beverages, and personal care products.
- *Services* (S): assistance or advice given to individuals.

[3]As mandated in the *Royal Decree of 4 July 2006 implementing Article 1411bis, § 2 and § 3 of the Judicial Code and establishing the entry into force of Articles 4 to 8 of the Act of 27 December 2005 containing various provisions*. Source: http://www.ejustice.just.fgov.be/eli/besluit/2006/07/04/2006009525/staatsblad.

[4]Every Point Of Sale terminal has to be registered to a merchant who is also obligated to report their Merchant Category Code to the terminal provider. The MCC is then linked to the POS terminal and is passed as metadata for every transaction that occurs through the terminal by the payment provider. A full list of MCC codes with their respective definition can be found at, for instance, https://usa.visa.com/content/dam/VCOM/download/merchants/visa-merchant-data-standards-manual.pdf.

This results in 58 consumption categories of which an exhaustive list and mapping to their durability type is given in Appendix B. Complications arise when companies provide several categories of consumption goods (e.g. a hypermarket sells both semi-durables such as clothing as well as non-durables such as food). Because the transaction metadata only allows to identify the type of counterparty and not the contents of the shopping basket, extra categories were added for these transactions which were assigned the *Mixed* (M) durability type. Similarly, the payment of credit card bills, since most goods or services can be paid with credit cards, are also labelled as *mixed*.

2.2 Constructing monthly income, consumption, and wealth panels

Constructing the monthly individual panels, leveraging all available information in the source data is done as follows. Firstly, we base our analysis on official calendar months[5]. For labour income, we straightforwardly sum up the labour income transactions per calendar month per individual. Similarly, we sum up replacement and social security income transactions per month to enable us to control for changes in these sources of income in our analyses.

Consumption is aggregated on a monthly basis per durability type. We define *total consumption* as the sum of all durability types. Note that we only include the actual credit card bill payments in the *total consumption*. We consider the moment when the payment is made as the moment when the consumption occured, even though the goods might have been received before the payment happened. If the individual credit card transactions were included in the month that they occurred, we would already be including a form of consumption smoothing through debt in our consumption measure and underestimate the actual response.

In the decomposition of the consumption sensitivity by durability type, we are limited to the categories of consumption that fall exclusively into one type of durability (i.e. not

[5]In future work we will account for the heterogeneity in timing of labour income payments. Complications, however, arise for those individuals who get paid across multiple dates in a month or get supplementary labour income such as holiday pay in separate transactions. We therefore leave this extension to future work and focus here on the average behaviour across these groups.

mixed). The mixed categories originate largely from companies that offer goods of multiple durability types (or both goods and services). As such, since we study changes, and thus estimate in differences over time, our estimates will be unbiased under the assumption that the average change in consumption of goods of a certain durability (e.g. *semi-durable*) is the same in stores who are labelled as that specific durability type (e.g. clothing stores) as in stores that are labelled as *mixed* (e.g. hypermarkets). If, for instance, individuals would buy less clothing in response to an income change but only do so at hypermarkets (which are *mixed* durability), this assumption would be violated[6]. Similarly, since we observe different methods of payments, a similar assumption must also hold over these different payment methods. If individuals suddenly move all their semi-durable consumption to cash, we will underestimate the actual consumption response for semi-durable goods.

The non-identifying individual data is provided on an end-of-month basis. From the end-of-month balances of the accounts, we construct a monthly measure of liquid financial wealth per individual defined as the sum of the balances across their accounts that can, if necessary, be liquidated on short notice. This includes the checking accounts, (term) savings accounts, pension savings accounts, and investment accounts.

2.3 Analysis sample

Our analysis sample is drawn from the 4.4 million clients who have an account in the BNPPF data. The unit of observation is client-by-month, from January 2016 through June 2022.

We restrict our analysis sample in two ways. The first is motivated by the fact that some individuals might have bank accounts at multiple financial institutions and our inability to observe spending out of non BNPPF bank accounts. To alleviate this constraint, we limit our sample selection to those *active clients* that use BNPPF as their primary bank. Cost of living statistics in Belgium (Storms et al., 2009) indicate that, taking into account government support, minimum income laws and minimal monthly consumption requirements, in 2009

[6]In future work, we plan to use a combination of consumption surveys and yearly reports of companies that are labelled as mixed to distribute every €1 spend in the mixed categories into the COICOP durability types.

a person needed an absolute minimum income of 650€ per month and a consumption of 145€ per month on food and drinks to fulfil her basic needs. We therefore restrict our analysis sample to those individuals who have a total income and non durable consumption above these thresholds (corrected for inflation with respect to the starting date of our sample) during the entire time frame (the *active clients*), retaining 1 % of the original sample[7]

To study the representativeness of our sample, we construct a measure of fiscal income which is as close as possible to the definition of that of the Belgian statistics institute (StatBel). We compare their published distribution with fiscal income we identify across the complete BNPPF sample in table 1 and find that these distributions are largely the same.

Table 1: Comparison between the fiscal income distribution of StatBel with the total labour income distribution for all clients in the BNPPF dataset of 2019. Total labour income is the sum of regular labour income, unemployment benefits, other replacement incomes and pensions.

Decile	Percentile	Statbel	Our results
1		543.00	567.61
2		1227.67	1287.33
3		1470.00	1667.23
4		1771.08	1895.45
5		2122.92	2166.65
6		2563.58	2532.32
7		3126.00	3076.98
8		4008.75	3912.22
9		5651.75	5403.65
	91	5901.67	5664.68
	92	6180.00	5974.14
	93	6493.00	6311.64
	94	6866.42	6761.84
	95	7319.58	7315.00
	96	7893.50	8016.60
	97	8687.75	9059.51
	98	9945.17	10 688.72
	99	12 669.58	14 241.69

[7]To check the robustness of this criterion, we will, in future work, compare it to several other *active client* criteria used in the literature.

The second restriction is motivated by our research goal, which is to measure consumption sensitivity to labour income changes that could beinduced by policy. To this end, we further restrict our analysis sample to those individuals that receive at least one labour income payment per month during the entire time frame. With this filter, we actively exclude full unemployment because this is not a labour income change that policy actively tries to induce. Our final sample includes 45 578 individuals. This is 1 % of all clients who make or receive a transactions in our sample from January 2016 until June 2022. For every client, we have 78 individual-month observations. Of these 78 individual-month observations, we can identify and classify shocks in 53 of these monthly observations leading to a final sample of 2 415 634 observations. Further details on the number of time periods in the final sample can be found in 3.2.

Despite the richness of the dataset, it is difficult to distinguish (single) individuals from households in our sample. The reason are twofold. Firstly, identifying household relationships between clients partially relies on the members of the household sharing this information with the bank. Secondly, shared account are assigned to the primary holder of the shared account. This is not an issue if a couple receives both their incomes on the shared account and does all their spending from this account. This will however inflate the average income and consumption of individuals in our sample.

3 Methodology

Life events, as well as policy measures can lead to significant changes in monthly labour income. These changes come in various dynamics. A one-time income subsidy is transient, while a pay rise due to a change in taxation is persistent. Since our goal is to understand if and how different types of labour income changes affect monthly consumption, we need a framework to extract and classify them.

To this end, we construct a taxonomy of the different types of income changes by combining the types of changes that have been defined and studied in literature. A framework is then designed that can automatically extract and classify the types of income changes from labour income time series. Finally, we apply this to our individual panel data and validate the results by comparing our income change labels with changes known from the Belgian context.

3.1 Taxonomy of income changes

3.1.1 Income change taxonomy framework

In a first step to our taxonomy, we follow Blundell et al. (2008); Jappelli and Pistaferri (2010) in decomposing log-labour income into two components: a *stable component* ($S_{i,t}$), and a *transient component* ($\nu_{i,t}$).

$$\text{Inc}_{i,t} = S_{i,t} + \nu_{i,t}. \tag{1}$$

Secondly, we take inspiration from the work of Ganong et al. (2020), who studies typical month-to-month income changes, and subdivide our transient component further into: an *atypical transient component* ($T_{i,t}$) (e.g. missing work due to illness) and a *typical transient component* ($Z_{i,t}$) (e.g. exogenously driven variable working hours).

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

Since we look at monthly labour income changes, we need to account for the fact that the changes in the stable component could contain seasonality. Otherwise, monthly changes that are due to this seasonal stable income (e.g. holiday pay) will be misclassified as transient. We therefore subdivide the changes in the stable component into: a *level shift* ($LS_{i,t}$) (e.g. increase in basic compensation) and a *recurrent change* ($RC_{i,t}$) (e.g. end-of-year bonus).

$$\Delta S_{i,t} = LS_{i,t} + RC_{i,t}. \tag{3}$$

Combining (1) with (2), taking the first difference, and then filling in (3) gives us our final taxonomy of labour income changes:

$$\Delta \text{Inc}_{i,t} = LS_{i,t} + RC_{i,t} + \Delta T_{i,t} + \Delta Z_{i,t}, \tag{4}$$

with $\Delta\text{Inc}_{i,t}$, the monthly labour income change, subdivided into the month-on-month: *level shifts* ($LS_{i,t}$) (e.g. pay rise); *recurrent changes* ($RC_{i,t}$) (e.g. holiday pay); change in the *atypical transient component* ($\Delta T_{i,t}$) (e.g. having to miss work due to illness); and change in the *typical transient component* ($\Delta Z_{i,t}$) (e.g. exogenously driven varying working hours).

3.1.2 Empirically identifying income changes

We now need an empirical strategy to differentiate between these different types of income changes in data. Before doing so, let us first fix notation. We use $m_{i,t}$ (resp. $y_{i,t}$) to denote the MoM (resp. YoY) log-difference in labour income such that:

$$m_{i,t} = \text{Inc}_{i,t} - \text{Inc}_{i,t-1} \tag{5}$$

$$y_{i,t} = \text{Inc}_{i,t} - \text{Inc}_{i,t-12}. \tag{6}$$

To decompose $m_{i,t}$ as in (4), we first separate the atypical income changes from the typical changes. We adopt the reasonable assumption that the distribution of typical changes only has a negligible overlap with the distribution of atypical changes. An atypical income change is then an outlier under the distribution of typical income changes. This allows that individuals will have a different consumption response when the stable or atypical transient component is larger in magnitude than the vast majority of typical changes. The economic rationale for this builds on the same ideas that Ganong et al. (2020) uses as motivation to look at typical income changes, namely that most consumption response literature focuses on *unusual* windfall income (e.g. lottery) but that this might not be indicative of responses to the typical temporary income variation experienced by the individuals on a month-to-month basis. We therefore want to differentiate between these typical and atypical changes in our framework and formalise the above as follows:

$$\Delta Z_{i,t} = m_{i,t} \quad \text{if} \quad |m_{i,t}| < \kappa_{i,t}^{\text{MoM}} = c^{\text{MoM}} \sigma_{i,t}. \tag{7}$$

with c^{MoM} a constant, and $\sigma_{i,t}$ the conditional standard deviation of the change in income around its stable component at time t when no atypical income change occurred. We will discuss how we estimate $\sigma_{i,t}$ and calibrate the threshold in section 3.1.4.

Equation (7) gives a statistical meaning to the concept "atypical", namely that its magnitude is probabilistically infrequent relative to the fluctuations experienced around stable income at time t. The constant c^{MoM} can then be interpreted as a parameter to change the restrictiveness ($\kappa_{i,t}^{\text{MoM}}$) applied in the definition of "atypical" [8].

Table 2: Identification of income change as a change in the *typical component* (TC) versus a change in the *atypical component* (AC).

$\lvert m_{i,t}\rvert \leq \kappa_{i,t}^{\text{MoM}}$	$m_{i,t} > \kappa_{i,t}^{\text{MoM}}$	$m_{i,t} < -\kappa_{i,t}^{\text{MoM}}$
No Income Shock (*NIS*)	Positive Atypical Change	Negative atypical change

In Table 2, we summarise how the rules to identify the month-on-month *typical changes*, also called No Income Shocks (*NIS*) from the *atypical component* changes.

3.1.3 Classification of income changes

A consequence of our approach is that our classification scheme will bundle all changes under the threshold $\kappa_{i,t}^{\text{MoM}}$ as typical and not allow for further differentiation in transient or stable. We argue that this does not pose a large constraint since firstly, the changes are small by construction and thus any heterogeneity would therefore be of a lesser economic

[8] In line with the characteristics view in Gelman (2021), The parameter c^{MoM} could also be interpreted as a personal characteristic of individuals. What one individuals might experience as an atypical income change and react on in one way, another might perceive as typical and react on in another way. Estimating this value per individual from data would however require at least one identifying assumption about consumption response to either typical or atypical income changes. Since we don't want to make any prior assumptions on the consumption response, we leave the exploration of this avenue to future work.

significance. Secondly, since these are changes that the individual often experiences, there is no a priori reason to expect that one would respond markedly different to stable income changes within the bounds of the transient changes experienced on a month-to-month basis.

Having identified the typical from the atypical income changes, we therefore now focus on further subdividing the atypical changes into transitory changes, level shifts, and recurrent changes. To make clear that we are only looking within the bounds of the atypical changes, we will refer to atypical changes as shocks and refer to the three components as transitory shocks, level shocks, and recurrent shocks respectively in the remainder of this paper. To distinguish between these three categories, we have to extend our classification scheme to include more temporal dynamics than just backward-looking month-on-month. We consider two additional reference points. First, we verify whether in the next month there is no reversal of income. Second, we verify whether next year's income has reverted. The reversal detection is based on comparing next month's MoM income growth $m_{i,t+1}$ and next year's YoY income growth $y_{i,t+12}$ with a threshold such as in (7).Note that both compare a future level of income with the income affected by the atypical income shock that needs to be classified.

While the choice of adding a one-month look ahead reference point is obvious to identify transience, the choice of a one-year look ahead reference points was chosen as follows. We need to capture temporal recurrence in month-on-month changes. If a change is truly transient, it should not be a level shock, nor a recurrent shock. To do so, we need to define an horizon at which something is considered stable. One-year look ahead ($y_{i,t+12}$) seems to be the most natural choice. The motivation is twofold. First, in order to detect level shocks, we need to set the horizon beyond which a level shift is considered permanent by individuals (and thus a true change to the stable component). According to Benartzi and Thaler (1995), most people's horizon seems to be one year. Second, to detect recurrence, we need to set the frequency of recurrence considered. A one-year window again seems to be the natural source since most employment-related income events are yearly (e.g. end-of-year bonuses and holiday pay). There may be events with a higher frequency, but regardless of their higher frequency, they still need to have a yearly recurrence to fit into the yearly cycle companies typically follow. A detailed description of the resulting rules of classification are given in table 3 and table 4. Note that for the one-year look ahead reference point, we use thresholds $\kappa^{NT}_{i,t+12}$ and $\kappa^{PT}_{i,t+12}$. Conceptually, their use-case in the classification scheme is the same as $\kappa^{MoM}_{i,t}$ but their estimation differs. The reasons why are explained in section 3.1.4 but for consistency's sake, we already use the correct notation here.

Table 3 presents the income shock labelling in case of a positive atypical monthly labour income growth. The first question is thus whether the observed income shock is compatible with a shock in the stable income part. We assume that this is not the case when the next year's income is substantially lower than the current income. We label this case as a *Positive Transient Shock (PTS)* in the third column of table 3.

An atypical positive income change (or positive income shock) is considered a shock in the stable component when next year's monthly income is not substantially lower than the increased income of the current month. Consistent with our description of the stable component, we classify the atypical stable income changes (or stable shocks) as either a level shock or a recurrent positive shock with a cycle of one year. These two shocks includes all income payment shocks with a 1, 2, 3, 4, 6 and 12 months periodicity. In the case of a *Positive Recurrent Shock (PRS)* with annual periodicity, we expect monthly income to drop in the next month and increase again in the next year. In contrast, in case the income shock is driven by a level shock, we should observe that both next month's and next year's income are at similar levels as the current month. We refer to the latter as a candidate case for a *Positive Level Shock (PLS)*. These candidate cases can include both level shifts driven by true economic events (e.g. promotions and pay rises) as well as reversions (or bounce backs) of transitory shocks (e.g. returning to ones stable income component after having received a yearly bonus). Since the nature of these two is vastly different, we classify them separately. As such, only positive income shocks that have not reverted in the following month or year, and that are not preceded by a negative transient or recurrent shocks, are labelled as *Positive Level Shock (PLS)*. Those that are preceded by a negative transient or recurrent shocks are referred to as *Positive Bounce Back (PBB)*. As far as the authors are aware, no research has been done on the consumption response to such bounce backs. We therefore exclude bounce backs from our analysis of consumption response.

An analogous reasoning can be applied in case of negative atypical changes. Table 4 shows the decision rules that lead to assigning the negative income shocks to the four possible labels: *Negative Transient Shock (NTS)*, *Negative Recurrent Shock (NRS)*, *Negative Level Shock (NLS)* or *Negative Bounce Back (NBB) income change*.

There a number of limitations of the proposed income change taxonomy. First, what we classify as typical income changes includes both transient and stable changes. As mentioned, this is not a large limitation since, by construction, the economic significant of this class will be low. Second, we are unable to identify the different components in compounds shocks. Here we make the implicit assumption that the label is assigned to the dominant shock for the observed monthly income dynamics. We use simple rules similar to the ones used in technical trading analysis. More complex procedures involving different types of time series component tests are available (see *e.g.* Tsay et al. (2000)). While we believe they are of value for the detailed analysis of a specific time series, we advocate for simple transparent rules in a large-scale setup as ours with tens of thousands of time series to analyse.

Table 3: Classification of a positive atypical income change as a positive transient shock, positive recurrent shock, positive level shock or positive bounce back income change

		Is *next year*'s income substantially lower than the income of this month?	
		Yes $y_{i,t+12} < \kappa^{\mathrm{PT}}_{i,t+12}$	No $y_{i,t+12} \geq \kappa^{\mathrm{PT}}_{i,t+12}$
Is *next month*'s income substantially lower than the income of this month?	Yes $m_{i,t+1} < -\kappa^{\mathrm{MoM}}_{i,t}$	Positive transient shock (*PTS*)	Positive recurrent shock (*PRS*)
	No $m_{i,t+1} \geq -\kappa^{\mathrm{MoM}}_{i,t}$	Positive transient shock (*PTS*)	Positive level shock (*PLS*) (if not preceded by negative recurrent or transient)
			Positive bounce back (*PBB*) (if preceded by negative recurrent or transient)

Table 4: Classification of a negative atypical income change as a negative transient shock, negative recurrent shock, negative level shock or negative bounce back income change

		Is *next year*'s income substantially higher than the income of this month?	
		Yes $y_{i,t+12} > \kappa^{\mathrm{NT}}_{i,t+12}$	No $y_{i,t+12} \leq \kappa^{\mathrm{NT}}_{i,t+12}$
Is *next month*'s income substantially higher than the income of this month?	Yes $m_{i,t+1} > \kappa^{\mathrm{MoM}}_{i,t}$	Negative Transient Shock (*NTS*)	Negative Recurrent Shock (*NRS*)
	No $m_{i,t+1} \leq \kappa^{\mathrm{MoM}}_{i,t}$	Negative Transient Shock (*NTS*)	Negative Level Shock (*NLS*) (if not preceded by positive recurrent or transient)
			Negative bounce back *(NBB)* (if preceded by positive recurrent or transient)

3.1.4 Calibration

The above taxonomy defines the general rules for classifying the income changes into nine possible categories. The concrete implementation requires a calibration of the time series of thresholds $\kappa_{i,t}^{\text{MoM}}$ and $\kappa_{i,t}^{\text{YoY}}$ used in the classification rules. In our large-scale setup, we recommend a data-driven calibration of these cutoff values aimed at controlling the number of false positives and achieving power to detect the income shocks. The approach is designed the be robust to time-variation in the income process and the model risk related to the unknown types and quantity of income shocks in the data used for calibration. Several other robust scale estimates can be considered (see *e.g.* Gelper et al. (2009), Boudt et al. (2011) and Andersen et al. (2012)).

The specific approach we use is inspired by the literature on robust outlier detection (see *e.g.* Maronna et al. (2019)). We calibrate $\kappa_{i,t}^{\text{MoM}}$ in order to separate the typical transient observations from the shock observations in $m_{i,t}$ under the assumption that the typical transient observations of log-income are normally distributed with a locally constant mean and variance and no autocorrelation: $\text{Inc}_{i,t-s} \sim N(c_i, \zeta_i^2)$ for $s = 0, \ldots, L-1$. If the window length $L \geq 2$, then $m_{i,t} = \text{Inc}_{i,t} - \text{Inc}_{i,t-1} \sim N(0, \sigma_i^2)$ with $\sigma_i^2 = 2\zeta_i^2$. Under this framework, it suffices to have a reliable estimate of σ_i to control for the false positives in the detection of income shocks.

There are a number of challenges for accurate estimation of σ_i. First, the model assumptions are an approximation of the true income data generating process. The larger the estimation window length L is, the less accurate the approximation becomes. Second, there can be a potentially large proportion of income shocks in the estimation window. The classical standard deviation estimation is inflated by such outliers which would lead to an under-detection of income shocks. To avoid such outlier masking, a robust estimator is needed such as the median absolution deviation (mad).

It seems natural to estimate σ_i using the mad of the monthly labour income observations over a window for which the income fluctuates around the same level. In practice, we need a large enough window to achieve a sufficient degree of accuracy and robustness. In the application, we take 12 observations leading to the concern that this time series may be characterised by a level shift leading to a bias in the mad estimator. A solution is to work with the income observations that are centered around a running median income. This approach remains consistent in case of no change in income level while remaining reliable if such a level shift occurs. This leads to the following local scale estimate :

$$\hat{\sigma}_{i,t} = \max\left\{\sqrt{2}\,\mathrm{mad}(\mathrm{Inc}_{i,t-12} - \overline{\mathrm{Inc}}_{i,t-12}, \ldots, \mathrm{Inc}_{i,t-1} - \overline{\mathrm{Inc}}_{i,t-1}); \varepsilon\right\}, \tag{8}$$

where $\varepsilon = 0.5\%$ safeguards the scale estimate against implosion to 0. This choice is motivated similar to the choice of not differentiating between typical income changes, namely that anything below $\varepsilon = 0.5\%$ will be of low economic significance. The factor $\sqrt{2}$ is needed to map the robust scale estimate of log-income to the scale of the MoM income growth. The income series are centered around a running median of 6 observations:

$$\overline{\mathrm{Inc}}_{i,t} = \mathrm{median}(\mathrm{Inc}_{i,t-1}, \ldots, \mathrm{Inc}_{i,t-6}). \tag{9}$$

The window length of six monthly observations strikes a balance between the consumption's sensitivity to a change in the income level, on the one hand, and the estimation efficiency of using a higher number of observations when the level is constant, on the other hand. Short windows lead to noisy estimates but a high sensitivity to a change in level. At the extreme, a window size of 1, coincides with estimating the mad using the MoM income growth series. This series is nearly insensitive to level shifts, but this comes at the expense of a higher sensitivity to transient and recurrent shocks. An analysis of the variability of the MAD estimator (available from the authors upon request) reveals that the mad estimate stabilises when using a window size of 6 months for the running median in (9).

The threshold value for the MoM separation of typical versus atypical observations is then set as a multiple c^{MoM} of the local scale estimate:

$$\kappa^{\mathrm{MoM}}_{i,t} = c^{\mathrm{MoM}} \hat{\sigma}_{it,}. \tag{10}$$

This threshold specification can be interpreted as an estimate of the quantile of the MoM income growth series for a typical month in which there is no change in the stable and atypical transient income component in (4). The multiple c^{MoM} determines the number of shocks that are detected. Lower values of c^{MoM} lead to a large number of income changes detected as atypical income changes, and vice versa. The constant c^{MoM} needs to be high enough to avoid a large number of spurious atypical income detections, but small enough to have enough power to detect the relevant shocks. For the exact calibration of c^{MoM} we draw inspiration from the critical values of a one-sided test, and accordingly set $c^{\mathrm{MoM}} = 1.645$, which is the 95 % quantile of the standard normal distribution.

The YoY threshold values $\kappa^{\mathrm{PT}}_{i,t+12}$ and $\kappa^{\mathrm{NT}}_{i,t+12}$ determine the separation between a transient income shock and a non-transient atypical income change. In case of a positive (resp. negative) atypical income change, the shock is transient when the next year's income is substantially lower (resp. higher) than the current month's income. Consider the case of a negative shock. As can be seen in table 4, the shock is classified as transient when $y_{i,t+12} > \kappa^{NT}_{i,t+12}$. Similarly, for positive shocks, there is only transience if $y_{i,t+12} < \kappa^{PT}_{i,t+12}$. In both cases, we observe that, the higher is the threshold, the less atypical observations are classified as transient, and vice versa.

To control for the number of false positives, we rely on the same reference model for the YoY income growth series as for the MoM income growth series, namely that, if there is no change in the stable and transient component, then $y_{i,t+12} = Inc_{i,t+12} - Inc_{i,t} \sim N(0, \sigma_i^2)$. One caveat is that, for a 12-month period, we may lack precision to detect transient shocks when there is a change in income level over the 12-month period. We adjust for this by adding a mean estimate in the quantile-based specification of the YoY threshold. Using the running 6-month median values for this, this then leads to the following specification for the YoY threshold:

$$\kappa^{\mathrm{PT}}_{i,t+12} = -c^{\mathrm{YoY}}\hat{\sigma}_{i,t} + \left(\overline{\mathrm{Inc}}_{i,t+12} - \overline{\mathrm{Inc}}_{i,t}\right)$$
$$\kappa^{\mathrm{NT}}_{i,t+12} = c^{\mathrm{YoY}}\hat{\sigma}_{i,t} + \left(\overline{\mathrm{Inc}}_{i,t+12} - \overline{\mathrm{Inc}}_{i,t}\right),$$

with $c^{\mathrm{YoY}} \geq 0$. Note that the proposed YoY approach is then equivalent to comparing the change in the YoY centered log-income with the diagnostic threshold used when the mean of $y_{i,t+12}$ is zero:

$$y_{i,t+12} < \kappa^{\mathrm{PT}}_{i,t+12} \iff \left(\mathrm{Inc}_{i,t+12} - \overline{\mathrm{Inc}}_{i,t+12}\right) - \left(\mathrm{Inc}_{i,t} - \overline{\mathrm{Inc}}_{i,t}\right) < -c^{\mathrm{YoY}}\hat{\sigma}_{i,t}$$
$$y_{i,t+12} > \kappa^{\mathrm{NT}}_{i,t+12} \iff \left(\mathrm{Inc}_{i,t+12} - \overline{\mathrm{Inc}}_{i,t+12}\right) - \left(\mathrm{Inc}_{i,t} - \overline{\mathrm{Inc}}_{i,t}\right) > c^{\mathrm{YoY}}\hat{\sigma}_{i,t}.$$

In the application, we set $c^{\mathrm{YoY}} = 1.645$, which is the 95 % quantile of the standard normal distribution. In the robustness analysis we illustrate the sensitivity of our results to the threshold choice.

3.2 Application of the income change classification

We now illustrate the application of the above taxonomy to a monthly labour income time series from our data. Figure 1 plots the income series of a random individual in our data set. From top to bottom: the first panel shows the monthly labour income series in euro; the second panel below shows the running 6 month median; the third panel shows the MoM income growth series together with the diagnostic MoM thresholds; and the bottom panel shows the YoY series with the diagnostic YoY thresholds.

The top panel is annotated using the labels of the income change classification. Note that the labels are missing for the first and last year of the data. This is true for all individuals. The reason is that we cannot label these income changes due to requirements of initialisation of the threshold calibration and the needed availability of the next year's monthly income.

More specifically, the estimation of the MAD requires to first center the log-income around the running median of the prior six months log-income. The mad calculation is done with a similar moving window of 12 months. Combined, this procedure requires a burn-in period of 18 observations. To limit the number of lost observations, the mad is calculated as soon as the moving window has 6 observations, reducing the required observation to start identifying shocks to 12. Finally, to identify bounce backs the shock of the previous period must be known. This removes the first observation of the period in which shock can be identified. As such we can only label income changes from the second month of the second year of income observations until the penultimate year.

A visual inspection of Figure 1 confirms that the classification approach works as expected. The method is powerful enough to detect the atypical income change observations, and exploits the information in the MoM and YoY income growth series to classify these atypical income changes as designed. We observe a large number of positive recurrent shocks followed by a negative bounce back. The running 6-month median income of this individual is slightly decreasing, which is explained by the negative level shocks detection. A visual analysis would pinpoint and classify the atypical observations in a similar way as done by the algorithm. The practical difference is the scalability of the proposed algorithm allowing to classify thousands of income changes in a matter of seconds.

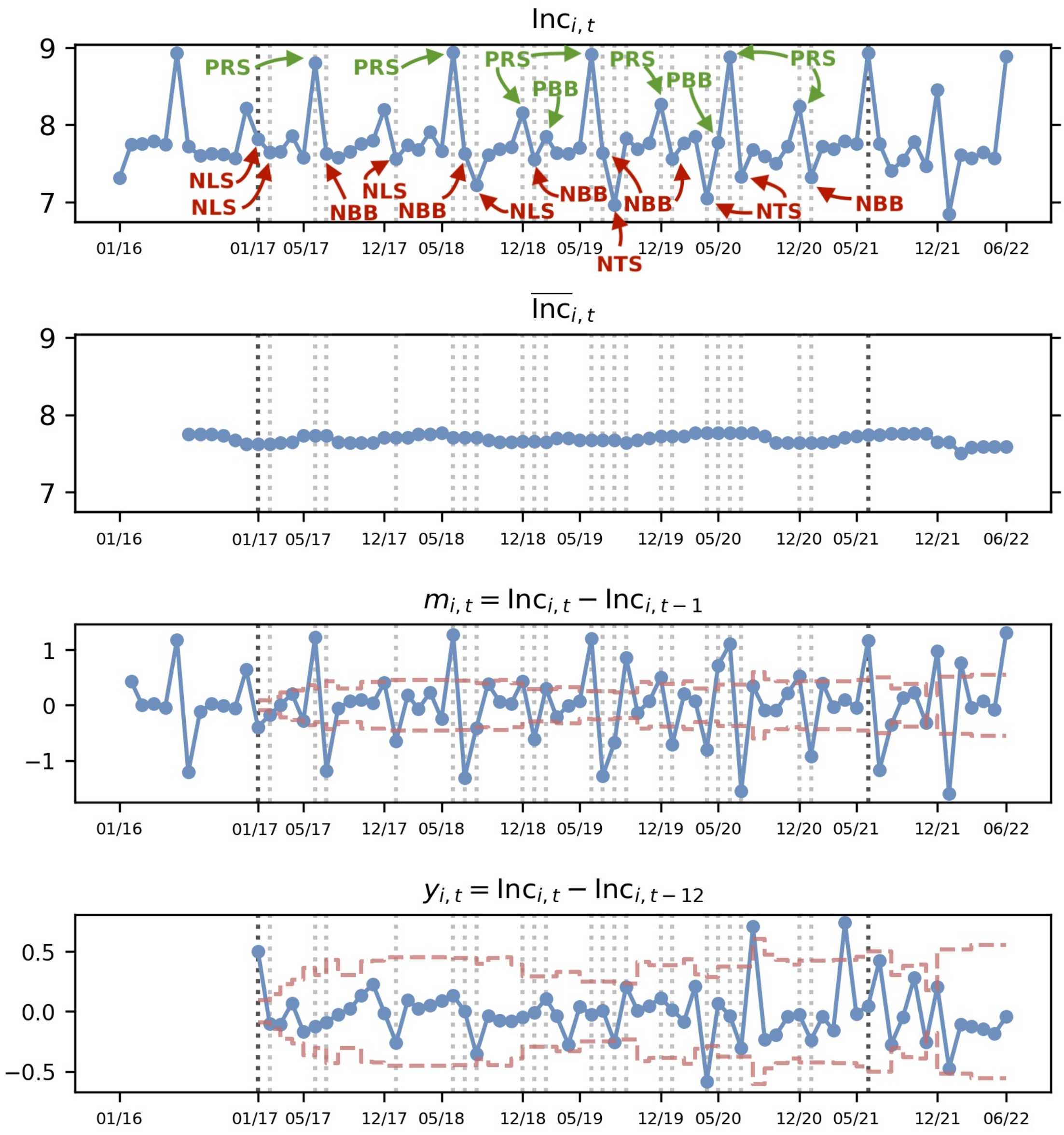


Figure 1: Annotated monthly income process of a random BNPPF client. The top row shows the income plot with on the left axis the income in log levels and on the right in levels. The second row show the stable income as approximated with $\overline{\text{Inc}}_{i,t}$. The third row and fourth row are the differenced series, respectively the $m_{i,t}$ and $y_{i,t}$ series both in log differences. The dark red boundaries in the bottom 2 plots is the MAD timeseries as calculated with (8). The vertical grey lines indicates shocks as identified by $|m_{i,t}| > \kappa_{i,t}^{\text{MoM}}$. The vertical black lines indicate the start and end of the period for which shocks can be identified. Finally, in the top plot the shocks are labelled according to the shock classification scheme of table 2, table 3 and table 4 where green shocks are positive shocks and red shocks are negative.

3.3 Income change occurrence patterns

The above analysis shows the results for one individual. We now extend our analysis to all individuals in our sample over the period January 2016 until June 2022. In Figure 2 we report the monthly distribution of income change types for every month. We see that positive recurrent shocks dominate in May and December, which is consistent with the payment of holiday pay and end-of-year bonus in Belgium.

To visualise the sequential relation between income change types, we draw a Sankey plot for the sequential occurrence of different pairs of income changes in Figure 3. Panel (a) of Figure 3 shows the Sankey plot for all income changes. Note first that one third of income changes are detected as atypical. The most prevalent atypical income changes is a positive recurrent shock, and its reversal shock, the negative bounce back. For clarity, we repeat the visualisation in panel (a) of Figure 3 in panel (b) but drop the No Income Shock (NIS) and Bounce Back (PBB and NBB) classes from the left-hand side.

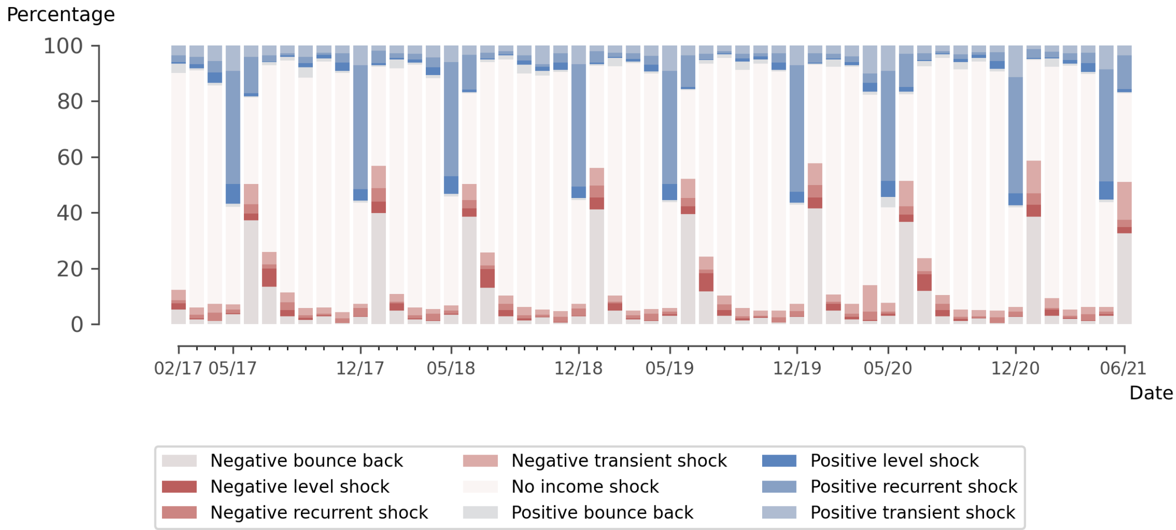
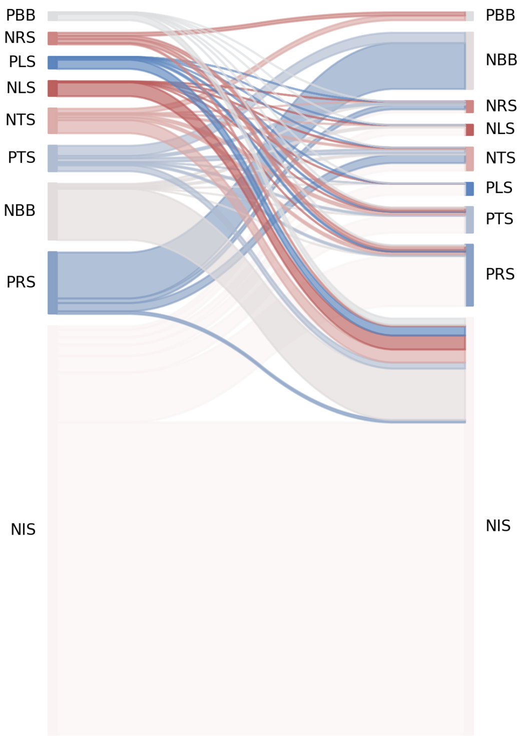
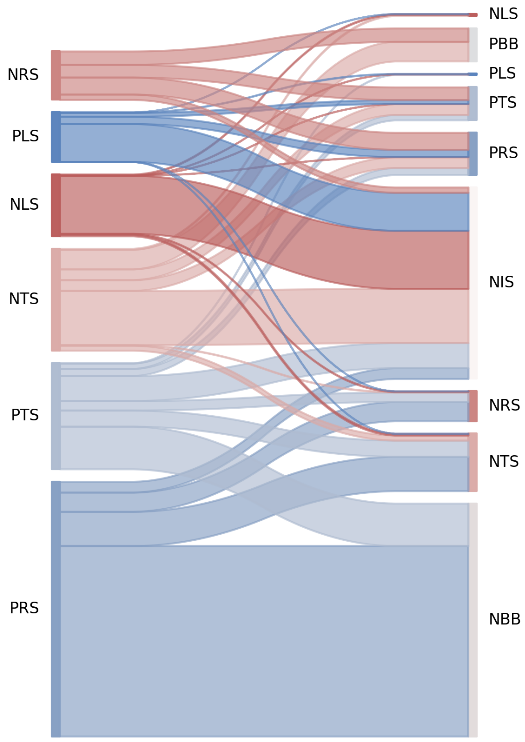


Figure 2: Distribution of the 9 types of income changes for every month in our sample. For every month, the frequencies are grouped with the positive shocks, in blue, at the top, the no income shock in the middle and the negative shocks, in red, at the bottom. Belgian's income is dominated by two positive recurrent shocks which occur in May and December. In these months, most Belgians receive, respectively, their yearly vacation pay and the end-of-year bonus. Following these months, we observe a lot of negative bounce back events. Income in the remaining months of the year is a lot less volatile on average.



(a) Sankey plot showing consecutive events where the initial events include both shocks, bounce backs and no income shock.



(b) Sankey plot showing consecutive events where the initial events include only events identified as shocks.

Figure 3: Sankey plots of consecutive monthly income change types. Positive shocks are in blue and negative shocks are in red.

4 Results

We have unravelled the different classes in income change. In this section we address our main research question about how much this income heterogeneity matters for explaining the monthly consumption response to labour income variation on income shocks. Below we first introduce the panel regression specification used. We then discuss our main findings.

4.1 Descriptive statistics on consumption changes versus income changes

Table 5 summarises the distribution of income as well as income changes and consumption changes for all individuals in our sample (excluding the bounce backs). We see that on average two thirds of all income changes are typical transient changes. As expected positive income shocks are associated with positive consumption responses, and vice versa for negative income shocks.

4.2 Panel regression model

We use a panel regression to estimate the effect of the type of income change on the consumption elasticity to labour income. We consider all income changes, except for the bounce-back changes which we exclude from our dataset[9].

We denote by $\Delta\mathrm{Inc}_{i,t}$ the change in log-income of household i in month t. Let $\Delta\mathrm{C}_{i,t}$ be the change in log-consumption in the corresponding income-month. For each individual i and income month t, we also have the shock definition variables represented as dummies $S_{i,t}^{\text{type}}$ indicating the occurrence of a shock of a certain type. The first letter in the shock type superscript stands for positive (P) or negative (N) shocks, the second letter code stands for the type of shock, being a level shock (LS), recurrent shock (RS) or a transient shock (TS).

[9]The consumption response to a bounce-back shock is ambiguous. The bounce-back is mechanic due to recurrent nature of the preceding shock. It is therefore of less economic interest.

Table 5: Summary statistics (averages) of both the level of income and the month-on-month changes in consumption and income in months that were labelled with a specific shock type.

	Frequency	$\overline{\text{Inc}}$	$\overline{\Delta\text{Inc}}$	$\overline{\Delta C}^{\text{ND}}$	$\overline{\Delta C}^{\text{D}}$	$\overline{\Delta C}^{\text{SD}}$	$\overline{\Delta C}^{\text{total}}$
Panel A: in euro							
NIS	66.07	3924.49	8.86	4.53	−3.56	−5.40	−17.45
PLS	1.94	5666.94	2070.21	68.04	25.11	23.14	284.61
PRS	10.07	6172.81	2669.04	107.05	16.67	31.68	350.85
PTS	4.10	6781.44	3157.23	59.20	16.15	16.66	291.25
NLS	1.66	3582.20	−2287.92	−90.40	−14.10	−21.11	−184.46
NRS	1.81	3150.10	−2473.65	−26.95	−3.18	−10.86	−158.68
NTS	3.76	2889.47	−2618.53	−34.10	2.81	−6.51	−168.45
Panel B: in log							
NIS	66.07	8.15	0.00	0.00	−0.02	−0.09	0.00
PLS	1.94	8.53	0.46	0.07	0.17	0.27	0.06
PRS	10.07	8.61	0.56	0.11	0.27	0.47	0.11
PTS	4.10	8.58	0.52	0.05	0.13	0.20	0.05
NLS	1.66	8.07	−0.49	−0.09	−0.09	−0.20	−0.06
NRS	1.81	7.90	−0.57	−0.02	−0.07	−0.10	−0.04
NTS	3.76	7.78	−0.64	−0.03	−0.05	−0.09	−0.03

The baseline panel regression is then specified as follows:

$$\begin{aligned}\Delta C_{i,t} = \Delta\text{Inc}_{i,t} \times \Big(&\beta + \delta^{\text{PLS}}\, S_{i,t}^{\text{PLS}} + \delta^{\text{PRS}}\, S_{i,t}^{\text{PRS}} + \delta^{\text{PTS}}\, S_{i,t}^{\text{PTS}} \\ &+ \delta^{\text{NLS}}\, S_{i,t}^{\text{NLS}} + \delta^{\text{NRS}}\, S_{i,t}^{\text{NRS}} + \delta^{\text{NTS}}\, S_{i,t}^{\text{NTS}}\Big) \\ &+ \lambda X_{i,t} + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{11}$$

where the vector of variables $X_{i,t-1}$ is a set of demographic control variables (age, gender, civil state, and an interaction between gender and civil state) as well as a control for any change in replace income, which is not included in $\text{Inc}_{i,t}$, and $\varepsilon_{i,t}$ is the error term. This basic model will also be extended with interaction terms between the changes in income and the personal characteristics to deeper explore the sources of heterogeneity. Note that the coefficient β in (11) can be interpreted as the elasticity of consumption to an income change in months without an income shock. In case of a positive level shock, the elasticity is $\beta + \delta^{\text{PLS}}$.

Summary statistics on all variables in the panel regression are reported in Table 6.

Table 6: Unconditional summary statistics of the key variables in euro. The civil state dummy is 0 for unmarried clients and 1 for married clients. The gender dummy is 0 for men and 1 for women. $W_{i,t}$ is the liquid wealth.

	mean	median	std
Gender	0.26	0.00	0.44
Civil state	0.66	1.00	0.47
$\text{Inc}_{i,t}$	4219.24	3659.18	3779.22
$W_{i,t}$	34 571.06	15 801.26	81 844.72
$\Delta\text{Inc}_{i,t}$	23.19	0.00	4435.44
C^{ND}	1016.66	920.49	1825.03
C^{SD}	221.34	140.00	345.86
C^{D}	384.49	70.00	2263.98
C^{total}	3378.37	2443.12	11 274.01

4.3 Panel regression estimates

We calculate and model the marginal propensity to consume analogously to van den Heuvel et al. (2022), which is based on the organising framework (Eq.14) of Jappelli and Pistaferri (2010). We will extend their method to a larger population of clients, with more demographic controls and more granular information about different kinds of consumption (durable, semi-durable and non durable consumption).

Given the empirical evidence in Gelman et al. (2020), Ganong and Noel (2019) and Ganong et al. (2020), we expect that individuals on average adjust their consumption to income changes leading to a positive value for the consumption elasticity to income. We thus expect $\beta > 0$. We also take into account the possibility that people react asymmetrically to positive and negative income shocks (Fuster et al., 2018). β is expected to be larger for positive than negative shocks) since habit formation may result in individuals desiring to preserve an existing consumption pattern in case of a negative shock.

The various $\delta > 0$ in our empirical specification reflect the extent to which the response to specific types of income shocks, be they level shocks, recurrent shocks or transient shocks, deviates from this average positive response of consumption to changes in income. In particular the body of theory around the permanent income hypothesis suggests rational individuals' consumption will respond less to transient shocks than to level shocks or recurrent shocks. Indeed this body of theory suggests transient shocks should be smoothed as they do not affect permanent income. Finally we will also verify whether these consumption responses to income shocks vary with individual wealth, which is expected to attenuate the effect of income shocks on consumption.

As a key contribution rooted in deep information on individual payments, we will also differentiate, across all results tables, between different types of consumption. As there is hardly any literature on this front we have, at this point in time, no clear expectation about what to expect here and consider our analysis to be explorative on this front.

All our specifications are estimated with a fixed set of individual-time specific controls, i.e. civil state, age, their interaction, replacement income and individual fixed effects η_i.

In a first set of results in Table 7 win inspect the average elasticity of separate types of consumption to income shocks across all types of income shocks. We find that the elasticity is especially pronounced for semi-durable consumption at 0.4033. The response of durable consumption to income shocks is only half that strong, while the response of non durable consumption to income is rather small at 0.908.

We proceed in Table 8 by differentiating between positive and negative income shocks and find, as expected, that consumption reacts much stronger to positive than negative incomes shocks. This exercise reveals that the responses to positive income shocks are are actually larger than erroneously deducted from Table 7, because in that set of results the responses to positive shocks are watered down by the much smaller responses to negative shocks. Clearly, individuals have a much stronger urge to preserve their level of consumption in the presence of negative income shocks, then to keep their consumption at the same level in the presence of positive income shocks.

In Table 9 we introduce the heterogeneity of the consumption elasticity to the type of income shock by interacting shock type dummies with our income change variable. For a correct interpretation the relevant shock type-specific δ has to be added to the baseline β to arrive at the full elasticity of consumption to a specific type of income shock. We start by considering positive income shocks; We observe that the consumption response is especially positive in the presence of a positive recurrent shock, where the total elasticity of consumption to positive recurrent income shocks rises to about almost 0.8. The additional consumption effect of positive level shocks is smaller, but still substantial, and especially so for durable and semi-durable consumption. The response to transient shocks, in turn, is comparatively small or even insignificant. With respect to negative shocks, however, we find much smaller consumption responses as indicated by the negative δ. For negative level shocks the net consumption response remains substantial, which is not unexpected. As an interesting exception negative level shocks even lead to a higher response in non-durable consumption than positive level shocks ($\delta = 0.0416 > 0.0101$), suggesting individuals reduce their spending and maybe the quality of their food and beverage consumption in case of relatively permanent income reductions.

Finally in Table 10 we focus on the possible mitigating role of wealth, by interacting the income change and the relevant shock variables with $S_{i,t}^{\text{low wealth}}$, a dummy equal to 1 if the individual's wealth is in the lowest quartile of the sample in any given month. As expected we see that consumption elasticity to income changes is substantially higher among low wealth individuals, irrespective of the type of consumption. Further inspection reveals that this is especially the case for positive recurrent shocks, that lead to especially large consumption responses from low wealth individuals (the total consumption elasticity exceeds 0.97 for semi-durables and about 0.5 for durables). Indeed, it seems that positive recurrent income shocks yield very strong responses in semi-durable and durable consumption by low wealth individuals and thus lead to large macroeconomic multiplier effects.

Table 7: Baseline regression , symmetric shocks.

	(1)	(2)	(3)	(4)
Dep. Variable	$C_{i,t}^{\mathrm{ND}}$	$C_{i,t}^{\mathrm{SD}}$	$C_{i,t}^{\mathrm{D}}$	$C_{i,t}^{\mathrm{total}}$
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS
Observations	2 158 508	2 158 508	2 158 508	2 158 508
Cov. Est.	Clustered	Clustered	Clustered	Clustered
R^2	0.0062	0.0038	0.0010	0.0041
F	2646.4	1599.0	417.10	1741.1
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
$m_{i,t}$	0.0908***	0.4033***	0.2219***	0.0956***
	(0.0011)	(0.0056)	(0.0061)	(0.0014)
gender × civil state	0.0010	0.0419**	0.0401*	−0.0035
	(0.0038)	(0.0206)	(0.0233)	(0.0064)
civil state	−0.0021	−0.0008	−0.0429***	−0.0076**
	(0.0020)	(0.0113)	(0.0123)	(0.0033)
age	0.0009***	0.0148***	0.0059***	−0.0005***
	(0.0001)	(0.0006)	(0.0007)	(0.0001)
$m_{i,t}^{\mathrm{repl}}$	0.0034***	0.0125***	0.0112***	0.0049***
	(0.0002)	(0.0010)	(0.0011)	(0.0002)
Effects	Entity	Entity	Entity	Entity

Table 8: Baseline regressions, asymmetric shocks.

	(1)	(2)	(3)	(4)
Dep. Variable	$C_{i,t}^{\mathrm{ND}}$	$C_{i,t}^{\mathrm{SD}}$	$C_{i,t}^{\mathrm{D}}$	$C_{i,t}^{\mathrm{total}}$
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS
Observations	2 158 508	2 158 508	2 158 508	2 158 508
Cov. Est.	Clustered	Clustered	Clustered	Clustered
R^2	0.0066	0.0052	0.0012	0.0045
F	2335.6	1843.0	424.55	1608.5
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
$m_{i,t}^{+}$	0.1170***	0.6989***	0.3482***	0.1334***
	(0.0014)	(0.0078)	(0.0080)	(0.0018)
$m_{i,t}^{-}$	0.0574***	0.0244***	0.0602***	0.0470***
	(0.0016)	(0.0083)	(0.0095)	(0.0020)
gender × civil state	0.0004	0.0358*	0.0375	−0.0043
	(0.0038)	(0.0206)	(0.0233)	(0.0064)
civil state	−0.0018	0.0025	−0.0415***	−0.0072**
	(0.0020)	(0.0113)	(0.0123)	(0.0033)
age	0.0007***	0.0123***	0.0049***	−0.0008***
	(0.0001)	(0.0006)	(0.0007)	(0.0001)
$m_{i,t}^{\mathrm{repl}}$	0.0034***	0.0121***	0.0110***	0.0049***
	(0.0002)	(0.0010)	(0.0011)	(0.0002)
Effects	Entity	Entity	Entity	Entity

Table 9: Regression results of (11) where the no income shock is the reference category.

	(1)	(2)	(3)	(4)
Dep. Variable	$C_{i,t}^{\mathrm{ND}}$	$C_{i,t}^{\mathrm{SD}}$	$C_{i,t}^{\mathrm{D}}$	$C_{i,t}^{\mathrm{total}}$
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS
Observations	2 158 508	2 158 508	2 158 508	2 158 508
Cov. Est.	Clustered	Clustered	Clustered	Clustered
R^2	0.0073	0.0053	0.0012	0.0049
F	1411.6	1019.5	239.29	939.24
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
$m_{i,t}$	0.0937***	0.3703***	0.2061***	0.0949***
	(0.0019)	(0.0108)	(0.0120)	(0.0025)
Positive level shock×$m_{i,t}$	0.0101**	0.2630***	0.1306***	0.0215***
	(0.0041)	(0.0240)	(0.0269)	(0.0056)
Positive recurrent shock×$m_{i,t}$	0.0485***	0.4194***	0.1913***	0.0632***
	(0.0025)	(0.0145)	(0.0157)	(0.0033)
Positive transient shock×$m_{i,t}$	−0.0291***	0.0311*	−0.0066	−0.0167***
	(0.0030)	(0.0169)	(0.0191)	(0.0041)
Negative level shock×$m_{i,t}$	0.0416***	−0.1832***	−0.0555*	−0.0004
	(0.0046)	(0.0246)	(0.0286)	(0.0059)
Negative recurrent shock×$m_{i,t}$	−0.0511***	−0.3176***	−0.1122***	−0.0361***
	(0.0040)	(0.0215)	(0.0245)	(0.0053)
Negative transient shock×$m_{i,t}$	−0.0564***	−0.3355***	−0.1556***	−0.0651***
	(0.0028)	(0.0152)	(0.0169)	(0.0036)
gender × civil state	0.0005	0.0385*	0.0386*	−0.0040
	(0.0038)	(0.0206)	(0.0233)	(0.0064)
civil state	−0.0018	0.0023	−0.0416***	−0.0072**
	(0.0020)	(0.0113)	(0.0123)	(0.0033)
age	0.0006***	0.0125***	0.0049***	−0.0009***
	(0.0001)	(0.0006)	(0.0007)	(0.0001)
$m_{i,t}^{\mathrm{repl}}$	0.0033***	0.0119***	0.0109***	0.0048***
	(0.0002)	(0.0010)	(0.0011)	(0.0002)
Effects	Entity	Entity	Entity	Entity

Table 10: Regression results of (11) extended with a low wealth dummy. This dummy is 1 for people who are in the lowest wealth quartile.

	(1)	(2)	(3)	(4)
Dep. Variable	$C^{\mathrm{ND}}_{i,t}$	$C^{\mathrm{SD}}_{i,t}$	$C^{\mathrm{D}}_{i,t}$	$C^{\mathrm{total}}_{i,t}$
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS
Observations	2 158 508	2 158 508	2 158 508	2 158 508
Cov. Est.	Clustered	Clustered	Clustered	Clustered
R^2	0.0076	0.0054	0.0013	0.0050
F	849.40	608.48	142.35	559.99
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
$m_{i,t}$	0.0819***	0.3241***	0.1869***	0.0852***
	(0.0022)	(0.0125)	(0.0142)	(0.0031)
$m_{i,t}$ ×Positive level shock	0.0118**	0.2307***	0.1299***	0.0211***
	(0.0047)	(0.0281)	(0.0318)	(0.0067)
$m_{i,t}$ ×Positive recurrent shock	0.0444***	0.4024***	0.1757***	0.0589***
	(0.0029)	(0.0167)	(0.0185)	(0.0040)
$m_{i,t}$ ×Positive transient shock	−0.0271***	0.0365*	−0.0135	−0.0148***
	(0.0034)	(0.0190)	(0.0220)	(0.0048)
$m_{i,t}$ ×Negative level shock	0.0425***	−0.1868***	−0.0722**	−0.0021
	(0.0053)	(0.0283)	(0.0334)	(0.0071)
$m_{i,t}$ ×Negative recurrent shock	−0.0427***	−0.2976***	−0.0965***	−0.0372***
	(0.0046)	(0.0247)	(0.0284)	(0.0064)
$m_{i,t}$ ×Negative transient shock	−0.0495***	−0.3151***	−0.1456***	−0.0621***
	(0.0032)	(0.0176)	(0.0202)	(0.0043)
$S^{\text{low wealth}}_{i,t}$	−0.0066***	−0.0266***	−0.0145**	−0.0046***
	(0.0010)	(0.0052)	(0.0057)	(0.0012)
$m_{i,t} \times S^{\text{low wealth}}_{i,t}$	0.0459***	0.1807***	0.0748***	0.0380***
	(0.0044)	(0.0245)	(0.0259)	(0.0052)
$m_{i,t} \times S^{\text{low wealth}}_{i,t}$ ×Positive level shock	−0.0065	0.1277**	0.0030	0.0017
	(0.0094)	(0.0537)	(0.0590)	(0.0116)
$m_{i,t} \times S^{\text{low wealth}}_{i,t}$ ×Positive recurrent shock	0.0178***	0.0735**	0.0648*	0.0185***
	(0.0058)	(0.0329)	(0.0341)	(0.0069)
$m_{i,t} \times S^{\text{low wealth}}_{i,t}$ ×Positive transient shock	0.0030	0.0257	0.0570	0.0021
	(0.0072)	(0.0412)	(0.0435)	(0.0088)
$m_{i,t} \times S^{\text{low wealth}}_{i,t}$ ×Negative level shock	−0.0016	0.0234	0.0715	0.0087
	(0.0103)	(0.0564)	(0.0638)	(0.0125)
$m_{i,t} \times S^{\text{low wealth}}_{i,t}$ ×Negative recurrent shock	−0.0313***	−0.0684	−0.0590	0.0079
	(0.0092)	(0.0494)	(0.0554)	(0.0108)
$m_{i,t} \times S^{\text{low wealth}}_{i,t}$ ×Negative transient shock	−0.0266***	−0.0786**	−0.0389	−0.0113
	(0.0062)	(0.0342)	(0.0362)	(0.0075)
gender × civil state	0.0007	0.0394*	0.0389*	−0.0038
	(0.0038)	(0.0206)	(0.0233)	(0.0064)
civil state	−0.0018	0.0020	−0.0416***	−0.0072**
	(0.0020)	(0.0113)	(0.0123)	(0.0033)
age	0.0006***	0.0125***	0.0049***	−0.0009***
	(0.0001)	(0.0006)	(0.0007)	(0.0001)
$m^{\mathrm{repl}}_{i,t}$	0.0033***	0.0120***	0.0109***	0.0048***
	(0.0002)	(0.0010)	(0.0011)	(0.0002)
Effects	Entity	Entity	Entity	Entity

5 Conclusion

Rapidly changing economic environments and their detrimental effect on businesses, like the great financial crisis (GFC) of 2007-2009, the eurocrisis of 2011-2012, the Covid-19 pandemic of 2020-2021 and the energy crisis of 2022, have confronted individuals with increased volatility and uncertainty about their labour income. Is my sector going to be closed down due to bank failures, COVID-19 lockdowns or outrageous energy prices? When will the next wage indexation occur? Will I get sick and be unable to work for a protracted period of time? Because governments fear the negative effect of these individual income shocks on the aggregate economy may be multiplied by a negative cascade of consumption responses, they have tried to dampen these shocks by resorting to a wide array of policy measures.

This brings to the fore the crucial policy questions of how consumption responds to income shocks and how this consumption response depends on the type of income shocks. Without answers to these questions, government tax and income policies to dampen macro shocks are in essence navigating blindly. Due to data restrictions and challenges in differentiating between different types of income shocks, the literature mostly looks either very broadly at average responses to changes in income, or very narrowly to one specific type of change (e.g. unemployment, tax rebate). In this paper, we present a methodology that employs individual income time series to identify and classify different types of income shocks. We then proceed by analysing how consumption responds to these different types of income shocks, controlling for unobserved individual characteristics by individual fixed effects. Our method also allows us to verify whether individual wealth moderates the consumption response to income shocks. Finally we are also able to delve deeper into the nature of consumption responses, by separating durable from non-durable consumption.

All in all, we find that the elasticity of consumption to income shocks is heterogeneous with respect to the sign of the income shock (positive or negative), the type of income shock (level shock, recurrent shock, transient shock), the type of consumption (durable, semi-durable non durable) and the level of wealth in economically sensible ways. Consumption is elastic to income changes in general. This elasticity is most pronounced for semi-durable goods and is much larger for positive than for negative income shocks. When considering different shock types, we find that individuals react much less to transient shocks than to level shocks or recurrent shocks, as correctly predicted by theories that involve the permanent income hypothesis. Finally and importantly for policy makers, low wealth individuals react much stronger to income changes, suggesting wealth is indeed instrumental in smoothing income shocks. This more elevated consumption elasticity for low wealth individuals is especially pronounced in case of positive recurrent income shocks in particular for semi-durable and durable consumption. This suggests that policy-driven recurrent income boosts targeted at low wealth individuals may be an especially potent policy tool to address downturns, as our results the macro-economic multiplier of such policies may be very high.

In future research we will delve deeper into consumption responses to specific government policies introduced explicitly to dampen income shocks in a series of policy assessment exercises. We will also in more detail into how personal behavioural characteristics, like myopia and risk aversion, moderate the consumption response to income shocks. Our transaction data does allow us to characterise this kind behavioural biases from the transaction data, allowing a unique window on the underlying mechanisms that underpin the marginal propensity to consume. Finally we are also interested in knowing how consumption responds to shocks in non-labour income, a increasingly important policy question given the rising share of capital income in both income and the rising share of the ageing population mainly depending on capital income for financing consumption

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A Identification of labour income and replacement income

A.1 /A/: Labour Income

The symbols /A/ need to be included in the communication for transactions related to amounts paid in execution of:

- an employment contract
- a learning agreement
- a statute
- a subscription
- as well as those paid to persons who perform work for wages under the authority of another person outside an employment contract
- the holiday pay paid under the legislation on annual leave

A.2 /B/: Replacement Income

The symbols /B/ need to be included in the communication for transactions related to amounts paid in execution of:

- income from activities other than those referred to in /A/
- the maintenance benefits, whether provisional or not, awarded by the court, as well as the benefits awarded to the spouse after divorce
- the pensions, adjustment benefits, transition benefits, annuities, interest contributions, or pension benefits paid under any law, statute or agreement
- the holiday pay and the supplementary allowance to the holiday pay paid under the legislation on the retirement and survivor's pension for employees
- unemployment benefits and benefits paid by social security funds

- the benefits for incapacity for work and the invalidity benefits paid under the legislation on sickness and invalidity insurance or the law of 16 June 1960, which guarantees, inter alia, social benefits for the benefit of former employees of the Belgian Congo and Ruanda-Urundi and the legislation concerning the overseas social security
- the benefits, annuities and allowances paid under the legislation on compensation for damage resulting from accidents at work or occupational diseases, the said Act of 16 June 1960 or insurance contracts entered into under the legislation on overseas social security, with the exception of the part of the benefit referred to in § 2, 4° of this article
- the militia allowances referred to in the law of 9 July 1951
- the benefit granted in the event of an interruption of the professional career

On top of the **/B/** symbols, the institutions that pay out unemployment add additional structure to their communication that can be leveraged to distinguish unemployment payments from other replacement income [10]

A.3 /C/: Social Security Income

The symbols /C/ need to be included in the communication for transactions related to amounts paid in execution of:

- the family benefits, including these paid under the law concerning the wage-earning soldiers
- orphan's pensions or annuities paid under a law, statute or agreement
- the allowances for the disabled
- the part of the compensation paid under the legislation on compensation for damage caused by accidents at work which is 100 pc. exceeds and is awarded to severely mutilated persons whose condition absolutely and normally requires the assistance

[10] A detailed description of the structure can be found (in dutch) at `https://www.hvw-capac.fgov.be/nl/infoblad-deeltijdse-werknemer-met-behoud-van-rechten-c131a`.

of another person, as well as the amounts allocated for the need of other persons' assistance under the Compulsory Health Insurance and Benefits Act, coordinated on 14 July 1994

- to pay out the amounts
  - to the person entitled to medical benefits as an allowance at the expense of the insurance for medical care and benefits or pursuant to the Act of 16 June 1960 or the legislation on overseas social security
  - as costs for medical, surgical, pharmaceutical and nursing care or as costs for prostheses and orthopaedic appliances to a person affected by an accident at work or an occupational disease under the legislation on accidents at work or occupational diseases
- the amounts paid out as guaranteed income for the elderly or as an income guarantee for the elderly
- the amounts paid as subsistence minimum
- the amounts disbursed as social services by the public centres for social welfare
- the financial benefit provided for in the law of 22 December 2016 introducing a bridging right in favour of self-employed persons
- the provisional or non-provisional reimbursements for prostheses, medical aids and implants
- the amounts specified in Article 120 of the Program Law (I) of December 27, 2006, paid out through the Compensation Fund for Asbestos Victims
- the expense allowances referred to in Article 10 of the Act of 3 July 2005 on the rights of volunteers
- the amounts specified in Articles 15 and 16 of Royal Decree no. 22 of 4 June 2020 establishing a Compensation Fund for volunteers COVID-19 victims paid out as an

intervention from the Compensation Fund for volunteers COVID-19 victims

On top of the **`/C/`** symbols, the institutions that pay out pensions add additional structure to their communication that can be leveraged to distinguish pension payments from other social security income.

B Consumption labels

Here we present the consumption labels that are present in our data. The COICOP consumption classifaction scheme was adopted as much as possible. The full details for this scheme can be found in UN (2018). The labels deviate from COICOP in two cases: first if categories exist which are out of scope for COICOP (e.g. cash withdrawals) but relevant to consumption, second if transaction data only allows to identify a subset or superset of COICOP categories. If the superset of COICOP categories that can be identified are of different durability types, the category was assigned the Mixed durability type.

Table 11: Table of consumption labels provided by BNP Paribas Fortis bank (BNPPF). The labels and corresponding durability follow the COICOP consumption classification scheme as much as possible. The Source column indicates if the label is directly taken from COICOP or defined by the bank. The durability column contains D for durable, SD for semi-durable, ND for non-durable, and S for services. If the source is COICOP, the label follows exactly the COICOP classification scheme and the corresponding COICOP code is given. If the source is BNPPF, the label was constructed by the bank. If only the name of the COICOP category was changed but the definition of an existing COICOP category was adopted, the corresponding COICOP code is provided. In all other cases the definition of the label is provided in the comments column.

Source	COICOP	BNPPF label	Durability	Comment
COICOP	11.2	Accomodation Services	S	
BNPPF		Alcoholic Beverages and Tobacco	ND	Only includes speciality stores. Based on COICOP 2 but without narcotics.
COICOP	6.1.3	Assistive Products	D	
BNPPF		Cash	Mixed	Cash withdrawals. Not in the scope of COICOP
COICOP	3.0	Clothing and Footwear	SD	
BNPPF		Credit Card Payments - Legacy	Mixed	Payment of end-of-month credit card bill. Not in the scope of COICOP.

Table 11 continued from previous page

BNPPF	9.1, 9.5	Cultural and Recreational Durables	D	Combines recreational and cultural durable goods.
BNPPF	9.4, 9.6	Cultural and Recreational Services	S	Combines cultural and recreational services.
COICOP	5.6.2	Domestic Services and Household Services	S	
BNPPF	10.1, 10.2, 10.3	Education - Mandatory	S	Includes all levels of education that are mandatory 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 the 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	Fuals and Lubricants for Personal Transport Equipment	ND	

Table 11 continued from previous page

COICOP	5.1	Furniture, Furnishings, and Loose Carpets	D	Does not include repair, installation and hire of furniture, furnishings and loose carpets which are services.
COICOP	9.3	Garden Products and Pets	ND	
BNPPF		Groceries	ND	Combines grocery stores (bakkeries, supermarkets, butchers, etc.) purchases with Food and Non-alcoholic Beverages speciality stores (COICOP 1.0).
BNPPF	6.2, 6.3, 6.4	Health Services	S	
COICOP	5.3	Household Appliances	Mixed	If the store does not allow us to discern which type of appliances were purchased (large appliances which are durable, or small appliances, they get this label. Does not include the repair, installation and hire of household appliances which are services.

Table 11 continued from previous page

BNPPF	5.2, 5.3.2, 5.4	Household Textiles, Tableware, and Small Appliances	SD	Does not include the repair, hire and sewing services of household textiles which are services.
COICOP	8.1	Information and Communication Equipment	D	Does not include unrecorded recording media which is a semi-durbale.
COICOP	8.3	Information and Communication Services	S	
COICOP	12.1	Insurance	S	
BNPPF		Luxery Goods	D	Bundles COICOP 13.2.1 with other luxery goods.
COICOP	6.1	Medicines and Health Products	ND	Does not include medical assistive products which are included in Assistive Products.
BNPPF		Mixed Retail - Building Materials	Mixed	purchases at building material stores, DIY stores, home improvement stores, etc.
BNPPF		Mixed Retail - Personal Use	Mixed	
COICOP	9.2	Other Cultural and Recreational Goods	SD	Includes e.g. books.
BNPPF		Other Durable goods	D	Other durable goods not elsewhere classified.

Table 11 continued from previous page

BNPPF		Other Non-Durable Goods	ND	Other non-durable goods not elsewhere classified. E.g. office supplies, paper stores,newspaper shops, etc.
BNPPF		Other Semi-Durable	SD	Other semi-durable goods not elsewhere classified.
BNPPF		Other Services	S	Based on COICOP 13.9 but more broad. Other services not elsewhere classified.
COICOP	4.4.4	Other Services Relating to the N.E.C	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	All ND items included in COICOP 13.1.

Table 11 continued from previous page

BNPPF		Personal Care Services	S	All S items included in COICOP 13.1.
COICOP	7.1	Purchase of Vehicles	D	
BNPPF		Second-Hand Retail	Mixed	Includes second-hand stores which mostly sell semi-durable or durable goods such as furniture and clothing. Not seperately classified in COICOP.
COICOP	4.3.1	Security Equipment and Materials for the Maintenance and Repair of the Dwelling	ND	Does not include products, materials and fixtures used for major maintenance and repair (intermediate consumption) or for extension and conversion of the dwelling (capital formation).
COICOP	4.3.2	Services for Maintenance, Repair and Security of the Dwelling	S	Does not include security equipment and materials for the maintenance and repair of the dwelling.
BNPPF	7.2.3, 7.2.4	Services in Report of Personal Transport Equipment	S	
COICOP	4.4.3	Sewage Collection	S	
COICOP	13.3	Social Protection	S	

Table 11 continued from previous page

COICOP	7.4	Transport Services of Goods	S	
BNPPF		Utilities	ND	Utilities that can not be classified in one of the more granular labels below. E.g. a utility company that provides multiple kinds of utilities.
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 and Cooling	ND	
COICOP	4.5.4	Utilities - Solid Fuels	ND	
COICOP	4.4.1	Utilities - Water Supply	ND	

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