The Consumption Response to Labour Income Changes

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Johannes Weytjens, Koen Schoors, Kris Boudt, Milan van den Heuvel



Excess sensitivity is very heterogeneous

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Motivation

- Recent economics crises highlight that many household are ill-equipped to withstand even modest amounts of income volatility (Narayan et al., 2022).
- The standard measure of the consumption response (ΔC) to income shocks (ΔI) is the marginal propensity to consume (MPC):

$$MPC = \frac{\Delta C}{\Delta I}$$

- MPC is heterogeneous with, amongst others:
 - household characteristics (Bernardini et al., 2020),
 - liquid wealth (Ganong et al., 2020; Kaplan et al., 2014),
 - perception of the (un)expectedness of the shock (Jappelli and Pistaferri, 2010),
 - shock type,
 - consumption durability type,

- ...

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- Lots of (potential) biases, small sample size, non representative sample, ...
- Broad range of MPC results spanning orders of magnitude, even for similar types of shocks, should make us cautious (Havranek and Sokolova, 2020).
- Nevertheless, they all highlight that MPC is very heterogeneous (Jappelli and Pistaferri, 2020).

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- Employs a data driven approach to identify a wide range of possible income shocks (indexation, flexible working schedules, policy interventions, ...).
- Constructs a labour income change identification and classification framework.
- Finds a much stronger reaction to positive level shifts than to transient changes.
 Negative transient and recurrent changes are smoothed.
- Strongest response in semi-durable consumption for all changes.

Data

- We leverage an anonymized bank dataset from BNP Paribas Fortis (BNPPF)
- BNPPF is active in all regions of Belgium and has ~30 % market share.
- Individual transactions, monthly balances and non-identifying demographics.
- Every transaction is enriched with a label indicating economic use e.g. labour income, groceries and apparel.
- Consumption is subdivided according to its durability type via UN's COICOP.
 - non-durable (e.g. food, utilities)
 - semi-durables (e.g. apparel, toaster)
- durables (e.g. fridge, car)
- services (e.g. musea, public transport)



Sample selection

- Determine active households with regular consumption and income, and remove inactive households, those with another main bank.
- Select households in a rolling window of 6 months that (Storms et al., 2009)
 - consumpe atleast € 150 every month,
 - have a labour income of atleast € 600 in at least 4 months.
- Our sample has on average 631 308 households observed monthly from 01/2012 to 05/2023.

Sample selection



Income process

- Changes in log labour income $(\Delta I_{i,t})$ are decomposed in a stable $(\Delta S_{i,t})$ and transient $(\Delta v_{i,t})$ component similar to Blundell et al. (2008) and Jappelli and Pistaferri (2010).
- Following Ganong et al. (2020), the transient component is further subdivided in a typical (ΔZ_{i,t}) and atypical (ΔT_{i,t}) part.
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$$\Delta I_{i,t} = \Delta T_{i,t} + \Delta Z_{i,t} + RC_{i,t} + LS_{i,t}$$

Change classification

- Previous work has focused on large, identifiable and atypical income shocks.
- Assumption

The distribution of typical income changes has a negligible overlap with the distribution of atypical income changes.

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The distribution of typical income changes has a negligible overlap with the distribution of atypical income changes.

- This assumptions translates the *typicalness* of a change to the size of a change.
- It allows us to differentiate between typical and atypical income changes:

$$\begin{split} m_{i,t} &= I_{i,t} - I_{i,t-1} \\ \Delta Z_{i,t} &= m_{i,t} \quad \text{if} \quad |m_{i,t}| < \kappa_{i,t} = c^{MoM} \sigma_{i,t} \end{split}$$

Recurrency and permanency

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- Further subdividing atypical changes requires an additional reference point.
- People act as if their financial horizon is 1 year (Benartzi and Thaler, 1995).
- Most employment related events have a yearly frequency.



Reversion

- By definition, any temporary change is followed by a reversion to the previous level of income.
- These reversals or bounce backs are classified as atypical permanent changes.
- We extend our classification to classify them seperately so we can exclude them in further analysis.



Change classification tree



Human readable change classification tree



Change identification

Assuming that log labour income has locally constant mean c with variance ζ^2 in a neighbourhood of size L,

$$I_{i,t-s} \sim N(c_i, \zeta_i^2)$$
 for $s = 0, ..., L - 1$

we want to estimate the variance σ of the month on month (MoM) changes.

$$m_{i,t} = I_{i,t} - I_{i,t-1} \sim N(0, \sigma_i^2)$$

Change identification in practice



- Every year a typical Belgian labour income time series contains at least
 - 1 level shift (indexation, promotion),
 - 2 positive recurrent changes (holiday pay, end-of-year bonus).
- We address these issues by
 - demedianing the time series,
 - using an outlier robust median absolute deviation (MAD) estimator with a moving window of 12 months.

Change identification in formulas

The demedianed income time series $\overline{I_{i,t}}$ is given by

 $\overline{I_{i,t}}$ = median($I_{i,t-1}$, ..., $I_{i,t-6}$)

And the variance is estimated as

$$\hat{\sigma}_{i,t} = max \Big[\sqrt{2} \cdot mad \left(I_{i,t-1} - \overline{I_{i,t-1}}, ..., I_{i,t-12} - \overline{I_{i,t-12}} \right), \epsilon \Big]$$

where we safeguard for individuals with low income volatility by setting ϵ to 0.5 %. The threshold for identifying an atypical change is then given by

$$\kappa_{i,t} = c \cdot \hat{\sigma}_{i,t}$$

where c, inspired by one sided tests, is set to 1.645.

Change identification visualized





Change time series





Change time series

Belgium has seen a period of strong inflation in 2022. Due to automatic wage indexation, the labour of income followed suit. About 500 000 households had a single permanent raise of 11 % in 01/2023.



Regression specifications

Baseline

$$\Delta C_{i,t} = \beta \Delta I_{i,t} + \lambda X_{i,t} + \eta_i + \varepsilon_{i,t}$$

Asymmetric

$$\Delta C_{i,t} = \beta^{+} \Delta I_{i,t}^{+} + \beta^{-} \Delta I_{i,t}^{-} + \lambda X_{i,t} + \eta_{i} + \varepsilon_{i,t}$$

Change classification

$$\Delta C_{i,t} = \Delta I_{i,t} \cdot \left(\beta + \sum_{shock} \delta^{shock} S^{shock}_{i,t}\right) + \beta' m^{repl}_{i,t} + \lambda X_{i,t} + \eta_i + \sum_{m=1}^{12} \delta^m S^m_{i,t} + \sum_{y=2012}^{2023} \delta^y S^y_{i,t} + \epsilon_{i,t}$$

where $X_{i,t}$ is a vector of household control variables (household size and average age), S^m and S^y are month and year fixed effects respectively and η_i are household fixed effects.

Regression results

	(1)	(2)	(3)	(4)
Dep. Variable	$\Delta C_{i,t}^{ND}$	$\Delta C_{i,t}^{SD}$	$\Delta C_{i,t}^{D}$	$\Delta C_{i,t}^{total}$
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS
Observations	51 150 020	51 150 020	51150 020	51 150 020
R ²	0.0032	0.0024	0.0007	0.0067
m _{i,t}	0.1139 ***	0.3283 ***	0.1778 ***	0.1343 ***
	(0.0004)	(0.0012)	(0.0012)	(0.0003)
Controls	True	True	True	True
Effects	Entity	Entity	Entity	Entity

Strong heterogeneity with respect to the type of consumption.

Regression results

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Dep. Variable	$\Delta C_{i,t}^{ND}$	$\Delta C_{i,t}^{SD}$	$\Delta C_{i,t}^{D}$	$\Delta C_{i,t}^{total}$
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS
Observations	51 150 020	51 150 020	51 150 020	51 150 020
R ²	0.0032	0.0015	0.0007	0.0068
m ⁺ _{i,t}	0.1491 ***	0.4272 ***	0.2202 ***	0.1540 ***
	(0.0006)	(0.0026)	(0.0015)	(0.0004)
m _{i,t}	0.1100 ***	0.1733 ***	0.1115 ***	0.1034 ***
	(0.0007)	(0.0020)	(0.0020)	(0.0005)
Controls	True	True	True	True
Effects	Entity	Entity	Entity	Entity

Strong heterogeneity with respect to the direction of the change.

Regression results



Strong heterogeneity with respect to the type of income change.

Conclusion

- We constructed a framework that can identify and classify income changes in high-frequency bank transaction data.
- Excess sensitivity is on average 10 % and heterogeneous with respect to both the type of consumption and type of income change.
- Stronger reactions to positive changes than to negative changes.

Conclusion

- We constructed a framework that can identify and classify income changes in high-frequency bank transaction data.
- Excess sensitivity is on average 10 % and heterogeneous with respect to both the type of consumption and type of income change.
- Stronger reactions to positive changes than to negative changes.
- (Belgian) households are resilient to negative income changes.
 - They strongly smooth negative recurrent and transient income changes,
 - but react strongly to permanent changes.
- (Belgian) households differentiate between positive income changes
 - Little reaction to positive recurrent changes,
 - but strong reactions to positive permanent changes.
- Consumption response for semi-durable consumption is twice as high as non-durable consumption.

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