WORKING PAPER

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Selien De Schryder
Nikolaos Koutounidis
Koen Schoors
Johannes Weytjens

July 2024
2024/1090

GHENT UNIVERSITY

Department of Economics

Faculty of Economics and Business Administration
Campus Tweekerken, St.-Pietersplein 5, 9000 Ghent - BELGIUM

Assessing the Heterogeneous Impact of COVID-19 on Consumption Using Bank Transactions

Selien De Schryder[1], Nikolaos Koutounidis[2], Koen Schoors[3], Johannes Weytjens[4]

Department of Economics, Ghent University, Sint-Pietersplein 5-6, 9000 Ghent, Belgium

Abstract

The transmission of the pandemic shock to the macroeconomy through the prism of consumer heterogeneity is the focal point of this paper. Based on a rich bank account and transactions micro dataset, we assess the roles of local COVID-19 severity, government measures against the spread of the virus, and vaccination rates for households' consumption behavior in Belgium. We induce that households living in areas that experienced high COVID-19 positivity rates and more stringent containment measures, decreased their consumption more. The relevance of these effects, however, shifted over the course of the pandemic. Higher local vaccination rates significantly counteracted these negative impacts on household consumption. Furthermore, our study highlights that the impact of these factors on consumption varied distinctly across households with different income, liquid wealth, and age characteristics.

Keywords: COVID-19, pandemic, lockdown, consumption, income, transactions data, heterogeneity
JEL: D12, E21, E65, G51

Acknowledgements

We gratefully acknowledge helpful comments from Raj Chetty, John S. Earle, Gerdie Everaert, John Friedman, Annik Goossens, Bart Hamers, Milan van den Heuvel, Gert Peersman, Manuel Piette, Michael Stepner, Emmanuel de Veirman, and the various participants at the workshops, seminars and conferences where this work was presented. We also acknowledge the assistance of Ruben Brondeel, the Sciensano COVID-19 data researcher involved in the preparation of the data.

1. Introduction

In the beginning of 2020, the global economy was hit by an unexpected shock. The coronavirus disease (COVID-19), caused by the SARS-CoV-2 virus, severely slowed down global economic activity. Although fiscal and monetary authorities took immediate policy actions to support the economy, economies were faced with severe macroeconomic consequences. In Belgium, the country studied in this paper, year-on-year GDP fell by 6.3% in 2020. This was the steepest drop since WWII, and more than 3 times larger than the 2% drop of 2009, at the pinnacle of the Global Financial Crisis (GFC). The biggest driver of this slump was

[1]Selien.Deschryder@UGent.be
[2]Nikolaos.Koutounidis@UGent.be
[3]Koen.Schoors@UGent.be
[4]Johannes.Weytjens@UGent.be

household consumption that fell by 8.7% (National Accounts Institute and National Bank of Belgium, 2021).

In this paper, we investigate the economic effects of the COVID-19 shock from the household perspective. In particular, we assess the impact of the pandemic's severity and the associated government responses on household consumption at the level of individual households and over subsequent COVID-19 waves. This comprehensive time-varying analysis, which spans the duration of the pandemic and thus includes periods of time following the vaccine roll-out, represents a major contribution of our study. It distinguishes our work from existing literature, which predominantly focuses on the pandemic's effects during its early waves. Our approach therefore provides a more holistic understanding of the pandemic's impact over its various stages, offering valuable insights into consumption patterns in the context of an evolving public health crisis. With the availability of highly granular household finance data in combination with local COVID-19, vaccination, and government response metrics over time, our study makes three contributions related to (i) the drivers of consumption dynamics (fear of infection or governmental non-pharmaceutical interventions (further NPIs), (ii) the heterogeneous impact on households (according to income, liquid wealth, and age), and (iii) the additional contribution of vaccinations.

The first aim of the paper is to disentangle the impact of COVID-19 severity from that of governmental NPIs on households' consumption behavior in Belgium. We conduct an empirical analysis based on a fixed effects panel model and data at a weekly frequency from March 2020 to October 2022. We utilize a rich micro dataset of Belgian retail bank accounts next to local (i.e., municipality-level) COVID-19 cases, tests, vaccinations, and NPIs against the spread of the virus. The cross-sectional units consist of households, being active bank clients who receive income on their bank account (see infra, section 2). In essence, we want to examine whether household consumption is affected by voluntary consumer actions - fueled by awareness or fear of infection or by a sense of social responsibility (Maloney and Taskin, 2020) - and/or the government-imposed restrictions to contain the spread of the virus. We do this via an assessment of the importance of municipal variation in the corona cases-over-tests (positivity) ratio while controlling for the intensity of NPIs and the percentage of fully vaccinated adults in the area.

Our study is connected to various papers that reach disparate conclusions concerning the underlying factor responsible for the reductions in consumption during the pandemic. First, Chen et al. (2021) use a difference-in-differences approach to show that Chinese cities with higher virus exposure are linked to stronger consumption declines. In the Netherlands, using geo-located transaction data, Kapetanios et al. (2022) likewise show that municipalities with larger COVID-19 outbreaks faced a bigger reduction in total local spending, albeit only during the first COVID-19 wave. Sheridan et al. (2020) instead conduct a natural experiment to disentangle the effects of the virus and the laws aiming to contain it by comparing the Swedish economy – on which no NPIs were applied – to the Danish one, where NPIs were imposed by the government. They find that the economic contraction was mainly driven by the virus itself, as consumption in Sweden dropped by 25%, only 4% less compared to the one of the restricted Danish economy (29%).

For the US, Goolsbee and Syverson (2021) and Sears et al. (2023) use mobility data from cell phones to assess the fall in consumer visits. Goolsbee and Syverson (2021) find that the government-imposed restrictions were less important than people's voluntary choice to stay home to avoid infection. Sears et al. (2023) document a sizeable drop in spending and employment before the activation of state-level shutdowns, but find a continued reduction in travel activity for persistent state-level stay-at-home mandates. Chetty et al. (2024) conclude that state-ordered shutdowns and reopenings had a modest effect on consumer spending and employment. The weak employment effect is also validated in Bartik et al. (2020) with the use of timesheet data on working hours. Chetty et al. (2024) also find that spending falls more in US counties with a higher incidence of COVID infections, albeit together with drops in spending in areas without high infection rates. A study conducted by Coibion et al. (2020) using US survey data on the other hand provides evidence suggesting that consumer spending declines are more closely associated with lockdown measures rather than infections. Hacıoğlu-Hoke et al. (2021) by contrast conclude that, while the lockdown measures did contribute to the decline in aggregate consumption, the onset of the drop in aggregate consumption in the UK before the enforcement of any lockdown measures suggests a significant role for fear and uncertainty regarding health and income in the beginning of the pandemic.

We find that the intensity of infections (measured by the cases-to-tests ratio) and the strictness of the containment measures affect consumption negatively. Our analysis further points to significant time variation in the magnitude of these effects. Specifically, we observe that the intensity of infections primarily drove the reduction in consumption in Belgium during the first wave of the COVID-19 pandemic (1 March 2020 until 21 June 2020). Conversely, during the second wave (31 August 2020 until 14 February 2021), it was the governmental containment measures that played a more dominant role in influencing consumption patterns. By the third wave (15 February 2021 to 27 June 2021), both the intensity of infections and containment measures significantly impacted household consumption, exerting a marked negative effect. Subsequently, the influence of both factors began to diminish.

Our second objective is to analyse the potential heterogeneity of household consumption reactions based on households' income, wealth, or age. For the US, findings in existing work are inconclusive. Baker et al. (2020) and Cox et al. (2020) conclude that consumption decreased homogeneously for different income groups. The former does find heterogeneous responses with respect to age, family structure, and checking account balances, while the latter pinpoint that consumption of low-income families rebounded faster once aggregate spending started recovering. In contrast, Chetty et al. (2024) conclude that consumption of high-income areas reduced more, especially in areas with high levels of infections. This finding has been used as input in epidemic models, like the one of Eichenbaum et al. (2022), to demonstrate the disproportionate effect of the pandemic on the well-being of poor people. Mixed results are also documented for the Spanish economy. Carvalho et al. (2021) show that postal codes with higher income and more COVID cases per capita are associated with larger consumption reductions, owing to the inability of richer residents to consume luxury items. Conversely, Montalvo and Reynal-Querol (2020) find that consumption decreased homogeneously among income groups, but rebounded somewhat faster for young and low-liquidity households. Hacıoğlu-Hoke et al. (2021) on the other hand conclude that wealthier individuals disproportionately reduced their expenditures during the pandemic. High-income individuals contributed to 45% of the overall decline in spending during 2020Q2 relative to their share of 35% in consumption levels the year before. The lowest-income individuals showed the opposite evolution, contributing to 9% of the 2020Q2 drop relative to 18% in 2019Q2.

Our study uncovers significant heterogeneity in household consumption responses to pandemic severity and NPIs, differentiated by income, liquid wealth, and age. We distinguish ourselves from existing research by dissecting the consumption effects driven by local pandemic severity and government containment measures. Our analysis reveals that lower-income households exhibit a markedly negative response to infection fears. In terms of age, older households significantly reduce consumption in reaction to higher local COVID-19 positivity rates and stringency measures. Furthermore, households with higher liquid wealth display more substantial consumption reductions under stringent containment measures. This outcome highlights that the imposition of lockdown measures disproportionately curtailed the spending habits of wealthier individuals, primarily because these restrictions significantly limited opportunities for discretionary expenditure, which is typically more predominant among affluent groups.

Our work, furthermore, contributes to the literature assessing the effect of vaccinations against COVID-19 on consumption. Tito and Sexton (2022) and Hansen and Mano (2023) assess the direct effects of local vaccinations on spending in the United States, finding a significantly positive relationship. Tito and Sexton (2022) document that a 1% increase in new vaccine administrations is associated with a maximum increase of 1.5% in retail spending around 30 days after receiving the vaccination dose. Hansen and Mano (2023) similarly document a 1.3% increase in spending over the 8 weeks following a 1% increase in new vaccinations. This effect is found to be heterogeneous across counties as spending rises more strongly in counties with ex ante worse socioeconomic conditions and lower education levels as well as in urban counties.

In this paper, we further consider the municipal percentage of vaccinated adults to examine the effects of vaccinations on household consumption while controlling for the local positivity rate and NPIs. In addition, we assess whether local vaccination rates affect household consumption heterogeneously based on household income, liquid wealth, or age, and examine the potential impact of vaccinations on the consumption response to new infections and NPIs. We find that a 1% increase of vaccination rates within a municipality boosts weekly household consumption by 0.0379%. The size of the effect varies across different household demographics. Notably, the consumption benefits of vaccination are less pronounced for lower liquid wealth households, while older households see a significant positive effect. The adverse impact of local pandemic severity and NPIs on consumption also diminishes with higher vaccination coverage.

Throughout the analyses, we focus on the case of Belgium. Belgium - being a small, open, and densely-populated country with high levels of commuting - was hit hard by the pandemic in 2020. More importantly, however, the country presents an intriguing case study given its unique characteristics that contribute to substantial variation in the data. Specifically, Belgium's local differences in pandemic severity and the implementation of NPIs at the regional, provincial, and municipal levels make it a compelling study subject to examine the relative effects of individuals' voluntary responses to the virus versus their responses to government-imposed NPIs.

There are a few papers that indirectly involve Belgium in their analysis. Christelis et al. (2020) utilize survey-based data for 6 eurozone countries, including Belgium, and find a negative relationship between households' financial concerns due to the pandemic and non-durable consumption. Arias et al. (2023) construct an epidemiological model with time-varying parameters to quantify the causal effect of NPIs on health and macroeconomic outcomes. They proceed by applying their theoretical model to COVID-19 data for Belgium and conclude that additional government-mandated mobility curtailments would have reduced deaths at a very small cost in terms of foregone GDP. Pappa et al. (2023) ascertain that the fiscal measures taken by 12 EU countries during the pandemic, including Belgium, were efficient in boosting output growth and restoring consumer confidence.

The remainder of this paper is organized as follows: In section 2 we describe the different datasets (i.e., the financial and pandemic-related data), provide details on the data processing, and illustrate selected data graphically. In section 3, we introduce the econometric model, while section 4 lays out the empirical results and the robustness of our analysis. Finally, section 5 contains our conclusions.

2. Data

2.1. Financial data

To construct series on household finances, we utilize an anonymized bank dataset provided by BNP Paribas Fortis (BNPPF). BNPPF is the largest bank in Belgium, holding a quarter of the commercial banking market, and is active across all regions of the country. This dataset includes all transactions related to the (non-identifiable) accounts of retail clients. It covers cash withdrawals, debit and credit card purchases, and wire or SEPA transfers executed within the bank since 2012 for around 4 million Belgium-based retail clients. The average number of weekly transactions is about 15 million, with a total volume exceeding €460 million. For the needs of our study we focus on financial transactions executed during the pandemic period (from March 2020 until October 2022).

The transaction data include the timestamp, an anonymized counterparty identifier, the transaction value (in €), the direction of the transaction (debit/credit), and a label indicating the economic goal of the transaction. The labeling process is conducted by proprietary methods within the bank where the communication patterns and metadata accompanying each transaction are exclusively accessible to the bank.

Beyond the financial transaction data, non-identifying client-level data is available, which comprises monthly balances as well as demographic information such as age, gender, civil status, and municipality of residence. These client characteristics offer scope to test heterogeneous reactions across different types of households. Additionally, the transaction-level economic labels enable us to differentiate among spending categories (see infra, section 2.1.1).

This dataset has several advantages over existing data sources. Compared to survey data, it does not suffer from recollection bias and the related measurement errors (Moore et al., 2000). Moreover, the series are not confined to a limited number of participants and survey topics or to cross-sectional information. Selection into the sample is only dependent on having an active bank account at BNPPF. Relative to third-party financial management and aggregator apps (Baker and Yannelis, 2017; Olafsson and Pagel, 2018; Gelman et al., 2020), which eliminate the reporting shortcomings of surveys, our data is not susceptible to the salience effect of platform usage on financial behavior (Baker, 2018) and avoids selection biases.

However, this is not to say that commercial bank data comes without limitations. An important one is the lack of knowledge on households' holding of bank accounts at other financial institutions or in-kind transfers. We observe households transactions based on their accounts at one financial institution. If a person has current accounts at multiple banks that are all actively used to both receive income and finance consumption, we might underestimate financial means and consumption.[5] In practice most households in Belgium pool their income and pay their expenditures from a single current account. Higher wealth households might spread their wealth across savings accounts at multiple banks in order to benefit from the EU Deposit Guarantee Scheme that protects 100,000€ per person per establishment. In this scenario, however, the bank accounts at different banks are savings accounts which would not violate our assumption that one single current account is used to both pool income and pay for expenditures. Therefore, we limit our sample to those accounts that exhibit a minimal monthly income and expenditure (see infra, section 2.1.2).

[5]Anecdotally, BNPPF has opened Payment Service Providers Directive (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 clients currently use the functionality actively, signalling either a limited inclination or need to merge multiple accounts.

In the remainder of this section, we outline the specific payment labels that are pertinent to our research focus and explain their use in our analysis. Furthermore, we describe how specific labels associated with the transaction data are used to construct income and consumption series, explain how the transaction-level data is aggregated into a household-level panel dataset, and visualize the eventual sample under analysis.

2.1.1. Income and consumption categories

Different income categories, namely labor, replacement, social security, and rental income, are identified based on the communication notes of the transactions. To identify rental income, the bank identifies rent-related keywords. For the other income categories, the focus is on identifying formal communication patterns. In Belgium, these income sources are (partially) safeguarded from debt confiscation by law, necessitating organizations and institutions to incorporate fixed patterns in transaction communication to maintain this protection.[6] Detailed information on the specific symbols that correspond to each income type are available in Appendix A of Boudt et al. (2022).

Various types of consumption are identified based on the transaction metadata, which includes the Merchant Category Code (MCC) for card transactions conducted at a Point of Sale (POS),[7] the NACE[8] sector code for the counterparty in the case of a SEPA transfer to a corporate entity, and a category code that designates the technical nature of the transaction (e.g., cash withdrawal from an ATM). These codes have been aligned by the bank with the Classification of Individual Consumption According to Purpose (COICOP) by the United Nations (United Nations, 2018), which also assigns a durability type to each category. This detailed classification results in 58 distinct consumption categories.

The consumption categories are classified into 5 consumption types. Non-durable goods, which primarily include single-use items such as food and personal care products; durables, which are goods intended for long-term use, often expensive, like cars and refrigerators; semi-durables, which have a shorter lifespan and lower cost than durables, exemplified by clothing and small household appliances; services, which include various forms of assistance or advice; and mixed, a category introduced for transactions that do not fit neatly into one category, such as those at businesses offering a range of goods or for credit card payments that can encompass any type of purchase. For more information, interested readers can consult Boudt et al. (2022).

2.1.2. Constructing household-specific series

To effectively analyze how households' consumption patterns responded to the pandemic waves, it is crucial that our dataset includes households actively utilizing their bank accounts. This active use is characterized by both receiving income and funding expenditures through

[6] As mandated in the Royal Decree of the 4th of July 2006, implementing Article 1409, 1410 and 1411 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 (in Dutch): `https://www.ejustice.just.fgov.be/eli/besluit/2006/07/04/2006009525/staatsblad`.

[7] In compliance with regulations, each POS terminal must be registered to a corresponding merchant, who is further obligated to disclose the associated MCC to the terminal provider. The MCC is subsequently linked to the POS terminal and transmitted as metadata for all ensuing transactions processed via the payment provider. A comprehensive compendium of MCC codes, with their corresponding definitions, is accessible through resources such as `https://usa.visa.com/content/dam/VCOM/download/merchants/visa-merchant-data-standards-manual.pdf`.

[8] The NACE codes comprise the system of statistical classification of economic activities in the European community, and comes from the French term "Nomenclature statistique des Activités économiques dans la Communauté Européenne".

the account. Specifically, we are interested in clients who predominantly use their BNPPF accounts. This focus is essential to avoid mismeasuring the impact of the pandemic on consumption, as spending from non-BNPPF accounts is not visible in our data.

In accordance with the methodology outlined by Boudt et al. (2022), we implement a dual restriction to identify active households. An 'active' household is defined as one where both the total nominal income and non-durable consumption consistently surpass the basic needs threshold for a single-person household in Belgium. Drawing on the findings of Storms and Van den Bosch (2009), these thresholds are set at a minimum income of 639€ per month and a minimum non-durable consumption of 166€ per month. These values are adjusted for inflation relative to the start of our sample period and remain fixed throughout the duration of the study. While we require the non-durable consumption threshold to be met monthly, we offer more flexibility with the income criterion, permitting up to two months per year without income. This allowance caters to situations such as temporary unemployment or transitions between jobs, considering that in Belgium, it can take up to two full months to start receiving unemployment benefits. Our approach yields a final sample of 337,531 active households.

Consumption is aggregated on a weekly basis per durability type, using the ISO week date system. The sum of all durability types makes up total household consumption. With regards to credit card purchases, we assume that consumption occurs when a household is paying down their credit card bill, and not when the goods are actually purchased, even though the goods might have been received before the payment happened. If 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.

To obtain income series at the household level, we sum up labor, replacement, social security and rental income transactions per week per household. To construct a measure of liquid financial wealth per household we sum end-of-month cash balances across bank accounts that can, if necessary, be liquidated on short notice. This includes checking accounts, (term) savings accounts, pension savings accounts, and investment accounts. Because we can only observe client balances at the monthly level, the measure of liquid financial wealth is constructed at the monthly frequency.

2.2. Pandemic data

To proxy the evolution and local intensity of the pandemic in Belgium we use weekly confirmed new cases of COVID-19 by municipality, divided by the official number of tests conducted in that municipality. The series are provided by Sciensano, the Belgian institute for health.

By dividing the number of new confirmed cases with the number of tests conducted, we take account of changes in testing capacity over time. Although the number of new cases itself is widely used in related literature to proxy pandemic severity, the epidemiological literature points to biases driven by time-varying errors - as pointed out in, e.g., Arias et al. (2023). Indicatively, in the beginning of the pandemic – when testing capacity was limited and mainly directed to healthcare workers – the number of new cases was biased downwards. Only by mid-May 2020, testing capacity in Belgium was extended sufficiently to cater for all persons with corona-related symptoms. A smaller underestimation also occurred by the end of 2021 as infections were high and testing capacity reached its maximum. The division also rectifies the underreporting of COVID-19 cases towards the end of the pandemic when the widespread use of self-administered testing protocols (self-tests) had led to a downward bias in the aggregate quantity of registered tests over time.

We decided to not use the number of COVID-19 deaths or the number of COVID-19-related hospitalizations as proxies for the evolution of the pandemic. First, these are lagging variables where the choice of the appropriate lag is subjective as hospitalization or death by COVID-19 can arise a few days to several months after the initial infection. Second, the data is not available per municipality. Beyond obvious privacy reasons concerning the cause of hospitalization or death, the place of hospitalization or death also does not necessarily inform us about the individual's place of residence which is needed to pick up the local incidence of the pandemic. In conclusion, we consider the number of new cases over tests to be the most suitable proxy of pandemic severity given the granularity, timeliness, and accuracy of the series.

We further utilize municipal vaccination data from Sciensano to create a variable that captures the local percentage of fully vaccinated adults. These are individuals that have completed their primary vaccination series. In other words, those who have received either one dose of a single-dose COVID-19 vaccine that has been licensed or authorized for use in Belgium (e.g., Johnson & Johnson's Janssen), or the second dose of a two-dose COVID-19 vaccine (e.g., Pfizer-BioNTech, Moderna).[9]

2.3. Governmental non-pharmaceutical interventions data

To assess the rigor of policy measures implemented by the Belgian government, we obtain data from the Oxford COVID-19 Government Response Tracker (OxCGRT). Out of the five NPIs available in the database, our analysis zeroes in on the Stringency Index (SI).[10] The SI encapsulates nine containment and closure policy indicators, such as stay-at-home-orders, cancellations of public events, and restrictions on gatherings. Each policy indicator is quantified by being assigned an ordinal value (ranging from 0 to 2, 3, 4, or 5, depending on the maximum value assigned to it). The final SI value is calculated as the average of the containment and closure policy indicators. This value is then normalized to fall within the range of 0 to 100. Although the OxCGRT indexes are provided at a daily frequency, we take weekly averages in order to match the frequency of our consumption data.[11]

The OxCGRT database covers national indices, where the most stringent government policy that is in place in the country determines the value. In other words, the country-wide policy indicators adopt the highest local ordinal value at each point in time. Although the federal government of Belgium took country-wide measures against the spread of the virus, regional and municipal authorities had the freedom to impose additional rules within their jurisdictions. The absence of sub-national data for Belgium in the OxCGRT database poses a hindrance to our analysis, as we aim to utilize the NPIs at the municipality level. For example, from July 28 to August 26 2020, the indicators of "Stay-at-home requirements" and "Restrictions on internal movement" for Belgium had a high value although only the province of Antwerp enforced a strict evening curfew. To surpass this obstacle, we utilize official announcements for local measures found in the data files (with notes) in the data section of OxCGRT's GitHub repository, and construct municipal NPI indicators that reflect more accurately the strictness and timing of measures at each municipality.

[9] According to covidsafe.be, *"In Belgium, you are considered fully vaccinated when you have received the final dose of your vaccine. For most vaccines, that is the second dose. For some vaccines only one dose is given."*

[10] The other four indexes refer to health, economic, vaccination, and miscellaneous policies. For more information, interested readers can refer to Hale et al. (2021) and the documentation section of the COVID policy tracker on the OxCGRT GitHub repository.

[11] Additionally, we have conducted our analysis using the Government Response Index (GRI), which - on top of containment and closure policies - also encompasses health system policies such as coverings, protection of the elderly, and level of contact tracing. We did not observe any substantial differences in our results, which can be made available upon request.

We next take the average of the respective indicators to obtain municipal SIs. This strategy allows to capture the time and geographical variation of the NPI series, thus painting a more accurate picture of the NPI intensity across the country. Nevertheless, it is important to bear in mind that two municipalities can differ in the level of compliance and enforcement of these measures despite being subjected to identical measures. Such differences in the level of obedience to and enforcement of the measures among municipalities, cannot be captured with our data (Kapetanios et al., 2022, p. 14) when varying over time.

The top panel of figure 1 presents the weekly evolution of the average COVID-19 cases-to-tests measure and SI in Belgium. Dark gray-shaded areas represent the seven COVID-19 waves that hit the country, as defined by Sciensano (Jurcevic et al., 2023). Light gray areas illustrate milder, inter-wave periods. To ensure comparability between the two variables and to simplify the interpretation of the graphs and coefficients, we employ the min-max scaling technique. This method transforms the distribution of the cases ratio, aligning it within a specified range of 0 to 100. It operates by subtracting the minimum value of the dataset from each data point and then dividing by the range of the dataset.

Figure 1 effectively conveys a key point of our work, which is that the evolution of the new COVID-19 cases ratio does not necessarily follow the same pattern as that of the SI. Moreover, data on the cases ratio demonstrate significantly greater cross-sectional variation at the municipal level compared to the SI data. This is because there are marked discrepancies in the intensity of COVID-19 outbreaks across different municipalities, as opposed to the SI measures that largely reflect uniform national policies. The differential time variation together with the extensive cross-sectional variation in the dataset, allows us to pinpoint the effects of each of these factors on consumption.

The bottom panel of figure 1 illustrates the evolution of average consumption of Belgian households in €, which shows an especially severe drop during the first wave of the pandemic. The green line displays smoothed average consumption as a four-week moving average, while the gray dashed line displays the actual value of weekly average consumption.

Figures 2 to 4 illustrate the distributions of income, liquid wealth, and age, delineated into color-coded quartiles. The intersecting segments of these distributions highlight the potential for dynamic shifts within the quartile groups. For instance, households with an annual income of 25,000€ might belong to the first income quartile in one year and move to the second quartile in another. This fluctuation occurs because our algorithm reassigns households to different groups on an annual basis, leading to minor adjustments in the quartile boundaries each year.

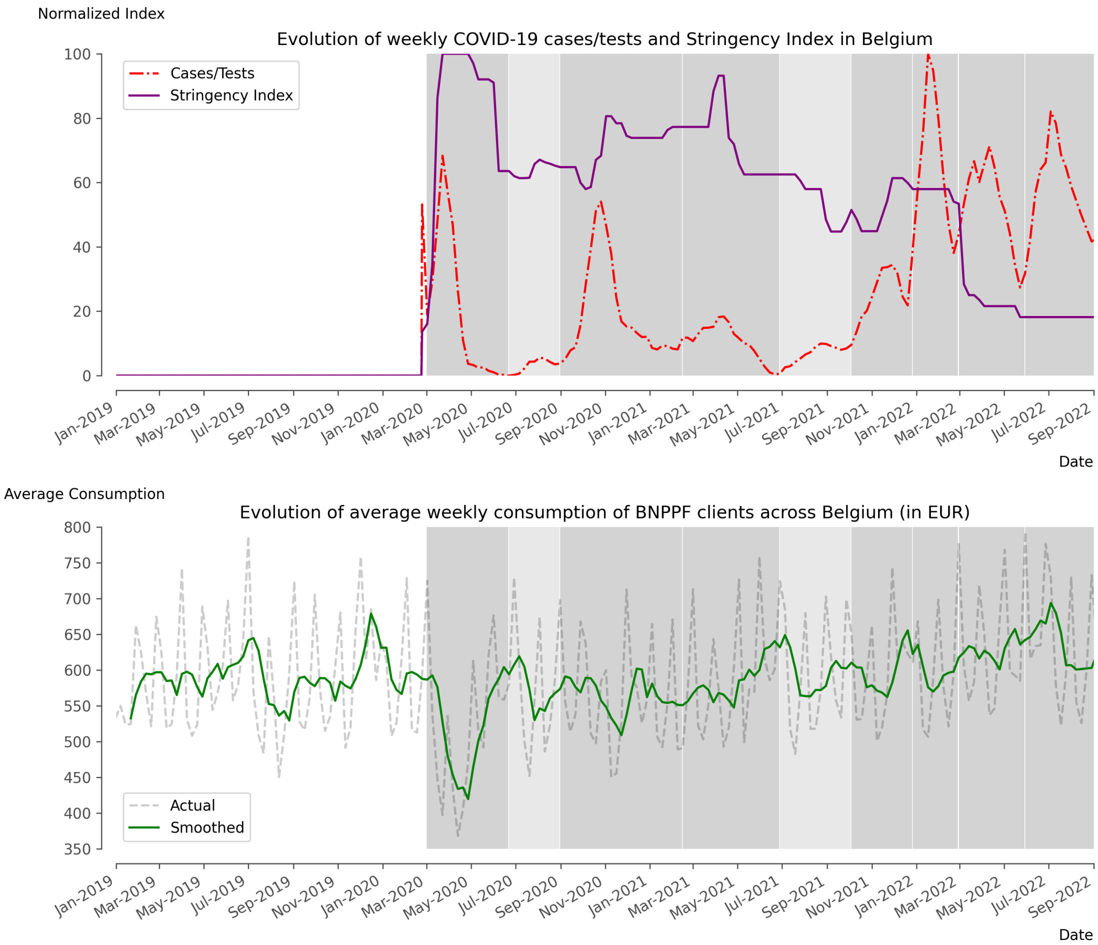

Figure 1: Overview of Pandemic Indicators and Consumption Patterns in Belgium. The dark gray-shaded areas indicate the periods of the seven COVID-19 waves, and the light gray-shaded areas signify the two periods between waves. Upper panel: Evolution of pandemic-related metrics (COVID-19 cases-to-tests ratio and the Stringency Index), both scaled to the min-max range. Lower panel: The dashed gray line charts the weekly consumption of active BNPPF households, with the green line representing its smoothed four-week moving average.

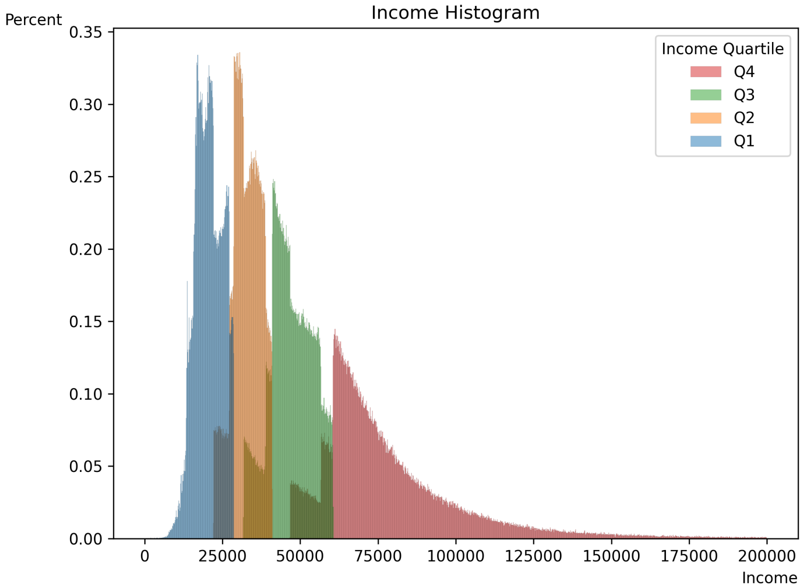

Figure 2: Distribution of annual household income

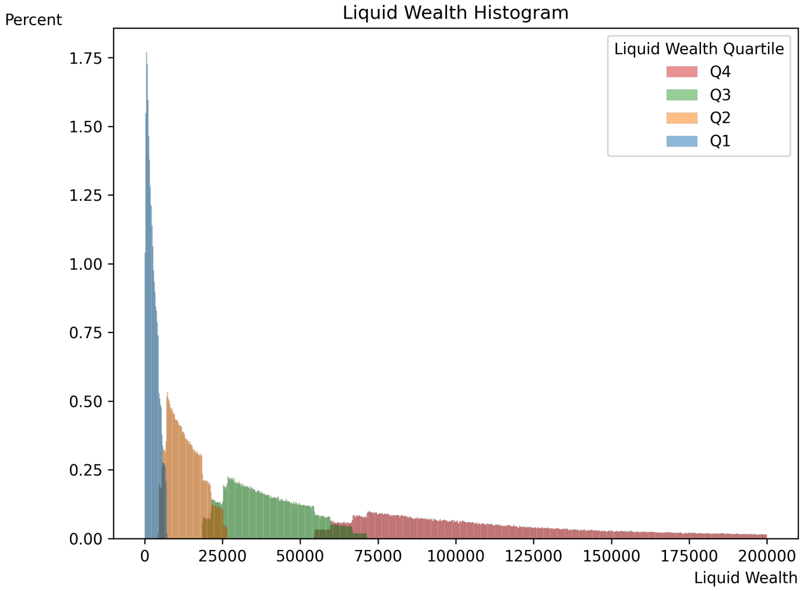

Figure 3: Distribution of household liquid wealth

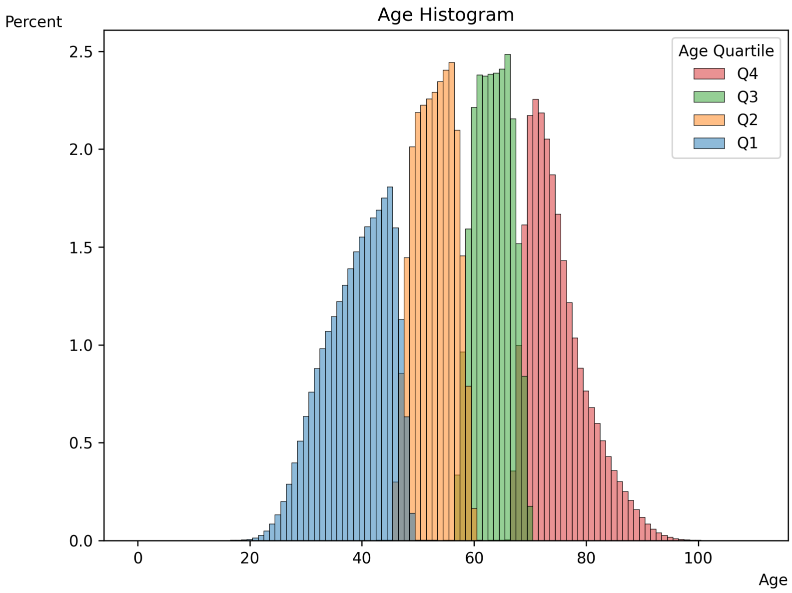

Figure 4: Distribution of household age, calculated as the age of the oldest household member.

3. Methodology

We employ a fixed effects panel model to estimate the impact of local pandemic intensity, governmental NPIs, and vaccination rates on consumption. Equation (1) represents our baseline regression:

$$C_{i,j,t} = \alpha_i + \gamma * CT_{j,t} + \delta * SI_{j,t} + \kappa * VACC_{j,t} + \varepsilon_{i,j,t} \tag{1}$$

$C_{i,j,t}$ is the dependent variable and denotes the natural logarithm of total consumption of household i, residing in municipality j, based on their aggregated transactions in week t. α_i is the term for household fixed effects which shields our model against omitted variable bias by accounting for heterogeneous, unobserved, and time-invariant characteristics of households. $CT_{j,t}$ represents the positivity rate index or the scaled ratio of new COVID-19 cases over tests in municipality j (where household i resides), during week t. $SI_{j,t}$ represents the stringency index, our benchmark indicator of government NPIs, in municipality j and week t. $VACC_{j,t}$ denotes the percentage of fully vaccinated adults in municipality j and week t. Finally, $\varepsilon_{i,j,t}$ represents the idiosyncratic errors, clustered at the municipality level.

Different to most papers in the literature, we explicitly account for the positivity rate in our analysis while estimating the size and significance of the SI effect on consumption. This allows us to scrutinize the extent to which household consumption changes because of the restrictions imposed by the NPIs while controlling for the severity of the pandemic and vice versa. Moreover, the inclusion of both variables at the same time also informs us about the relative importance of these two factors in driving consumption, i.e., to answer the question whether household consumption was predominantly being driven by the spread of the virus - the fear of infection - or by the containment measures. To the extent that the SI variable is relevant, not controlling for it could also trigger an omitted variable bias of the γ coefficient.

An alternative approach has been followed in Kapetanios et al. (2022), where the authors use time fixed effects to capture the lockdown effect in their regression for the Netherlands since the stringency and timing of containment measures were the same across all Dutch municipalities. Such a nationally coherent policy was absent in Belgium where the more fragmented governance setting introduced spatial variations in how measures were applied. While the stringency and timing of the NPIs in Belgium shared a substantial national common component, nuances arose at the local level. These differences were a result of special measures enacted by regional governments or municipal authorities, providing spatial variation that can be exploited to gauge a quantification of the NPI effect on consumption through the δ coefficient. Time fixed effects also do not solely capture the evolution in NPI and would thus not allow to separate the relative contributions of the government-mandated NPIs and the pandemic-related positivity rates.

One other potential concern raised by Kapetanios et al. (2022) relates to reverse causality driven by the fact that increased consumer spending at the municipality level potentially heightens COVID-19 transmission through more frequent shopping interactions. Our measure of household consumption is, however, more granular in nature as we pick up the consumption of individual households i within municipalities j. The potential of one household's consumption to affect the municipality-level positivity rate index within a week is therefore extremely unlikely.

In a next step, we extend the baseline model to an interaction model to assess whether differences in income, liquid wealth, and age of households shape heterogeneous consumption reactions.

$$\begin{aligned} C_{i,j,t} = {} & \alpha_i + \gamma * CT_{j,t} + \delta * SI_{j,t} + \kappa * VACC_{j,t} + \zeta * \boldsymbol{X_{i,j,t}} \\ & + \eta * \boldsymbol{X_{i,j,t}} * CT_{j,t} + \theta * \boldsymbol{X_{i,j,t}} * SI_{j,t} + \rho * \boldsymbol{X_{i,j,t}} * VACC_{j,t} + \varepsilon_{i,j,t} \end{aligned} \tag{2}$$

Equation (2) extends model (1) by including interactions of $\boldsymbol{X_{i,j,t}}$, a vector of control variables, with the pandemic-related variables to capture the potential heterogeneity in the effects of the local infections, NPIs, and vaccination rates on consumption. $\boldsymbol{X_{i,j,t}}$ includes the binary dummy variables representing income, liquid wealth, and age quartiles. *Income quartile* 1 equals 1 for households with the lowest annual income (below 26,783€), *income quartile* 2 for households with medium-low annual income (26,783€ - 38,643€), *income quartile* 3 for medium-high income (38,643€ - 56,868€), and *income quartile* 4 for high income (over 56,868€); *liquid wealth quartile* 1 is 1 for households with low liquid wealth (below 5,405€), *liquid wealth quartile* 2 for medium-low wealth (5,405€ - 21,927€), *liquid wealth quartile* 3 for medium-high wealth (21,927€ - 62,218€), and *liquid wealth quartile* 4 for high wealth (over 62,218€); *age quartile* 1 is 1 for "young" households (the oldest member age is below 47 years), *age quartile* 2 and *age quartile* 3 for older households (respectively for 47-58 and 59-68 years), and *age quartile* 4 for the oldest households (over 68 years).[12]

4. Empirical Results

Table 1 displays the estimation output of baseline model (1) (column 1) and the interaction model (2) (columns 2-7) utilizing the FE estimator. All regressions include household fixed effects and display the coefficients when controlling for seasonal factors affecting household consumption during the year - by adding monthly dummies as control variables - and during the course of the month - via inclusion of weekly dummy variables. Controlling for these month and week-of-the-month effects, however, does not substantially affect the slope coefficients of interest.

4.1. Baseline model

The coefficients of the pandemic variables are negative and statistically significant at the 1% level. Indicatively, a 1 unit increase in the positivity rate index in a household's municipality of residence is associated with a 0.0052% drop in its consumption. For the SI, a 1 unit increase is associated with a consumption drop of 0.0035%. Naturally, the effect of the vaccination program on consumption is positive. A 1% increase in the percentage of vaccinated adults in one's municipality translates into a 0.0379% increase in local consumption. The significant consumption response to the local pandemic severity, even while controlling for municipal-level NPI and vaccination data, underscores the influence of the fear of infection in driving the observed consumption effects.

To put these coefficients' values into context, we interpret them along with the descriptive statistics of our variables of interest. With the positivity index's standard deviation at 5.935, a one standard deviation change translates to a 9.71€ decrease in consumption from the average weekly level of 327.34€ (this is the exponent of the mean natural logarithm of consumption which equals 5.791) to 317.64€. Considering a one standard deviation increase of SI - which equals 23.94, the weekly consumption is predicted to decrease by 26.64€ from the average of 327.34€ to 300.70€. Finally, with a one standard deviation increase in the adult vaccination rate - measured at 0.34, weekly consumption is expected to rise by 4.40€. While the observed decreases in consumption may appear modest, it is crucial to emphasize that these are average reductions across all seven waves of the pandemic period. As will be demonstrated in subsequent analysis, the impact on consumption was considerably more pronounced during specific waves of the pandemic.

[12] As highlighted in section 2.3, the quartile boundaries within our dataset are subject to annual adjustments. In this context, the boundaries presented here represent the quartile cutoffs for the entire sample period.

All in all, the baseline model provides clear evidence that households residing in municipalities that were hit harder by the pandemic and that experienced stricter NPIs, decreased their consumption more compared to households living in municipalities where the impact of the pandemic and the NPIs was milder. It also shows that both the pandemic severity and the government measures significantly reduced household consumption in Belgium. The SI coefficient's significance and value might seem at odds with existing empirical findings, like Chetty et al. (2024), Chen et al. (2021), Kapetanios et al. (2022), and Sheridan et al. (2020), which indicate that NPIs had a short-term impact but accounted for only a small fraction of the observed consumption declines. However, it is crucial to highlight that the aforementioned studies focus on the first wave of the pandemic - and second wave, in the case of Kapetanios et al. (2022), while our coefficients encompass a substantially longer period - from March 2020 to October 2022 - capturing all seven COVID-19 pandemic waves.

To get a grasp on the effects over the pandemic waves, we examine the evolution of the reaction of consumption as the pandemic unravels. To do this we execute a rolling-window estimation of the baseline model with a 16 week-window, which is the average duration of a COVID-19 wave in Belgium. The upper panel of Figure 5 depicts the evolution of the coefficient of the positivity rate index (γ) over time and the lower panel does this for the SI (δ). As expected, we observe that at the height of the pandemic during wave 1 - when the starting date of the window is in the second week of April 2020 - the positivity coefficient drops at its most negative value, which is around 10 times larger than the overall coefficient. Some local minima are also observed during the third wave (March and May 2021). On the other hand, the SI coefficient showcases a negligible effect during the first COVID-19 wave, a result that is in line with the bulk of the literature that focuses on the beginning of the pandemic. Yet, our analysis reveals that the time-varying SI coefficient exhibits significantly negative values of -0.022 and -0.027 during the pandemic's second and third waves, respectively. This underscores the importance of considering the pandemic in its entirety to fully capture the effects of the local pandemic measures on consumption.

In conclusion, our research corroborates existing studies that emphasize the more pronounced impact of the pandemic's severity over government interventions in reducing consumption during the pandemic's initial wave. At the same time, our analysis offers new insights into the evolving interplay between these two factors throughout the pandemic's progression. Despite a relative weakening, the influence of the pandemic's severity on consumption patterns persists in subsequent waves, even post-vaccination roll-out, underlining a sustained, albeit attenuated, impact on consumer behavior dynamics.

4.2. Extended model

The rest of table 1 showcases the estimation output of model (2). In line with the approach recommended by Giesselmann and Schmidt-Catran (2022), we have grand-mean centered all data before estimation. This procedure ensures that the main effect coefficients in model (2) are interpreted at the mean level of the other variable in the interaction term. Such normalization is standard, but also needed to directly compare the coefficients to those derived from the dd-IE model discussed in section 4.3.

Columns 2, 4, and 6 address the question whether the consumption response of households to pandemic severity and NPIs differs based on their income, liquid wealth, and age distribution, respectively. To avoid multicolinearity in our model we omit the interaction term associated with the first quartile.[13] Importantly, applying grand-mean centering to our

[13]For income, that is households of low annual income (639€ - 26,783€), for liquid wealth households of low liquid wealth (up to 5,405€), and for age, young households (whose oldest member does not exceed 47

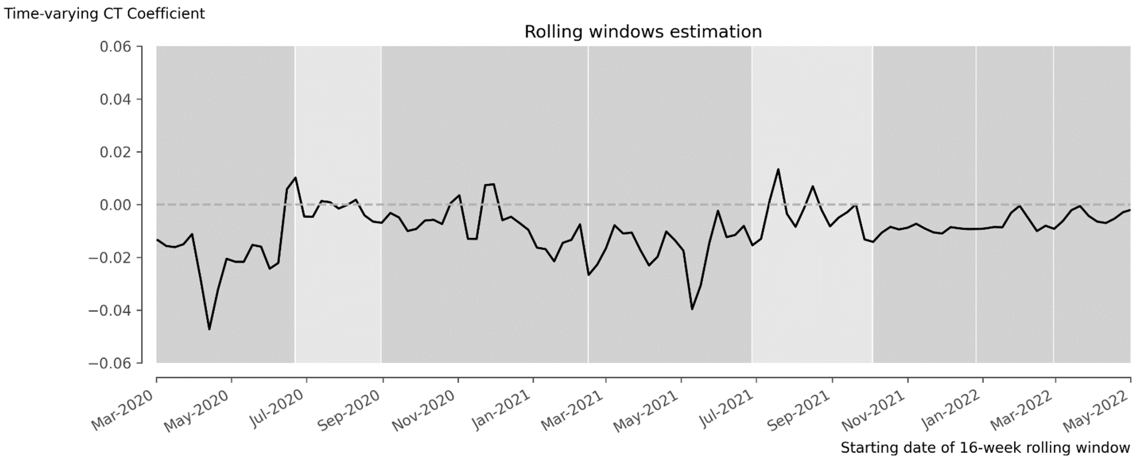

Figure 5: Rolling window estimation of Table 1, column 1. Evolution of cases-to-tests and stringency index parameters over time. The dark gray-shaded areas indicate the periods of the seven COVID-19 waves, and the light gray-shaded areas signify the two periods between waves.

variables — including quartile dummies — shifts the intercept but preserves the interpretation of the interaction terms (Yaremych et al., 2023).[14] The baseline coefficients of CT and SI therefore reflect the consumption reaction of *quartile* 1.[15]

We first focus on the interaction terms involving CT to gauge the heterogeneity in the consumption reaction due to local pandemic severity. Two basic insights arise from the analysis of quartile-CT interaction terms. First, we observe a more negative impact of the fear of infection, as indicated by local pandemic severity, for individuals with lower incomes and liquid wealth across the entire sample. Second, we note a significant behavioral difference across age groups. Household consumption in the highest age quartile (fourth quartile) responds most

years of age).

[14]In particular, the model's intercept no longer just represents the scenario for quartile 1 but shifts to show the average consumption across quartiles, based on their distribution in the dataset. This change affects how we interpret the intercept but, crucially, the fundamental comparisons across quartiles—how different quartiles compare to the first in terms of consumption—stay the same. To enhance readability, we refrain from including the coefficients of the quartile dummy constituent terms ζ in our table. For all three heterogeneity categories - income, liquid wealth, and age - they are positive, statistically significant, and increasing. The full regression output can be made available upon request.

[15]We have conducted estimations across alternative specifications by systematically excluding one quartile at a time. This approach allows us to verify that the statistical significance of the differences remains robust, regardless of the specific quartile selected as the reference category. The results of these estimations are available upon request.

strongly to the COVID-19 positivity rate in their municipality. This statistically significant response among older households is in line with what one would expect in a full-information, rational expectations (FIRE) model, which predicts a heightened behavioral response among older demographics due to a rational evaluation of increased mortality risk from infectious diseases like COVID-19 (Eichenbaum et al., 2024).

Examination of quartile-SI interactions uncovers a pattern of heterogeneity as well. Similar to CT, the negative effect of SI is strongest for households in the lowest income quartile, albeit marginally. However, households across higher liquid wealth quartiles exhibit a greater reduction in consumption relative to the first quartile, in response to local containment measures. For age, we only find a more negative reaction for quartile 4.

In columns 3, 5, and 7, we put the focus on the percentage of fully vaccinated adults and its interactions with the household-level dummy indicators to assess whether the vaccination effects on consumption differ over income, liquid wealth, or age quartiles. The results indicate that the impact of the local vaccination rate on household consumption varies significantly among different household groups. Notably, the increase in consumption due to higher municipal vaccination rates is least pronounced for households in the lowest liquid wealth quartiles, with the effect growing as liquid wealth increases. For income, this impact is significantly larger only for households in the highest income quartile. According to column 7 of table 1, local vaccination rates provide the biggest consumption boost to the oldest households. This observation is consistent with the anticipation that older, more vulnerable households may derive greater benefits from vaccination programs compared to their younger counterparts.

Table 1: Comparative Regression Outcomes of Household Consumption on Various Pandemic-Related Predictors - standard fixed effect - interaction estimator (FE-IE) (centered)

		Income models		Liq. Wealth models		Age models	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$
Estimator	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE
R-squared	0.249	0.249	0.249	0.249	0.249	0.249	0.249
F	70,470	48,130	54,130	47,710	53,650	47,160	53,000
$p-value(F)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	0.0227***	0.0227***	0.0227***	0.0231***	0.0229***	0.0228***	0.0227***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$CT_{j,t}$	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
$SI_{j,t}$	-0.0035***	-0.0035***	-0.0035***	-0.0035***	-0.0035***	-0.0035***	-0.0035***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
$VACC_{j,t}$	0.0379***	0.0378***	0.0379***	0.0373***	0.0367***	0.0378***	0.0378***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$Quartile\ 2 \times CT_{j,t}$		0.0006***		0.0007***		-0.0005***	
		(0.00009)		(0.00009)		(0.00008)	
$Quartile\ 3 \times CT_{j,t}$		0.0011***		0.0007***		-0.0002**	
		(0.00009)		(0.00009)		(0.00008)	
$Quartile\ 4 \times CT_{j,t}$		0.0016***		0.0010***		-0.0016***	
		(0.00009)		(0.00009)		(0.00009)	
$Quartile\ 2 \times SI_{j,t}$		0.00001		-0.0007***		0.0003***	
		(0.00003)		(0.00003)		(0.00003)	
$Quartile\ 3 \times SI_{j,t}$		0.0002***		-0.0009***		0.0002***	
		(0.00003)		(0.00003)		(0.00003)	
$Quartile\ 4 \times SI_{j,t}$		0.0002***		-0.0010***		-0.0008***	
		(0.00003)		(0.00003)		(0.00003)	
$Quartile\ 2 \times VACC_{j,t}$			0.0027		0.0521***		-0.0272***
			(0.0020)		(0.0020)		(0.0020)
$Quartile\ 3 \times VACC_{j,t}$			-0.0034*		0.0651***		-0.0235***
			(0.0020)		(0.0020)		(0.0020)
$Quartile\ 4 \times VACC_{j,t}$			0.0040**		0.0723***		0.0279***
			(0.0020)		(0.0020)		(0.0020)
Quartile Controls	No	Income	Income	Liq. Wealth	Liq. Wealth	Age	Age
Monthly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

4.3. Double-Demeaned Interaction Estimator

To safeguard against bias in our standard fixed effects interaction estimator (FE-IE), we implement a secondary analysis in accordance with Giesselmann and Schmidt-Catran (2022). This involves estimating a double-demeaned FE-interaction (dd-IE) estimator. The procedure for dd-IE requires initially demeaning each individual interacted variable, followed by demeaning their product to derive the interaction term. As Giesselmann and Schmidt-Catran (2022) show, simply demeaning interaction terms using the FE-IE yields a combination of between- and within-entity interdependencies rather than a within-entity estimator. This FE-IE approach could lead to biased interaction coefficients, especially when the interaction involves two time-varying variables. This bias will be present if one of the interacted variables is correlated with an unobserved entity-specific moderator of the other. The dd-IE is not subject to this bias of the standard FE-IE but is less efficient "if the interacted variables' within-entity variation is small or the number of measures per unit is low." (Giesselmann and Schmidt-Catran, 2022, p. 1120).

The outcomes of the dd-IE approach are detailed in Table 2. Overall, the majority of the conclusions concerning the pandemic's heterogeneous effects observed in the FE-IE are maintained. In several instances, these effects are even more pronounced. Some differences can, however, be noted. Indicatively, the influence of CT on consumption proves to be no longer significantly different at the 5% significance level for the different liquid wealth quartiles. In addition, the adverse impact of the fear of infection is significantly more substantial for households in the highest age quartile. With respect to government containment measures, the stringency index's impact on consumption is now uniform across all age groups, indicating no longer significantly different effects in this dimension. Moreover, the impact is now documented to be increasingly negative over the different income quartiles. In examining the heterogeneous effect of the vaccinations program on consumption in the dd-IE model, we note that the interaction coefficients in column 6 are substantially higher in absolute terms compared to their FE-IE counterparts and are all negative.

As elucidated by Giesselmann and Schmidt-Catran (2022), the dd-IE model is less efficient than the FE-IE model, with imprecision in estimates potentially arising from limited within-entity variation in the interacted variables. To identify systematic differences between the dd-IE and FE-IE estimates, we adopt an adapted version of the Hausman (1978) test as recommended by Giesselmann and Schmidt-Catran (2022). This nuanced approach is designed to assess whether the standard FE-IE estimates are comparable to those derived from the dd-IE estimates. The test evaluates the null hypothesis that interaction terms from the efficient, albeit potentially biased FE-IE, are identical to those from the dd-IE.

The results of the Hausman test are displayed in the last row of table 2. For columns 1 and 4, the null hypothesis can be rejected, indicating that the FE-IE estimates are statistically different from the dd-IE estimates. For columns 2 and 6, the Hausman statistic suggests no significant systematic difference between the dd-IE and FE-IE model estimates and recommends the adoption of the more efficient FE-IE model. When interactions include the $VACC$ variable, the standard errors increase substantially, especially in combination with the age quartiles. In the latter case, the imprecise estimates are likely explained by limited within-entity variation in the household age quartiles. These quartiles show notable stability over time, with a standard deviation nearly tenfold smaller than that observed for income and liquid wealth quartiles. For columns 3 and 5, the Hausman statistic χ_2 is negative, implying that we should refrain from interpreting the statistic (Giesselmann and Schmidt-Catran, 2022).

Taken together, the more robust dd-IE indicates interaction effects that have the same direction and are in general stronger in magnitude. The exceptions concern the lack of heterogeneous consumption effects of CT for the liquid wealth quartiles and the increasing negative consumption effects of SI for higher income households. The limited within-variation of the age quartiles furthermore makes the dd-IE model inappropriate for the analysis of these quartiles' interaction effects on household consumption.

4.4. Alternative types of consumption

In this section, we further utilize the BNPPF transactions dataset to evaluate the heterogeneous effects of the pandemic on various types of consumption. Table 3 presents the impact of the pandemic on non-durable consumption. The results reveal a smaller effect of the cases-to-tests index (CT) and an even lesser impact of stringency measures (SI) on non-durable consumption compared to overall consumption as detailed in table 1. These findings suggest that the pandemic's severity influenced non-durable consumption to a lesser extent compared to total consumption. Notably, the implementation of stringent measures had a minimal impact on households' non-durable consumption, an effect which was anticipated given that such consumption typically encompasses essential goods like food, unlikely to be reduced significantly.

Across all consumption types, most estimates point to a positive and statistically significant effect of $VACC_{j,t}$ (tables 3 to 7). This finding highlights the crucial role of the vaccination program in boosting consumption for households. For non-durable consumption, however, the impact decreases across the income quartiles and even turns negative for the highest income groups. The impact of vaccinations is also heterogeneous across the age quartiles.

Table 4 focuses on durable consumption and reveals a reduced impact of CT and SI when compared to overall consumption. It is noteworthy that the influence of vaccinations on durable goods is more than double compared to their impact on total consumption. In contrast to the patterns observed for total and non-durable consumption, the severity of the pandemic (CT) and the intensity of the containment measures (SI) exert a negative and overall more pronounced effect for households with higher income and liquid assets. The same holds for semi-durable and services consumption (see infra). The impact of vaccinations furthermore turns negative for households with older family members.

In the context of semi-durable goods, table 5 documents a greater sensitivity to CT and SI. Furthermore, we note occasional disparities in the heterogeneity of semi-durable goods consumption patterns, as contrasted with the aggregate consumption data depicted in Table 1. For example, semi-durable consumption of high-income and high-liquid wealth households decreases more driven by fear of infection but is more muted for older households.

The analysis of services consumption, as detailed in table 6, highlights a more substantial negative impact from SI than CT, an outcome anticipated due to the profound challenges lockdown measures imposed on the service sector. Remarkably, the positive influence of vaccinations on services consumption surpasses its effect on all other types of consumption, indicating a robust recovery driver. In addition, the negative impact of CT on consumption is more moderate for older households. Finally, regarding mixed consumption, table 7 indicates elevated coefficients for both CT and SI, with the impact of the former on mixed consumption almost doubling the latter.

Table 2: Comparative Regression Outcomes of Household Consumption on Various Pandemic-Related Predictors - double-demeaned FE-interaction estimator (dd-IE)

	Income models		Liq. Wealth models		Age models	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$
Estimator	dd-IE	dd-IE	dd-IE	dd-IE	dd-IE	dd-IE
R-squared	0.249	0.249	0.249	0.249	0.249	0.249
F	48,520	54,540	47,920	53,890	47,360	53,290
$p-value(F)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	0.0227***	0.0227***	0.0227***	0.0227***	0.0227***	0.0227***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$CT_{j,t}$	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***	-0.0052***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
$SI_{j,t}$	-0.0035***	-0.0035***	-0.0035***	-0.0035***	-0.0035***	-0.0035***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
$VACC_{j,t}$	0.0379***	0.0379***	0.0379***	0.0379***	0.0379***	0.0380***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$Quartile\ 2 \times CT_{j,t}$	0.0014***		0.0003*		-0.0003	
	(0.0003)		(0.0002)		(0.0024)	
$Quartile\ 3 \times CT_{j,t}$	0.0023***		-0.00008		0.0002	
	(0.0003)		(0.0002)		(0.0033)	
$Quartile\ 4 \times CT_{j,t}$	0.0031***		-0.0006*		-0.0099**	
	(0.0003)		(0.0003)		(0.0038)	
$Quartile\ 2 \times SI_{j,t}$	-0.0007***		-0.0008***		0.0005	
	(0.00007)		(0.00005)		(0.0006)	
$Quartile\ 3 \times SI_{j,t}$	-0.0013***		-0.0014***		0.0003	
	(0.00008)		(0.00007)		(0.0009)	
$Quartile\ 4 \times SI_{j,t}$	-0.0020***		-0.0019***		-0.00007	
	(0.0001)		(0.00009)		(0.0011)	
$Quartile\ 2 \times VACC_{j,t}$		0.0293***		0.0489***		-0.4653***
		(0.0057)		(0.0043)		(0.0908)
$Quartile\ 3 \times VACC_{j,t}$		0.0492***		0.0864***		-0.7194***
		(0.0069)		(0.0057)		(0.1142)
$Quartile\ 4 \times VACC_{j,t}$		0.0746***		0.0971***		-0.9090***
		(0.0077)		(0.0070)		(0.1409)
Quartile Controls	Income	Income	Liq. Wealth	Liq. Wealth	Age	Age
Monthly Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test (p-value)	0.00	0.65	$\chi^2 < 0$	0.00	$\chi^2 < 0$	0.99

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

Table 3: Comparative Regression Outcomes of Household Non-Durable Consumption on Various Pandemic-Related Predictors - standard fixed effect - interaction estimator (FE-IE) (centered)

		Income models		Liq. Wealth models		Age models	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	$\log(C^{ND}_{i,j,t})$	$\log(C^{ND}_{i,j,t})$	$\log(C^{ND}_{i,j,t})$	$\log(C^{ND}_{i,j,t})$	$\log(C^{ND}_{i,j,t})$	$\log(C^{ND}_{i,j,t})$	$\log(C^{ND}_{i,j,t})$
Estimator	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE
R-squared	0.276	0.276	0.276	0.276	0.276	0.276	0.276
F	19,900	14,230	15,920	13,550	15,220	13,800	15,360
$p-value(F)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	0.0339*** (0.0007)	0.0336*** (0.0007)	0.0337*** (0.0007)	0.0339*** (0.0007)	0.0339*** (0.0007)	0.0340*** (0.0007)	0.0340*** (0.0007)
$CT_{j,t}$	-0.0040*** (0.00005)	-0.0040*** (0.00005)	-0.0040*** (0.00005)	-0.0040*** (0.00005)	-0.0040*** (0.00005)	-0.0040*** (0.00005)	-0.0040*** (0.00005)
$SI_{j,t}$	-0.0004*** (0.00002)	-0.0003*** (0.00002)	-0.0003*** (0.00002)	-0.0004*** (0.00002)	-0.0004*** (0.00002)	-0.0004*** (0.00002)	-0.0004*** (0.00002)
$VACC_{j,t}$	0.0412*** (0.0011)	0.0414*** (0.0011)	0.0419*** (0.0011)	0.0410*** (0.0011)	0.0413*** (0.0011)	0.0410*** (0.0011)	0.0407*** (0.0011)
$Quartile\ 2 \times CT_{j,t}$		0.0008*** (0.0001)		0.0013*** (0.0001)		-0.0001 (0.0001)	
$Quartile\ 3 \times CT_{j,t}$		0.0014*** (0.0001)		0.0015*** (0.0001)		0.0004*** (0.0001)	
$Quartile\ 4 \times CT_{j,t}$		0.0022*** (0.0001)		0.0017*** (0.0001)		-0.0014*** (0.0001)	
$Quartile\ 2 \times SI_{j,t}$		0.0005*** (0.00004)		-0.0001*** (0.00004)		0.0006*** (0.00004)	
$Quartile\ 3 \times SI_{j,t}$		0.0010*** (0.00004)		-0.000003 (0.00004)		0.00004 (0.00004)	
$Quartile\ 4 \times SI_{j,t}$		0.0017*** (0.00004)		0.0001*** (0.00004)		-0.0018*** (0.00004)	
$Quartile\ 2 \times VACC_{j,t}$			-0.0245*** (0.0030)		0.0107*** (0.0029)		-0.0417*** (0.0027)
$Quartile\ 3 \times VACC_{j,t}$			-0.0546*** (0.0029)		0.0048 (0.0029)		-0.0042 (0.0027)
$Quartile\ 4 \times VACC_{j,t}$			-0.0922*** (0.0028)		-0.0048 (0.0029)		0.0932*** (0.0028)
Quartile Controls	No	Income	Income	Liq. Wealth	Liq. Wealth	Age	Age
Monthly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

Table 4: Comparative Regression Outcomes of Household Durable Consumption on Various Pandemic-Related Predictors - standard fixed effect - interaction estimator (FE-IE) (centered)

		Income models		Liq. Wealth models		Age models	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	$\log(C^D_{i,j,t})$	$\log(C^D_{i,j,t})$	$\log(C^D_{i,j,t})$	$\log(C^D_{i,j,t})$	$\log(C^D_{i,j,t})$	$\log(C^D_{i,j,t})$	$\log(C^D_{i,j,t})$
Estimator	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE
R-squared	0.120	0.121	0.121	0.121	0.121	0.121	0.121
F	10,320	8,323	9,324	7,180	8,039	7,785	8,933
$p-value(F)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	0.0359***	0.0366***	0.0364***	0.0364***	0.0362***	0.0357***	0.0358***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$CT_{j,t}$	-0.0038***	-0.0039***	-0.0039***	-0.0039***	-0.0039***	-0.0038***	-0.0038***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)
$SI_{j,t}$	-0.0022***	-0.0023***	-0.0023***	-0.0023***	-0.0023***	-0.0022***	-0.0022***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
$VACC_{j,t}$	0.0962***	0.0956***	0.0943***	0.0957***	0.0948***	0.0968***	0.0978***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
$Quartile\ 2 \times CT_{j,t}$		-0.0011***		-0.0003**		-0.0018***	
		(0.0001)		(0.0001)		(0.0001)	
$Quartile\ 3 \times CT_{j,t}$		-0.0019***		-0.0008***		-0.0017***	
		(0.0001)		(0.0001)		(0.0001)	
$Quartile\ 4 \times CT_{j,t}$		-0.0028***		-0.0016***		-0.0007***	
		(0.0001)		(0.0001)		(0.0001)	
$Quartile\ 2 \times SI_{j,t}$		-0.0010***		-0.0011***		0.0003***	
		(0.00003)		(0.00003)		(0.00004)	
$Quartile\ 3 \times SI_{j,t}$		-0.0020***		-0.0013***		0.0021***	
		(0.00003)		(0.00003)		(0.00004)	
$Quartile\ 4 \times SI_{j,t}$		-0.0044***		-0.0015***		0.0031***	
		(0.00003)		(0.00003)		(0.00003)	
$Quartile\ 2 \times VACC_{j,t}$			0.0571***		0.0739***		-0.0431***
			(0.0022)		(0.0027)		(0.0032)
$Quartile\ 3 \times VACC_{j,t}$			0.1248***		0.0845***		-0.1836***
			(0.0025)		(0.0028)		(0.0029)
$Quartile\ 4 \times VACC_{j,t}$			0.2858***		0.0861***		-0.2463***
			(0.0028)		(0.0028)		(0.0026)
Quartile Controls	No	Income	Income	Liq. Wealth	Liq. Wealth	Age	Age
Monthly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

Table 5: Comparative Regression Outcomes of Household Semi-Durable Consumption on Various Pandemic-Related Predictors - standard fixed effect - interaction estimator (FE-IE) (centered)

		Income models		Liq. Wealth models		Age models	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	$\log(C^{SD}_{i,j,t})$	$\log(C^{SD}_{i,j,t})$	$\log(C^{SD}_{i,j,t})$	$\log(C^{SD}_{i,j,t})$	$\log(C^{SD}_{i,j,t})$	$\log(C^{SD}_{i,j,t})$	$\log(C^{SD}_{i,j,t})$
Estimator	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE
R-squared	0.179	0.179	0.179	0.179	0.179	0.179	0.179
F	36,780	25,630	28,290	24,900	27,990	24,920	27,750
$p-value(F)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	0.1541***	0.1546***	0.1544***	0.1547***	0.1545***	0.1539***	0.1541***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
$CT_{j,t}$	-0.0117***	-0.0118***	-0.0118***	-0.0118***	-0.0118***	-0.0117***	-0.0117***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$SI_{j,t}$	-0.0062***	-0.0062***	-0.0062***	-0.0062***	-0.0062***	-0.0062***	-0.0062***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
$VACC_{j,t}$	0.0311***	0.0309***	0.0298***	0.0305***	0.0290***	0.0310***	0.0317***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
$Quartile\ 2 \times CT_{j,t}$		-0.0038***		-0.0015***		-0.0003	
		(0.0001)		(0.0002)		(0.0002)	
$Quartile\ 3 \times CT_{j,t}$		-0.0071***		-0.0019***		0.0042***	
		(0.0001)		(0.0002)		(0.0002)	
$Quartile\ 4 \times CT_{j,t}$		-0.0111***		-0.0022***		0.0078***	
		(0.0002)		(0.0002)		(0.0001)	
$Quartile\ 2 \times SI_{j,t}$		-0.0018***		-0.0013***		-0.0003***	
		(0.00004)		(0.00005)		(0.00005)	
$Quartile\ 3 \times SI_{j,t}$		-0.0031***		-0.0018***		0.0010***	
		(0.00005)		(0.00005)		(0.00005)	
$Quartile\ 4 \times SI_{j,t}$		-0.0048***		-0.0022***		0.0027***	
		(0.00005)		(0.00005)		(0.00004)	
$Quartile\ 2 \times VACC_{j,t}$			0.0781***		0.0824***		0.0099***
			(0.0030)		(0.0033)		(0.0035)
$Quartile\ 3 \times VACC_{j,t}$			0.1270***		0.1109***		-0.0398***
			(0.0031)		(0.0033)		(0.0034)
$Quartile\ 4 \times VACC_{j,t}$			0.2071***		0.1331***		-0.1080***
			(0.0033)		(0.0033)		(0.0032)
Quartile Controls	No	Income	Income	Liq. Wealth	Liq. Wealth	Age	Age
Monthly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

Table 6: Comparative Regression Outcomes of Household Services Consumption on Various Pandemic-Related Predictors - standard fixed effect - interaction estimator (FE-IE) (centered)

		Income models		Liq. Wealth models		Age models	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	$\log(C_{i,j,t}^{SERV})$	$\log(C_{i,j,t}^{SERV})$	$\log(C_{i,j,t}^{SERV})$	$\log(C_{i,j,t}^{SERV})$	$\log(C_{i,j,t}^{SERV})$	$\log(C_{i,j,t}^{SERV})$	$\log(C_{i,j,t}^{SERV})$
Estimator	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE
R-squared	0.274	0.274	0.274	0.274	0.274	0.274	0.274
F	182,700	122,700	137,900	122,100	137,400	122,000	137,200
$p-value(F)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	-0.0182***	-0.0178***	-0.0179***	-0.0173***	-0.0176***	-0.0183***	-0.0182***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
$CT_{j,t}$	-0.0059***	-0.0060***	-0.0060***	-0.0060***	-0.0060***	-0.0059***	-0.0059***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$SI_{j,t}$	-0.0086***	-0.0086***	-0.0086***	-0.0086***	-0.0086***	-0.0085***	-0.0085***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
$VACC_{j,t}$	0.1376***	0.1374***	0.1366***	0.1365***	0.1346***	0.1377***	0.1383***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
$Quartile\ 2 \times CT_{j,t}$		-0.0017***		-0.0006***		-0.0005***	
		(0.0002)		(0.0002)		(0.0001)	
$Quartile\ 3 \times CT_{j,t}$		-0.0025***		-0.0007***		0.0026***	
		(0.0002)		(0.0002)		(0.0001)	
$Quartile\ 4 \times CT_{j,t}$		-0.0045***		-0.0002		0.0040***	
		(0.0002)		(0.0002)		(0.0001)	
$Quartile\ 2 \times SI_{j,t}$		-0.0015***		-0.0017***		0.0008***	
		(0.00005)		(0.00005)		(0.00005)	
$Quartile\ 3 \times SI_{j,t}$		-0.0019***		-0.0022***		0.0019***	
		(0.00005)		(0.00005)		(0.00005)	
$Quartile\ 4 \times SI_{j,t}$		-0.0030***		-0.0027***		0.0021***	
		(0.00005)		(0.00005)		(0.00005)	
$Quartile\ 2 \times VACC_{j,t}$			0.0787***		0.1179***		-0.0709***
			(0.0039)		(0.0040)		(0.0038)
$Quartile\ 3 \times VACC_{j,t}$			0.1016***		0.1556***		-0.1231***
			(0.0038)		(0.0040)		(0.0039)
$Quartile\ 4 \times VACC_{j,t}$			0.1644***		0.1972***		-0.1064***
			(0.0038)		(0.0040)		(0.0038)
Quartile Controls	No	Income	Income	Liq. Wealth	Liq. Wealth	Age	Age
Monthly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

Table 7: Comparative Regression Outcomes of Household Mixed Consumption on Various Pandemic-Related Predictors - standard fixed effect - interaction estimator (FE-IE) (centered)

		Income models		Liq. Wealth models		Age models	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	$\log(C^{MIX}_{i,j,t})$	$\log(C^{MIX}_{i,j,t})$	$\log(C^{MIX}_{i,j,t})$	$\log(C^{MIX}_{i,j,t})$	$\log(C^{MIX}_{i,j,t})$	$\log(C^{MIX}_{i,j,t})$	$\log(C^{MIX}_{i,j,t})$
Estimator	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE	FE-IE
R-squared	0.236	0.236	0.236	0.236	0.236	0.236	0.236
F	23,700	16,910	18,510	16,110	18,080	16,180	17,980
$p-value(F)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	-0.1010***	-0.1001***	-0.1006***	-0.1001***	-0.1005***	-0.1011***	-0.1010***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
$CT_{j,t}$	-0.0126***	-0.0128***	-0.0127***	-0.0127***	-0.0127***	-0.0126***	-0.0126***
	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
$SI_{j,t}$	-0.0070***	-0.0071***	-0.0071***	-0.0071***	-0.0071***	-0.0070***	-0.0070***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
$VACC_{j,t}$	0.0313***	0.0306***	0.0297***	0.0299***	0.0287***	0.0314***	0.0318***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
$Quartile\ 2 \times CT_{j,t}$		-0.0020***		-0.00001		-0.0012***	
		(0.0002)		(0.0002)		(0.0002)	
$Quartile\ 3 \times CT_{j,t}$		-0.0040***		0.0010***		0.0017***	
		(0.0002)		(0.0002)		(0.0002)	
$Quartile\ 4 \times CT_{j,t}$		-0.0057***		0.0027***		0.0034***	
		(0.0002)		(0.0002)		(0.0002)	
$Quartile\ 2 \times SI_{j,t}$		-0.0016***		-0.0017***		-0.0011***	
		(0.00006)		(0.00006)		(0.00006)	
$Quartile\ 3 \times SI_{j,t}$		-0.0032***		-0.0021***		0.0002***	
		(0.00006)		(0.00006)		(0.00006)	
$Quartile\ 4 \times SI_{j,t}$		-0.0056***		-0.0021***		0.0026***	
		(0.00006)		(0.00006)		(0.00006)	
$Quartile\ 2 \times VACC_{j,t}$			0.0707***		0.1132***		0.0597***
			(0.0048)		(0.0051)		(0.0048)
$Quartile\ 3 \times VACC_{j,t}$			0.1448***		0.1475***		0.0140***
			(0.0048)		(0.0050)		(0.0049)
$Quartile\ 4 \times VACC_{j,t}$			0.2492***		0.1576***		-0.1029***
			(0.0049)		(0.0050)		(0.0048)
Quartile Controls	No	Income	Income	Liq. Wealth	Liq. Wealth	Age	Age
Monthly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

4.5. Moderating Effects of the Vaccination Program

In table 8, we augment model (1) by including two non-dummy interaction terms to account for the interaction effects of the cases-to-tests and the stringency index with the percentage of vaccinations. This analysis aims to determine whether the influence of infection fear or government interventions on household consumption reduces as the proportion of fully vaccinated adults increases. Isolating the impact of the interaction terms, the coefficient for CT in column 3 indicates that at average vaccination rates, an increase in the cases-to-tests index is associated with a 0.0041% decrease in consumption. The impact of SI is slightly less, at 0.0029%. Furthermore, the coefficient for $VACC$ of 0.0583 implies that, at average CT and SI values, a 1% increase in the vaccination rate is associated with a 5.83% increase in weekly household consumption. The interaction coefficient $VACC_{j,t} \times CT_{j,t}$ suggests that a 1% increase in the vaccination rate diminishes the negative impact of infection fear on household consumption by 0.0150%. Likewise, the interaction coefficient $VACC_{j,t} \times SI_{j,t}$ shows that a 1% rise in the vaccination rate lessens the adverse effects of stringency measures on consumption by 0.0043%.

Collectively, these results underscore a significant moderating role of vaccinations on consumption patterns during the pandemic: as the fraction of fully vaccinated adults increases, the reduction in consumption associated with infection fear and government non-pharmaceutical interventions (NPIs) decreases.

Table 8: Comparative Regression Outcomes of the Moderating Impact of Vaccination Rates on Household Consumption Relative to Cases-to-Tests Index and Stringency Index - standard fixed effect - interaction estimator (FE-IE) (centered)

	(1)	(2)	(3)
Dep. Variable	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$	$\log(C_{i,j,t})$
Estimator	FE-IE	FE-IE	FE-IE
R-squared	0.249	0.249	0.249
F	67,680	67,610	65,400
$p-value(F)$	0.0000	0.0000	0.0000
Intercept	-0.0157***	0.0236***	-0.0214***
	(0.0006)	(0.0006)	(0.0006)
$CT_{j,t}$	-0.0061***	-0.0034***	-0.0041***
	(0.00003)	(0.00003)	(0.00004)
$SI_{j,t}$	-0.0030***	-0.0035***	-0.0029***
	(0.00001)	(0.00001)	(0.00001)
$VACC_{j,t}$	0.0616***	0.0316***	0.0583***
	(0.0008)	(0.0008)	(0.0008)
$VACC_{j,t} \times CT_{j,t}$	0.0128***		0.0150***
	(0.0001)		(0.0001)
$VACC_{j,t} \times SI_{j,t}$		0.0037***	0.0043***
		(0.00003)	(0.00003)
Monthly Controls	Yes	Yes	Yes
Weekly Controls	Yes	Yes	Yes

No. Observations: 46,034,313; **Covariance estimator**: Clustered over municipalities; **Standard errors** in parentheses; $***$: **P-value** $\leq$ 1%; $**$: **P-value** $\leq$ 5%; $*$: **P-value** $\leq$ 10%;

5. Conclusion

This paper presents a comprehensive analysis of the impacts of the COVID-19 pandemic on household consumption. Based on a rich Belgian dataset of bank transactions alongside local COVID-19 data during various waves of the pandemic, our empirical results illuminate how the local severity of the pandemic, the government-imposed non-pharmaceutical interventions (NPIs), and the vaccine roll-out influenced household consumption behavior.

Our research unveils substantial variation in the timing and magnitude of these impacts. Specifically, while infection intensity predominantly drove consumption reductions during the first wave, governmental containment measures turned out to be more significant during the second. By the third wave, both the severity of infections and containment strategies jointly exerted a negative influence on household consumption. Finally, in the following four waves, the impact of these factors appeared to diminish.

Moreover, our study documents significant heterogeneity of the pandemic's impact on consumption across households, specifically in relation to income, liquid wealth, and age. We find that lower-income, lower liquid wealth, and older households demonstrated larger reductions in consumption due to infection fears. In contrast, households with higher liquid wealth exhibited more substantial consumption reductions under stringent NPIs. The upward effect of the local vaccination rate on household consumption also varies significantly among different household groups. It is found to be least pronounced for households in lower liquid wealth quartiles, and most pronounced for household with the highest income and the oldest members. These differential responses underscore the uneven effects of pandemic intensity, lockdown measures, and vaccinations across socioeconomic strata, highlighting the importance of considering these disparities in policy formulation.

Additionally, our analysis points to the nuanced impact of the pandemic across various consumption types which further emphasizes the heterogeneous nature of the pandemic's economic consequences. Our estimates reveal that non-durable goods were less affected by stringency measures, highlighting their essential nature. The impact on durable, semi-durable, mixed, and services consumption also varied, with vaccinations playing a crucial role in these effects.

Our research thus contributes to a deeper understanding of consumer behavior under pandemic conditions, suggesting the need for more nuanced and targeted policy measures that recognize the varied impacts across diverse population segments. As we emerged from the COVID-19 crisis, it is imperative for policymakers to integrate these insights and build a readily deployable arsenal of economic and public health strategies, preparing for any future crises that may arise. Accounting for the differential impacts of a pandemic on various segments of the population is crucial for an efficient allocation of resources during times of crisis.

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