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DISCUSSION PAPER SERIES

IZA DP No. 17311

The IZA / Fable Swipe Consumption Index

Nikos Askitas
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Nikos Askitas
IZA and CESifo

Anoop Bindra Martinez
Fable Data

Fabio Saia Cereda
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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The IZA / Fable Swipe Consumption Index

This paper introduces a novel monthly consumption indicator: the IZA / Fable Data consumption indicator for Germany. It is based on credit card transactions data collected and anonymised by Fable Data from 2017 onwards. We study some of the properties of the data and use a so-called "one year look back rolling panel" method to construct a monthly consumption indicator which expresses the year on year change. The data provisioning is fast and data is updated daily so that our indicator is stable with a 3 day lag. Moreover preliminary results for a month can be delivered as early as the middle of the month by comparing months partially. Our indicator is a new experimental early indicator ideal for nowcasting purposes and forecasting of breaking trends in consumer behaviour.

JEL Classification: D12, E2, C8

Keywords: credit card transactions, consumption expenditures, nowcasting

Corresponding author:
Nikos Askitas
Institute of Labor Economics (IZA)
Schaumburg-Lippe-Strasse 5-9
53113 Bonn
Germany
E-mail: askitas@iza.org

1 Introduction

In our digital age, the proliferation of data born digital has the potential of revolutionising the way we collect, understand and interact with information in a variety of domains (see e.g. some work of the first author of this paper on different topics such as nowcasting business cycles in Askitas and Zimmermann (2013), health in Askitas and Zimmermann (2015a), elections in Askitas (2015), housing market in Askitas (2016b), traffic in Askitas (2016a)). Markets of all kinds move online because digitisation solves their main problem: the matching of supply and demand. From social media interactions, job boards and dating sites to credit card transactions, sensor readings and streaming services, the vast amount of digital transaction data generated daily holds unprecedented potential for insight and innovation in analysis, prediction, and decision-making. Researchers and practitioners can extract valuable insights (Askitas and Zimmermann (2015b)) from these previously elusive data streams. Moreover, the real-time nature of digital data enables timely decision-making and responsive actions, allowing businesses, governments, and organisations to respond swiftly to emerging trends.

Credit card transactions are an example of such data and offer a unique perspective, providing insights into consumer behaviour with remarkably high detail and frequency. Unlike traditional official economic indicators, typically released on a quarterly basis and often published with significant lag, aggregated credit card transaction data offer near real-time information on consumer spending patterns.

This paper introduces a new consumption indicator for Germany based on transaction data aggregated by Fable Data. It is the first transactions based, big data type of consumption indicator we know of for Germany[1] and offers insights complementary to other existing survey based or interview based, propensity-to-purchase type of indicators[2]. It is organised as follows. In section 2 we discuss the data and some properties of the data acquisition

[1] Credit card data from Fable are also fed into the Bundesbank weekly activity index

[2] e.g. Handelsblatt Research Institute HDE-Konsumbarometer or GfK Konsumklima.

process, in sections 3 and 4 we describe our methodology and introduce our consumption indicator and its relationship to official data. In the last section 5 we summarise our work.

2 Data

We use credit card transactions from January 2017 to March 2024 collected and anonymised by Fable Data,[3] an aggregator of anonymised card payment data, to construct a monthly consumption indicator for Germany from January 2018 onwards, which expresses the percentage change from the same month a year ago. Fable typically makes transactions available with a 3-day lag.

As well as providing details about the transaction itself (e.g. date, spend amount), the dataset also contains information regarding the customer and merchant involved in each transaction. Some of the cardholders' demographic details are made available, such as geolocation and a corresponding age band. On the other side of the transaction, the merchant involved is identified and classified using a Merchant Category Code. The location of the merchant is also made available.

Our spending data captures consumption on items such as food & non-alcoholic beverages, alcohol & tobacco, clothing & footwear, furnishings, health, operation of personal transport equipment, transport services, recreation & culture, restaurants & hotels, and personal care. It is less likely to capture vehicle purchases, education, housing, communication and other expenses such as financial services etc. It must be mentioned that Germans' preference for cash might be a limiting factor for the extend to which our data expresses the big picture.[4].

Not all credit cards are observed each month hence we have a growing but unbalanced monthly panel dataset. In fact of a total number of 2,251,422 unique credit cards observed

[3]Fable Data obtains card payment data directly from various financial institutions across Europe. The ingested data is enriched by proprietary models from Fable and is then homogenised and productised to generate a single pan-European dataset that's updated on a daily basis.

[4]https://www.bundesbank.de/en/press/press-releases/payment-behaviour-in-germany-in-2021-894120

across the entire 7-year period only 24,751 are observed across all months. Moreover when a credit card is captured only sporadically we cannot tell with certainty whether in the months it is not present a zero expenditure can be assumed or that simply it dropped out and back into the sample.

Figure 1 shows the development of the number of unique cards captured in each month from January 2018 to March 2024.

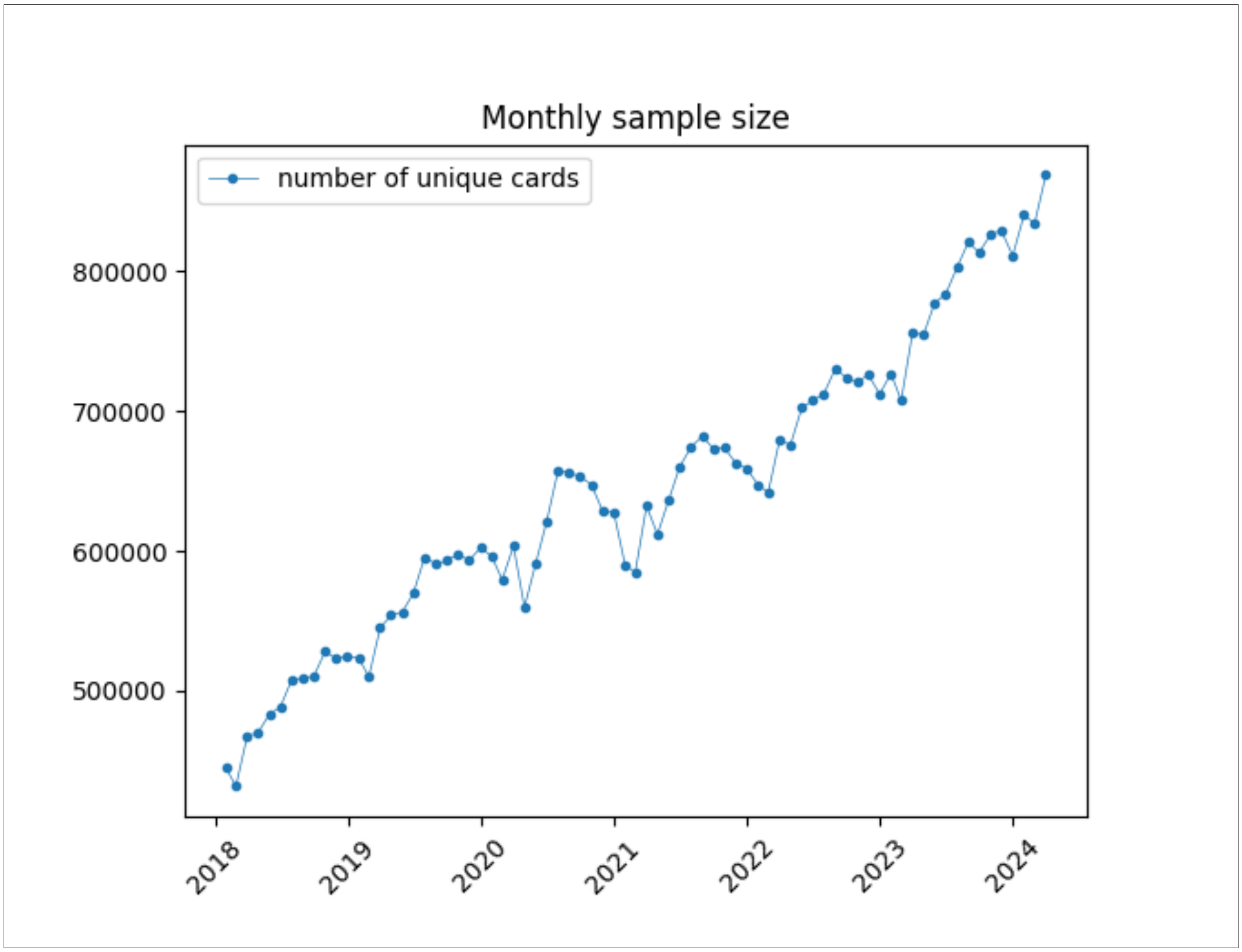

Figure 1: Fable Data samples an increasing number of unique credit cards per month

Figure 2 shows the development of the expenditures captured by Fable Data as a share of total private household consumption.

The mean monthly expenditure across all credit cards in the sample equals 433.3 euros per

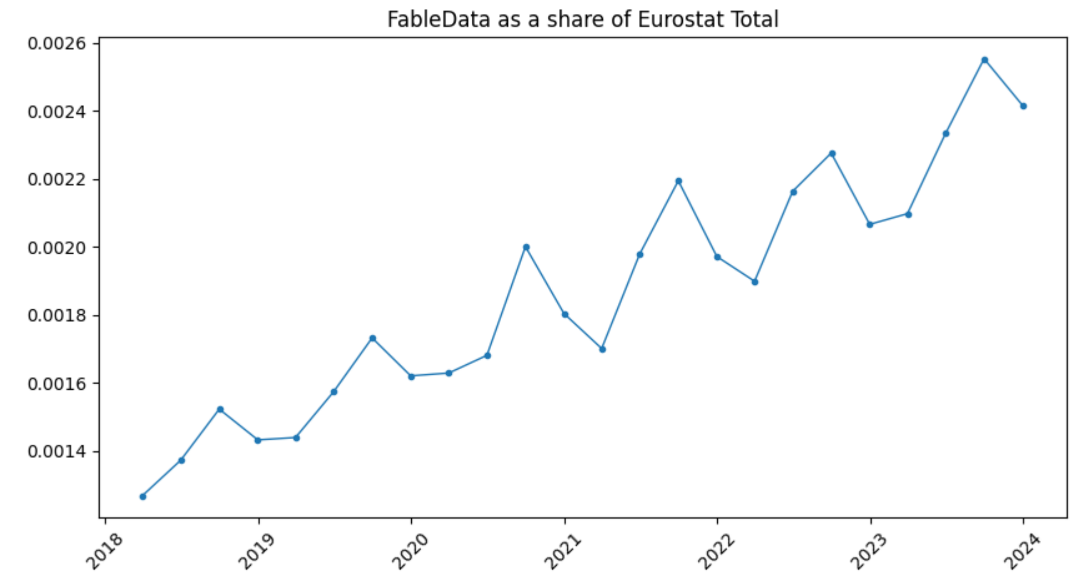

Figure 2: Quarterly Fable Data consumption data as a share of the consumption data from Eurostat. The Fable Data sample is seen to grow in time and to account for .176% of the total from Eurostat on average.

month with a standard deviation of 711.7. Figure 3 shows a heat map of expenditures in time. The y-axis contains all credits sorted by date first observed and coloured by amount spend. It provides an overview of sample development and sample expenditure patterns. Fading horizontal lines indicate attrition, vertical fading or darkening indicate seasonal patterns (winter lows and summer highs) whereas in each month we see the replenishing of the sample i.e. newly captured credits cards (bottom of the plot).

Figures 4 and 5 shed a bit more light on our sample. Figure 4 shows the share of cards and expenditures each month which are based on cards which are also captured in the previous month. Figure 5 show the monthly percentage change of raw Fable Data expenditures vs those that are based on the cards shared with the month before. Notice that starting in March, as we are coming out of the winter low in January/February, the raw data dominates the data from the overlap with the previous month which implies a correlation between consumption levels and the probability that a card be captured.

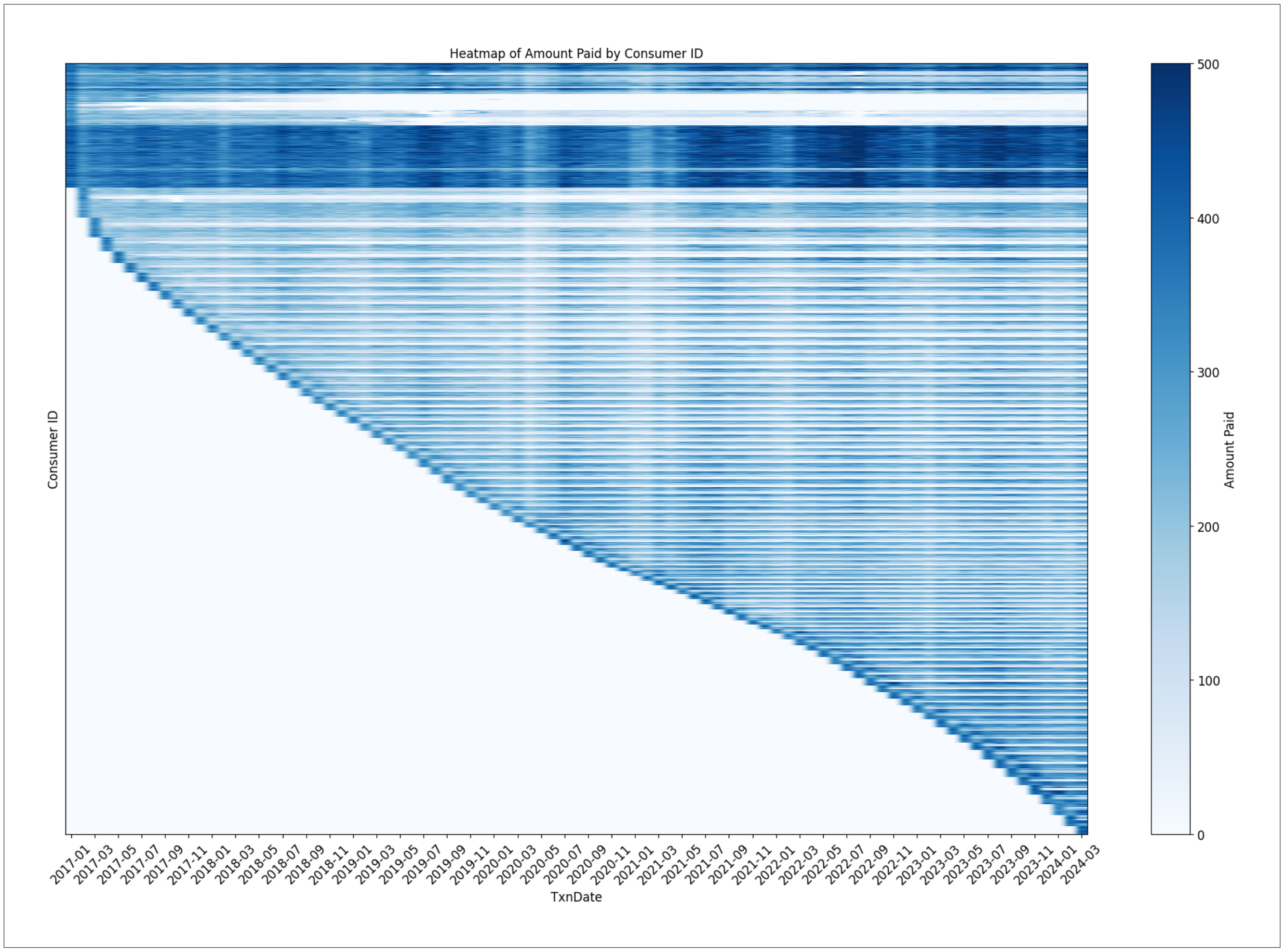

Figure 3: Heatmap (2D histogram) of monthly expenses of unique credit cards in our sample sorted by cohort i.e. by date of first appearance older to younger from top to bottom. We see sample attrition (horizontal fading) and replenishing (bottom of plot) but also seasonal effects (vertical white lines i.e. winter lows in January/February) and summer highs (i.e. darker blue lines in July/August). We restrict to monthly amounts below 500 euros which account for 3/4 of all monthly amounts spent.

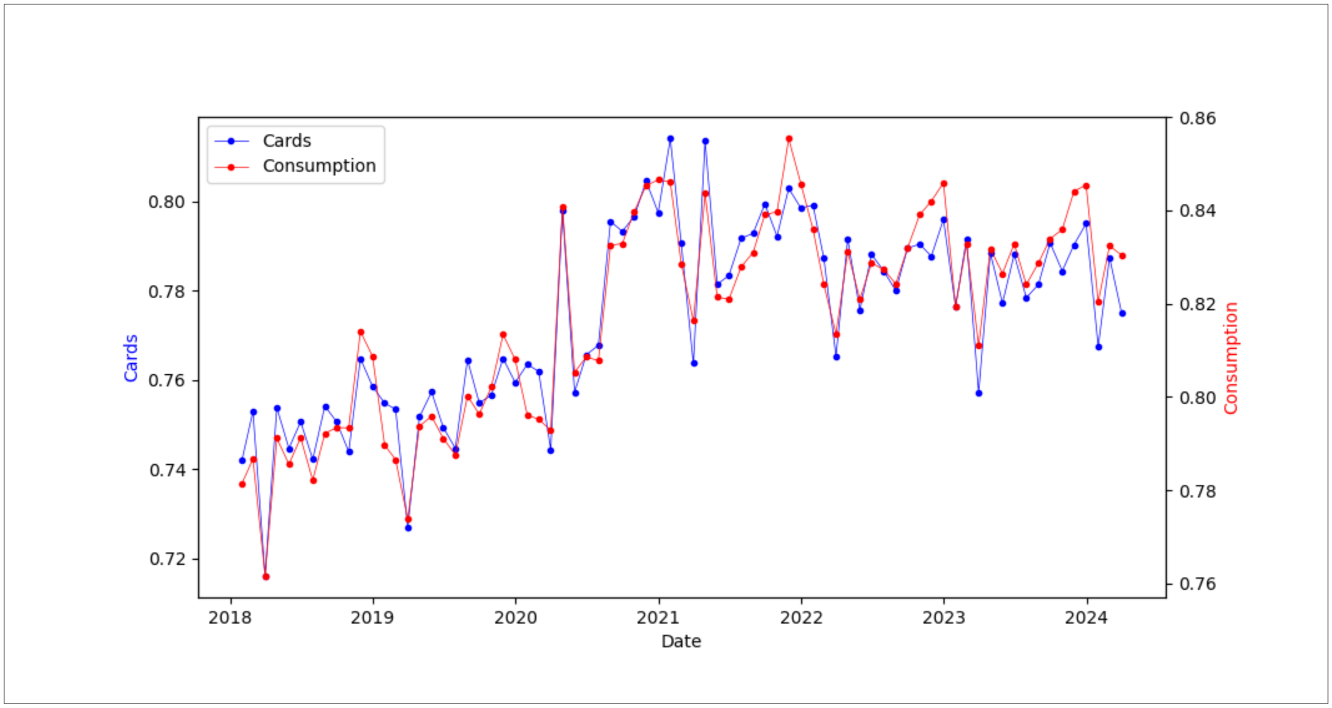

Figure 4: Cards (and their expenditure) in each month which were also captured the previous month. A high share of the credit cards captured in a given month was also captured in the previous month.

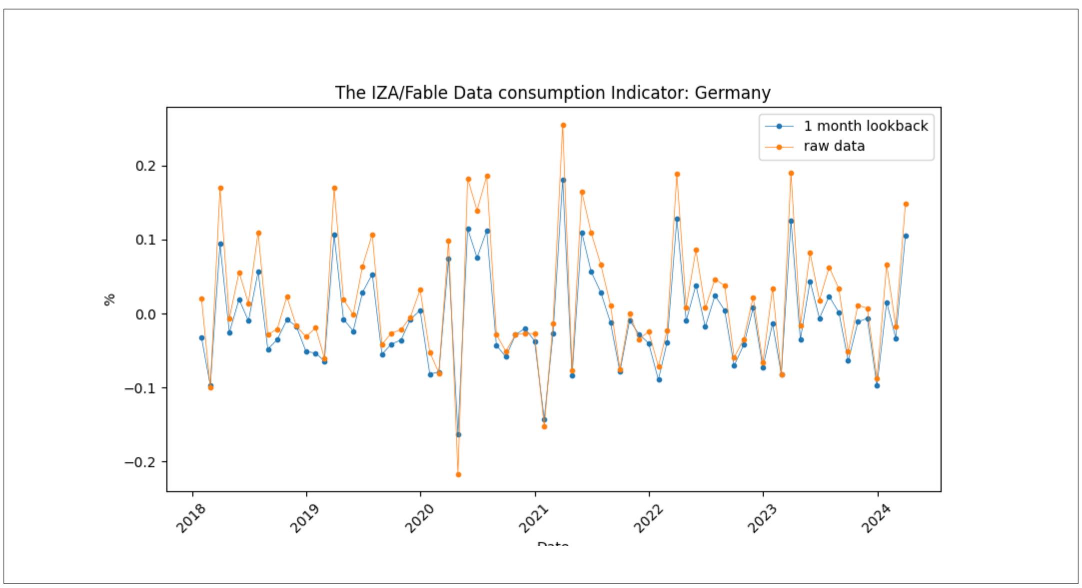

Figure 5: Month on month rates with raw data and 1 month look-back rolling panel look qualitatively similar but produce opposite long term trends. What accounts for that is that coming out of the winter low in January/February raw sample expenditures surpass expenditures by the cards in the one month look-back rolling panel because in a consumption-slow season the probability to observe any card is lower hence coming out of the winter deep is due to credit cards outside the overlap with the previous month.

Finally Figure 6 shows raw monthly Fable Data data aggregate expenditures vs quarterly expenditures from Eurostat[5].

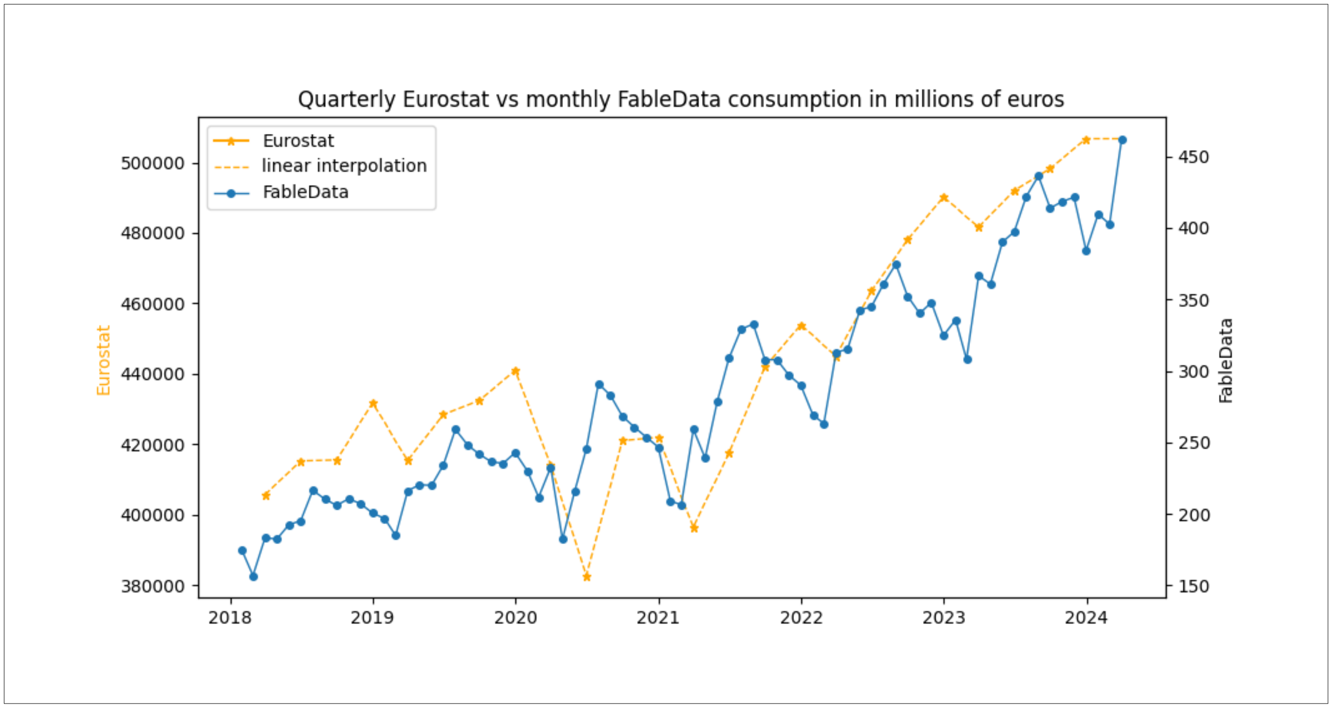

Figure 6: Eurostat consumption data (variable: P31_S14) from NAMQ_10_FCS (Quarterly consumption in Current Prices - Millions of Euros - Non Seasonally Adjusted for Germany) vs Fable Data for Germany. Mean year on year change for Fable Data equals .041 and .035 for Eurostat (https://ec.europa.eu/eurostat/databrowser/product/page/NAMQ_10_FCS).

To recap our sample's expenditures, are sourced from a growing but unbalanced panel, relate well to official data, have a seasonal component and our sampling probability is correlated with (seasonal) consumption levels all of which leads us to the choice of our methodology of a one-year look back rolling panel, which we will describe in section 3.

3 Methodology

Each transaction in our data contains the amount paid the transaction date and an identifier for the credit card used. For the reasons mentioned in the previous section for each month

[5]Overall Fable Data consumption data explain over 80% of the variation in official consumption data from Eurostat. In fact regressing quarterly Eurostat consumption on the Fable Data spending during the first month of the quarter with month fixed effects results in an $R^2 = 0.83$.

we compute and report the percentage change of monthly aggregate spending from the same month a year ago by restricting to transactions of cards that appear in both months i.e. we use a *one year look-back rolling panel* methodology.

In each month M of a year Y our indicator $I_{Y,m}$ reports the percentage change of consumption in that month compared to the consumption in the same month M of the previous year $Y-1$. We restrict ourselves to considering only credit card numbers in the intersection:

$$C_{Y-1,Y,M} = C_{Y,M} \cap C_{Y-1,M},$$

where $C_{y,m}$ indicates the set of credit card in our sample in year y and month m. Formally if $E_{c,y,m}$ is the aggregate expenditures of credit card number c in month m of year y then we take the aggregate expenditure in month m of year $y = Y-1, Y$ to be:

$$E_{y,m} = \sum_{c \in C_{Y-1,Y,m}} E_{c,y,m},$$

so that our consumer indicator is written as:

$$I_{Y,M} = \frac{E_{Y,M} - E_{Y-1,M}}{E_{Y-1,M}}.$$

By means of elementary algebra we can easily see that if $I_{y,q}$ in year y and quarter q expresses the quarterly version of our indicator then:

$$I_{y,q} = \frac{\sum_{m \in q} I_{y,m} E_{y-1,m}}{\sum_{m \in q} E_{y-1,m}}. \quad (1)$$

Equation 1 will be useful when we benchmark our monthly indicator to official quarterly expenditures data from Eurostat[6].

Our methodological choice aims at taking some of the sampling noise as well as seasonal

[6] https://ec.europa.eu/eurostat/databrowser/product/page/NAMQ_10_FCS

effects out of the way at the expense of losing some transaction data.

4 Results

Figure 7 shows the monthly retention rates of our data during the monthly one year look back rolling panel method in terms of number of cards and amounts spent. We see that on average we retain over 60% of our data.

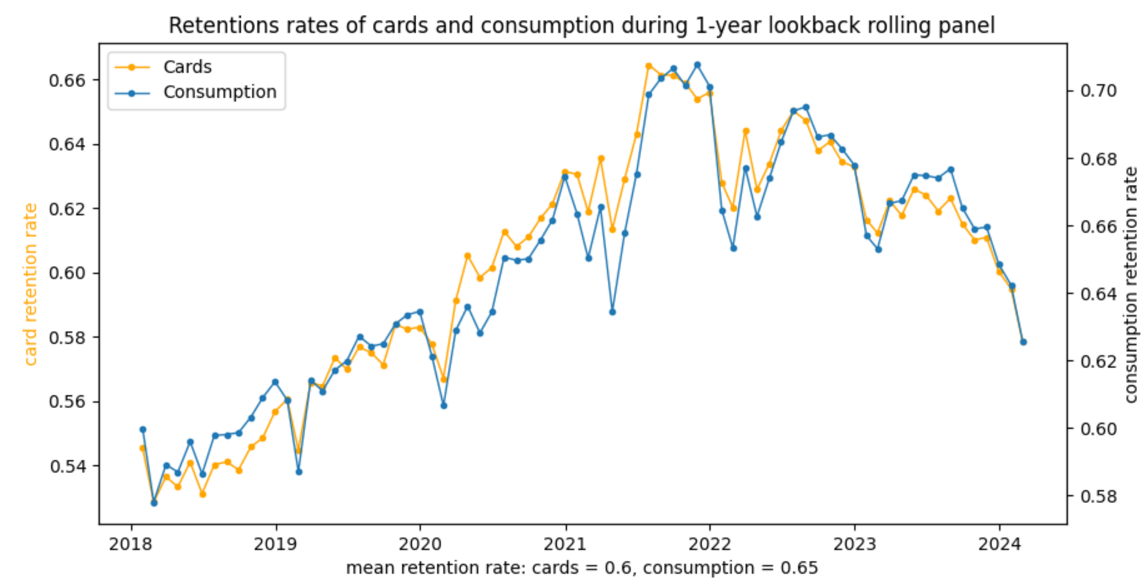

Figure 7: Taking the overlap of card numbers each month with the same month a year ago during the one year look-back rolling panel process retains about 60% of cards and consumption.

Figure 8 shows how our monthly consumption indicator leads the change in the quarterly year on year changes of official consumption data while figure 9 shows the quarterly version of our indicator derived using equation 1. We should note here that the official data we are benchmarking agains may not represent the absolute truth. As of April 2024 all quarters from 2019q1 onwards are still listed as "provisional" in the Eurostat tables.

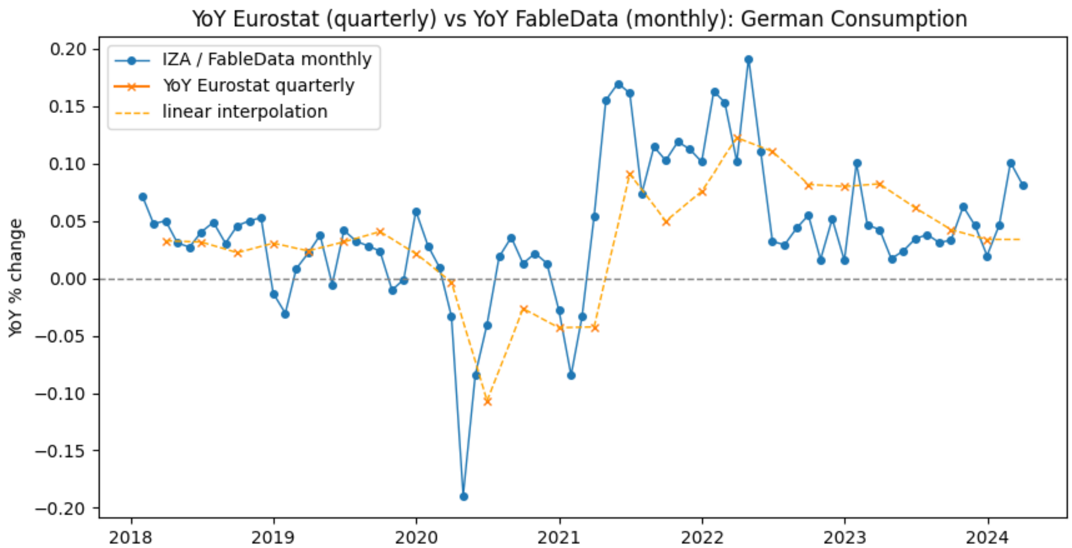

Figure 8: The monthly IZA / Fable Data Consumption Indicator for Germany vs the year on year changes of the official quarterly data

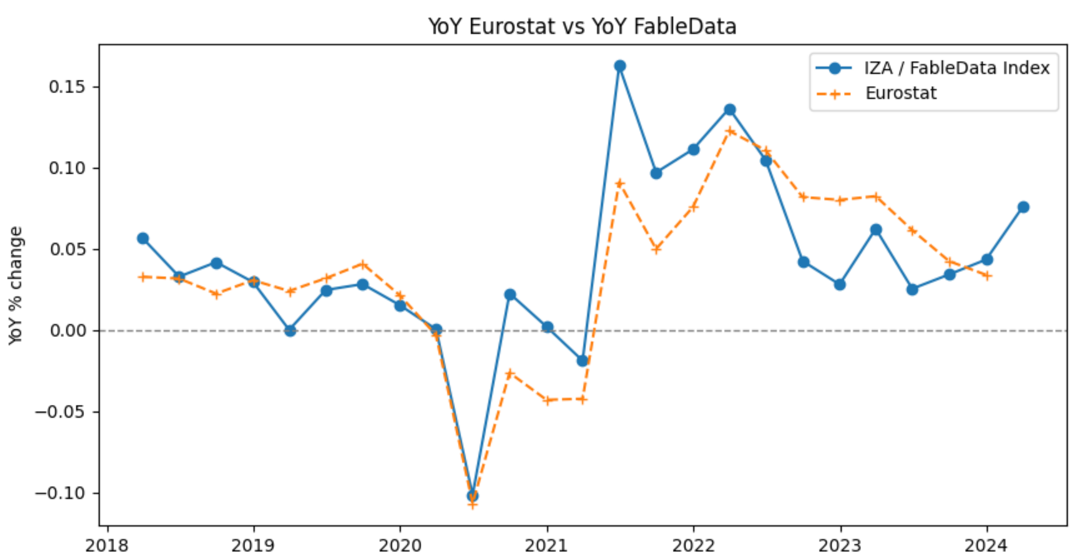

Figure 9: The quarterly IZA / Fable Data Consumption Indicator for Germany (derived using Equation 1) vs the year on year changes of the official quarterly data

5 Discussion

We used credit card transactions data from a growing but unbalanced panel of data collected and anonymised by Fable Data and using a one year look back rolling panel method to remedy some unknowns in the data acquisition process we constructed a monthly private consumption indicator for Germany available to researchers, practitioners, policy makers and the public. Our indicator will be part of a number of indicators assembled at the IDSC of IZA related to the German Labor Market that will be presented in an interactive labor dashboard. We hope that it will help nowcast the interplay between consumption and the labor market. The latter is currently work in progress.

Data of the same nature are available for the UK and France and we plan to produce similar consumption indicators for these countries as well in the future. We should mention that from our data further partial indicators can be derived for components of consumption such as online retail sales or Food & Beverage etc. In future work we might explore that route as well.

Our joint work is an example of good data citizenship and a mutually beneficial cooperation between the private sector and academic research for wider societal benefit. We hope that it will help inspire more such cooperations.

Data

The microdata for our indicator are property of Fable. The first author has acquired the data under contract from Fable Data and is actively researching them at the IDSC of IZA. Access to the data for academics, government researchers, central bankers and national statisticians is free of charge and only constraint by Fable's internal support capacities. Interested parties can contact Fable directly[7]. Data and code to replicate Figures 8 and 9 can be found at the IDSC - Dataverse the data repository of IDSC - Research Data Center of IZA.

[7] Info https://www.fabledata.com/data-for-good/

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