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# From Shopping to Statistics: Tracking and Nowcasting Private Consumption Expenditures in Real-Time

## Abstract

In this paper, we use high-frequency transaction data to develop a weekly tracker for private consumption expenditures. Furthermore, we apply the transaction data in a nowcasting experiment and compare their performance with other, readily available indicators that are regularly linked to private consumption in Germany. The weekly tracker produces precise estimates and can thus be used in real-time, especially in very turbulent times such as a pandemic or the high-inflation-phase in its aftermath. In terms of nowcast accuracy, the tracker outperforms all remaining indicators, making it a powerful tool for applied forecasting work. We plan to regularly publish the weekly consumption tracker in the future, thereby complementing the database for Germany.

JEL-Codes: C320, C530, E010, E210, E270.

Keywords: private consumption expenditures, real-time tracker, high-frequency transaction data, mixed-frequency vectorautoregression, Bayesian estimation.

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# 1 Introduction

The demand for tracking economic activity in real-time and in higher frequency got a boost since the outbreak of the COVID-19 pandemic. While gross domestic product (GDP) is unquestionably one of the most looked at figures to assess an economy's well-being, private consumption expenditures—the component that contributes more than half to several states' economic output—were hit hard due to policy interventions worldwide to fight the pandemic. The effects on the latter, however, cannot be tracked in a timely manner as high-frequency information are basically not available at all. In this paper, we explore a new source of transaction data to develop a weekly tracker for private consumption expenditures in Germany and to formulate reliable nowcasts for this major GDP component.

Housholds' consumption expenditures serve as a cornerstone of economic performance and are closely intertwined with the overall health of a nation's economy. Timely and precise consumption data help policy-makers in designing, for example, appropriate strategies that counteract potential economic burdens on households or central banks to communicate on possible future paths of monetary policy. In addition, having these data available regularly and at high frequency allows to understand well-known issues of, for example, inequality or the effect of monetary and fiscal policy interventions more granularly—in terms of timing, regional or consumer characteristics.

For Germany, information on private consumption patterns that go beyond the national account figures or survey data are rare. Conventional data collection and reporting processes thus lag behind real-time developments and if available, the frequency at which they track those spending patterns is low. Yet, all of us reveal valuable insights into consumption choices whenever paying for goods or services consumed. By virtue of its business, Mastercard leverages its information on in-store and online retail sales based on aggregates sales activity in the Mastercard payments network, coupled with survey-based estimates for certain other payment forms, such as cash and check. While cash payments remain the dominant means of payment up to date, an increasingly growing share of transactions is made via cards. In combination, Mastercard SpendingPulse™ thus serves as an ideal alternative data source. Up front, after a thorough cleaning on the raw data, SpendingPulse shows a high correlation with the consumption statistics. In addition, these data come with the advantage of a short publication delay of only two weeks and are available at a daily frequency. We exploit the information available in SpendingPulse to generate a weekly consumption tracker for Germany that is compatible with the quarterly series published by the Federal Statistical Office of Germany. Besides, we also show that the information from Mastercard's SpendingPulse outperform various competing indicators in nowcasting German private consumption expenditures. We plan to publish the weekly consumption tracker on a regular basis in the future, thus, adding to the data infrastructure in Germany.

The paper is organized as follows. In Section 2 we embed our paper in the existing literature on both tracking and forecasting economic activity in real-time. Section 3 introduces the transaction data together with some data transformation issues, followed by the methodology in Section 4. In Section 5 we present our main results, followed by a discussion in Section 6. The last section concludes.

# 2 Related Literature

The literature on near real-time indices that exploits variables at a monthly (Baumeister *et al.*, 2022a; Mariano and Murasawa, 2003; Stock, J. H. and Watson, M. W., 1988), weekly (Baumeister *et al.*, 2022b; Lewis *et al.*, 2022; Aaronson *et al.*, 2021; Eraslan and Götz, 2021) or even daily (Andersen *et al.*, 2022; Diebold, 2020; Aruoba *et al.*, 2009) frequency experienced a considerable boost in interest since the outbreak of the COVID-19 pandemic. Often, the main focus is on aggregate macroeconomic variables such as gross domestic product (GDP) at the national level. Recent work also elicits the usefulness of non-conventional data in providing high-frequency indicators of real economic activity (see, among others, Brinke *et al.*, 2023; Baumeister *et al.*, 2022b; Aastveit *et al.*, 2020; Duarte *et al.*, 2017), which is driven by an attempt to timely inform about economic conditions ahead of the national accounts release that usually come with publication delays of several weeks.

Our work relates to the literature of using non-conventional data for macroeconomic assessments and nowcasting designs. In particular, we supplement the literature by providing a granular time series of German private consumption expenditures, constructed with the addition of transaction data. One strand of the literature stands out that exploits information on card transactions to introduce high-frequency indices of real economic activity. While Andersen *et al.* (2022); Aladangady *et al.* (2022); Hacioglu Hoke *et al.* (2020) are just a few examples of authors providing mainly descriptive evidence on the suitability of card transaction data in anticipating movements in consumer spending, others model the relation between the mixed-frequency series within comprise econometric frameworks. The resulting indices either come as pure forecasting indicators or simultaneously allow to retrieve high-frequency historic time series of macroeconomic aggregates.

The majority of studies is concerned with tracking overall economic well-being, materialising in GDP developments (Baumeister *et al.*, 2022b; Bentsen and Gorea, 2021; Lourenço and Rua, 2021; Aprigliano *et al.*, 2019; Galbraith and Tkacz, 2018). Baumeister *et al.* (2022b) develop weekly economic activity series for US states based on a mixed-frequency dynamic factor model including weekly, monthly and quarterly data that may build an unbalanced panel dataset. Including, among others, credit card transaction data they can trace back potentially heterogeneous developments across the various states to core economic piles. In different applications, the authors show the usefulness of the higher frequency GDP tracking series in analysing drivers of economic downturns or in understanding the effect of policy interventions, for example, the Paycheck Protection Program. Focusing exclusively on the nowcasting properties of transaction data, Lourenço and Rua (2021) construct a daily composite indicator of economic activity for Spain as the latent factor from a dynamic factor model including card-based payment transaction data as well as information on road and heavy vehicles traffic, cargo and mail landed, electricity and natural gas consumption. In a second step, they regress the coincident index on quarterly GDP and attest that their index holds statistically significant information about GDP developments and thus serves well in a nowcasting context.

Alternatively, Aprigliano *et al.* (2019) employ a mostly data driven approach to forecasting Italian GDP and some of its components. They run a LASSO regression to assess the ability of around 50 macro and transaction data series to anticipate the economic indicators of interest. Based on this selection, the authors estimate a dynamic mixed-frequency factor model and use its outcome as input in nowcasting and forecasting a target variable. Their results suggest that transaction data improve the forecasting performance and, in contrast to previous results, the high-frequency information on retail activity becomes especially important for one and two quarter ahead forecasts. Assessing a similar target, Bentsen and Gorea (2021) make use of transaction data for Denmark to construct monthly nowcasts of quarterly GDP and some of its components within a Mixed-Data Sampling (MIDAS) regression setting. Even though the transaction data outperform alternative indicators in terms of overall nowcast accuracy, they note that these data perform worse at the beginning of the COVID-19 pandemic than they did before. Galbraith and Tkacz (2018) additionally show that for Canada, including payment data next to traditionally used indicators mainly improves the accuracy for early nowcasts during the quarter, whereas they do not contribute much to enhancing the nowcasting performance beyond early estimates.

As one of the most important GDP aggregates, some authors exclusively target private consumption expenditures (Aaronson *et al.*, 2021; Bentsen and Gorea, 2021; Aastveit *et al.*, 2020; Duarte *et al.*, 2017; Vosen and Schmidt, 2011). Aastveit *et al.* (2020) rely on MIDAS regressions including weekly Norwegian transaction data and quarterly consumption figures and find that transaction data are superior to any other alternative indicator tested. This is particularly true for the value and volume of private goods consumption as opposed to services. In a similar vein, Duarte *et al.* (2017) resort to MIDAS regressions and experiment with various lag polynomial specifications on the daily data to produce forecasts of Portuguese private consumption expenditures. Irrespective of the polynomial specification, the inclusion of automated teller machines (ATM) data always outperforms any other specification. They note that aggregated to the monthly frequency, ATM data outperform the daily estimates. In addition, the authors find that the gains from including the high-frequency transaction data are especially pronounced for nowcasts, whereas the gains compared to an autoregressive process substantially decline for forecasts at longer horizons. Vosen and Schmidt (2011), as some of the first and only authors to date to target German private consumption expenditures, build a monthly indicator based on Google Trends search terms on consumption related queries that allows to provide early nowcasts. Their newly developed indicator outperforms commonly used survey-based measures in terms of forecast accuracy.

Closely related to our work in terms of data and nowcasting set up are Brinke *et al.* (2023) and Aaronson *et al.* (2021) who show that card transaction data are useful for nowcasting retail trade turnover in Latvia and the US, respectively. While Brinke *et al.* (2023) estimate autoregressive distributed lag models, Aaronson *et al.* (2021) provide a weekly series of retail spending based on a dynamic factor model that ensures that the weekly series, aggregated at a monthly frequency, matches the official statistics.

In terms of methodology, these paper cover the most prominent econometric approaches that explicitly account for the mixed-frequency nature of the data, where the model set up is regularly influenced by the exact application. Besides those already mentioned, ranging from distributed lag models to MIDAS and dynamic factor models, the nowcasting literature also employs mixed-frequency vectorautoregressive (MF-VAR) models (Koop *et al.*, 2020; Schorfheide and Song, 2015). Koop *et al.* (2020) present a Bayesian MF-VAR model that allows to estimate a high-frequency proxy time series for a lower frequency target series that adheres to a temporal constraint aligning the high-frequency estimate with the official statistics. In their application, Koop *et al.* (2020) estimate quarterly GDP series for UK regions based on information from the annual regional GDP series, quarterly UK-wide GDP and additional macro related high-frequency indicators; Lehmann and Wikman (2023) adapt their approach for the German states. Our paper applies the MF-VAR to track and nowcast German private consumption expenditures in real-time, thus, providing a new high-frequency time series and extending the sparse forecasting literature for Germany.

# 3 Credit Card and Transaction Data

## 3.1 Mastercard's SpendingPulse

Historically, Germany is a cash-dominated country, where only since the onset of the COVID-19 pandemic cashless alternatives caught up and gained an increase in popularity according to the European and German Central Bank. Transaction data is available from the Payments and Settlement Systems Statistics (PSS) of the European Central Bank (ECB) that provides, among others, details on payment behaviour across German households, including information on volume of transactions by different payment means as well as the number of both cash withdrawals from ATM and cards in circulation.[1] The latter are separately reported for debit cards and credit cards with and without a credit function. Transactions made via debit cards are immediately charged from the consumer's bank account (for the

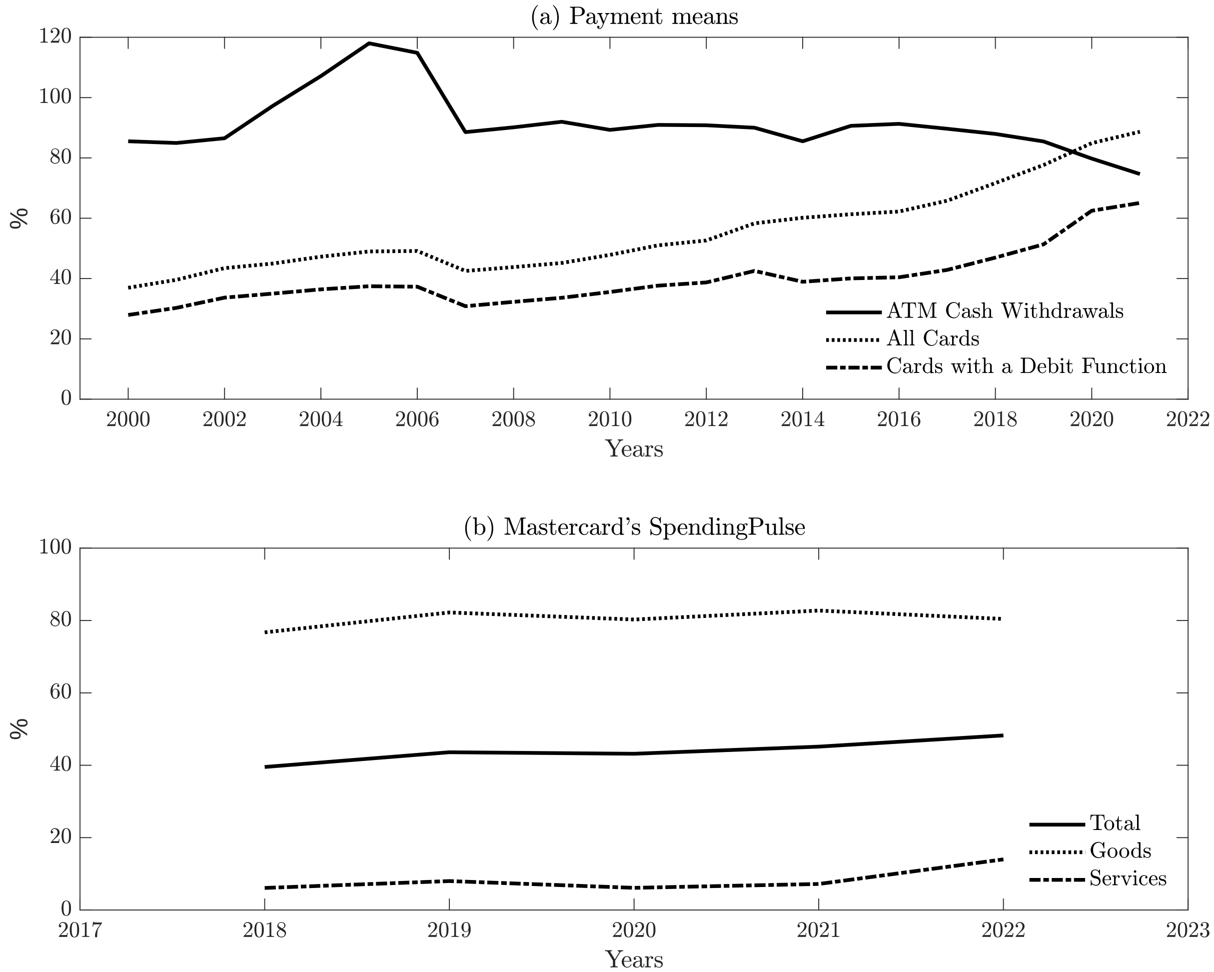
[1] If not otherwise stated, all detailed information on data issues, classification standards, indicators, descriptive statistics or original sources are discussed in the manuscript's Supplementary Material.

definitions of the card types, see the ECB glossary here and thereafter). Credit cards without a credit function, also known as delayed debit cards, are, with respect to their set up, similar to debit cards with the major difference being that the amount of a transaction is only charged by the end of a pre-specified period instead of immediately at the time of transaction. Credit cards with an additional credit function allow the card holder to eventually settle costs beyond the account balance, whereby taking up a credit with an interest usually charged onto the remainder not paid back by the end of the specified period. Furthermore, we take information on ATM cash withdrawals as a proxy for cash payments, noting that despite some limits, they should capture a large share of cash in circulation.

For Germany, the volume of cash-based transactions was about twice as large as the volume of all card payments combined in 2007, while the number of card transactions was already slightly higher for card payments. Since then, we observe a steady increase in card dissemination. Card transactions grew in numbers much faster than ATM withdrawals, that, in fact, remained relatively constant until around 2017 whereafter the PSS report declining ATM withdrawals. Similarly, also the value of transactions made via cards constantly grew, whereas the increase in cash payments was moderate. It is only since 2020 that the value of cash transactions falls short off the value of total card payments, yet cash payments are far from being negligible. This development comes along with an increase in the total number of cards available, that until now does not affect the distribution of card types. With a share of more than three-fourth throughout the years, debit cards are by far the most popular cashless alternatives while credit cards with a credit function take up a share of only less than 5%. Today, less than a third of overall card transactions and less than half of the total transaction volume is due to credit cards. This stands in contrast to various other Euro Area countries or the US, where credit cards are much more relevant than in Germany (Cubides and O'Brien, 2023; European Central Bank, 2019).

Panel (a) of Figure 1 provides a first idea about the extent transaction data can tab consumption trends by plotting the share of transaction volumes relative to total private consumption expenditures by various payment means. Overall, the importance of cash payments in total private consumption expenditures is slowly but steadily declining and rested at 75% in 2021. The total value of card payments as a share of household consumption, in turn, was increasing at a faster pace than cash payments declined and stood at 80% in 2021, which is mainly driven by debit card payments. These trends, however, suggest that transaction data serve as a candidate for tracking private consumption expenditures, with potential value added if readily and steadily available. In total, cash and card transactions exceed total consumption expenditures due to differing data sources, inconsistent data collection standards and importantly because the PSS data collect all transaction volumes no matter their purpose. Importantly, it captures transactions made abroad with (credit) cards registered in Germany what may explain the excess in consumer spending taking into account all card types and cash payments.

**Figure 1:** Transaction Volumes and Private Consumption Expenditures in Germany




*Notes:* Panel (a) shows the share of transaction volumes by payment means relative to total private consumption expenditures based on data from the PSS. Panel (b) shows the coverage of the entire turnover as reported in Mastercard's SpendingPulse relative to private expenditures for either goods, services or total consumption expenditures. All data are unadjusted and at an annual level. Taken together, cash and card transactions exceed total consumption expenditures due to differences in data collection and classification standards. *Sources:* Payments and Settlement Systems Statistics, Mastercard's SpendingPulse, Federal Statistical Office of Germany.

Despite Mastercard's focus on cards, SpendingPulse provides a macroeconomic indicator of retail sales' volumes across all payment types that is based on aggregate sales activity in the Mastercard payments network, coupled with survey-based estimates for other payment forms including cash and check. The data are classified into ten distinct retail and hospitality categories, including apparel, electronics, fuel & convenience, home furniture & furnishings, home improvement, jewelry, restaurants and lodging / hotels. In contrast to most of the data on card transactions cited in the literature, SpendingPulse should thus be read as a sales indicator across all means of payment. The series are available at a daily frequency starting from 2018 and are published once a week with a lag of two weeks. Sales across the retail industry contribute most to overall spending captured in the data provided by Mastercard, with grocery taking up the the largest and jewelery the smallest share. Within the hospitality industry, spending on restaurant visits accounts for a majority of overall spending (about 90%) with a relatively stable distribution across the years.

While the relative positioning of different sectors in terms of their total sales remained stable over time, the data capture some major trends observed in the recent past: First, during the pandemic, restaurant and hotel turnover declined and caught up in 2022 again, with the relative importance of these two sectors for the hospitality sector being unaffected. Second, retailers offering home furnishings and fixtures saw an increase in total sales with the onset of the pandemic, increasing their importance in terms of total retail turnover, but facing declining sales after major containment measures were lifted again. Third, SpendingPulse also captures the tendency in fuel expenses that were first affected by containment measures and afterwards exhausted due to the sharp oil price increase.

Even though we focus on the suitability of SpendingPulse to capture overall consumption trends, it is insightful to compare it with sales across different sectors from the official statistics first. Hence, we compare the monthly growth rates in total retail sales and those in restaurants and hotels (neither price nor seasonally adjusted) reported in SpendingPulse to those from the Federal Statistical Office of Germany. Overall, the differences across the two sources are small. As we show below again, movements across the two sources are particularly close during the pandemic, suggesting that exceptional movements are equally well captured across different sources.

Not only does SpendingPulse seem to descriptively match the official sales statistics fairly well, it also captures a decent share of overall consumption expenditures; the exact data mapping is described in the next Section 3.2. Based on the raw data aggregated to an annual frequency, the sum of sales of goods in SpendingPulse captures, on average since 2018, about 80% of total consumption expenditures on goods as shown in panel (b) of Figure 1. For services, this share is less than 10%. Two points are worthwhile to mention. First, sales in services in SpendingPulse exclusively stem from the hospitality industry while the consumption statistics cover a more diverse range of service providers such as rents that are evolving quite stable over time; we elaborate more on this issue after discussing the data transformations. Second, even though small, this share increased substantially especially within the last two years, potentially reflecting both the desire to return to dining and holiday experiences after lockdown-induced consumption restraints and the progressively increasing share of cashless payments also in the hospitality industry allowing to more rigorously capture these spending as well. Taken together, since 2018, SpendingPulse grows richer in information and lately managed to capture about 50% of total nominal and unadjusted consumption spending. As a reference, for Norway, Aastveit *et al.* (2020) document that the total value of credit card transactions recorded by the national payment system accounts for about 40% of total household consumption (based on price and seasonally unadjusted data). In addition, we note that the correlation coefficient between the quarterly (unadjusted) consumption series from the Federal Statistical Office of Germany and the to a quarterly frequency aggregated

SpendingPulse raw data stands at about 0.92 in terms of levels and 0.90 when comparing the growth rates across the series; these correlations are not driven by the pandemic year 2020. Overall, SpendingPulse seems to be a promising data source for Germany.

## 3.2 Data Transformation

We clean and process the raw data by means of price and seasonal adjustments to construct a final series used in our applications. This is necessary to ensure our SpendingPulse series indeed tracks business cycle relevant news and developments that are not purely driven by either price or recurring seasonal patterns. Since SpendingPulse comes as series of nominal and seasonally unadjusted sales volumes, simply using the raw data in our analysis might disguise the real value of these data. From a business cycle perspective, to understand the phases of the cycle and pin point its current stance, forecasters work with price and seasonally adjusted data wherefore the natural conjunction is to prepare our data in a similar vein. Data cleaning and preparation proceeds in five steps that are described in the following.

**Data mapping.** Because of different classification standards we need to match Mastercard's SpendingPulse to the data from the Federal Statistical Office of Germany to capture similar expenses across all sources. In particular, the price adjustment requires to find a match with the respective price indices. To gauge consumption patterns, we need to match SpendingPulse with the components of household consumption expenditures. In fact, we have a unique match between the price statistics and SpendingPulse for all series but turnover in grocery stores. For grocery, we construct a unique price series as the weighted average of the two corresponding monthly official price statistics, where we use the official CPI series' weights for aggregation.[2] Similarly, we need to combine some SpendingPulse categories into one aggregate series to have them cover (approximately) the same expenditures that are represented in the consumption statistics. For aggregation, we sum across the respective unadjusted series.

**Weekly time schedule.** Our target series, private consumption expenditures, is available at a quarterly frequency. Since the number of calendar weeks within a month tends to differ across months and years, we follow Aaronson *et al.* (2021) and implement a regular week schedule where each month consists of exactly four weeks such that every quarter holds

[2]In the present analysis, we exclusively focus on the properties of SpendingPulse in the context of total private consumption expenditures. SpendingPulse also performs well at a more granular level based on a breakdown of total household consumption into its individual components. As part of the cooperation with Mastercard, we also evaluated the usefulness of the individual SpendingPulse series for nowcasting sales in the various spending categories based on a similar methodology. Overall, SpendingPulse performs well and provides early and accurate nowcasts for sales in various retail and hospitality branches. Our results hence substantiate the results for sales forecasting already available in the literature (see, e.g., Andersen *et al.*, 2022; Aaronson *et al.*, 2021; García *et al.*, 2021; Bodas *et al.*, 2019). The results are available upon request.

precisely twelve weeks. Independent of the weekdays, the first three weeks of each month hold seven days, whereas the fourth week allocates all remaining days of the month and thus differs in length between seven and ten days. Every week comprises at least one weekend, i.e. Saturday and Sunday. The fourth week eventually captures an additional weekend day. Based on this defined pattern, we aggregate the daily data to the weekly frequency to avoid extreme volatile data patterns.

**Price adjustment.** We proceed by correcting the weekly series for price effects based on weekly price indices constructed as cubic spline interpolations of the corresponding monthly producer prices (for retail sales) or consumer prices (for sales in the hospitality industry). The cubic spline interpolation models the (unobserved) weekly values of the monthly price indices as piece-wise cubic polynomials bounded by the preceding and current monthly values (see, e.g., Forsythe *et al.*, 1977). The weekly price series thus approximate the weekly evolution in prices between two consecutive months ensuring first that the values in the final weeks of a month correspond to the ones published by the Federal Statistical Office of Germany and second that the weekly series transitions smoothly across months. The latter is achieved by constraints on the derivatives of the polynomial that always need to be finite.

**Aggregation.** We aggregate the individual weekly SpendingPulse series into one condense weekly "consumption-representative" series by adding up the price adjusted values across all sectors. This procedure is not the most accurate one due to the definition of the price indices. As we cannot access the "true" weights for a price-adjusted SpendingPulse series by construction, our approach should be a good approximation and the bias very small.

**Seasonal adjustment.** Finally, we account for seasonal patterns in the weekly Spending-Pulse "consumption-representative" series. There exist different approaches to seasonally adjust high-frequency data that come along with different advantages and drawbacks. We follow Aaronson *et al.* (2021) and run a seasonal adjustment procedure that operates on the weeks of the quarter respecting the week schedule established above.[3]

To do so, we construct weekly seasonal-calendar factors for the aggregate SpendingPulse series based on the official quarterly factors for total private consumption expenditures from the Federal Statistical Office of Germany. The weekly seasonal-calendar factor for private consumption expenditures ($c$), $SCF^{W,c}_{w,\tau,t}$, is a weighted average of the combined official quarterly seasonal and calendar factors, $SCF^{Q,c}_{\tau,t}$, corrected for the number of days that fall within a week of a quarter. This weekly factor has the following form:

[3]To verify that our results do not hinge on a particular seasonal adjustment procedure, we re-run our analysis with seasonally adjusted data based on the algorithm in Ollech (2021) that operates directly on the daily raw data. Qualitatively, the results remain unchanged and do not seem to be driven by the exact adjustment procedure.

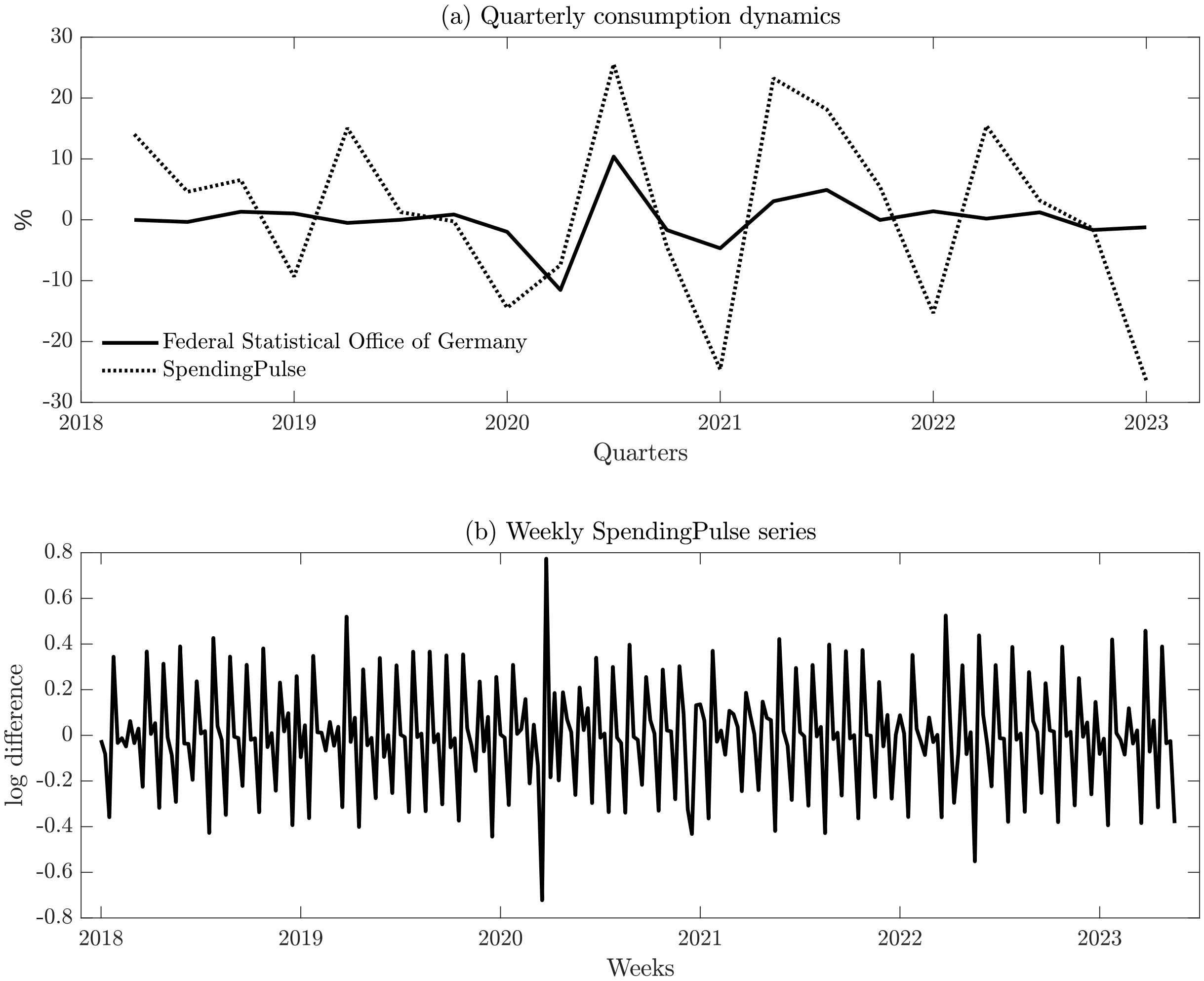
$$SCF^{W,c}_{w,\tau,t} = \frac{1}{12} \frac{1}{\varnothing_{w,\tau}\left[\frac{y_{w,\tau,t}/D_{w,\tau,t}}{y_{\tau,t}/D_{\tau}}\right]\frac{D_{w,\tau,t}}{D_{\tau}}} SCF^{Q,c}_{\tau,t}, \tag{1}$$

where $w = 1, \ldots, 12$ denotes the twelve weeks of quarter $\tau = 1, \ldots, 4$ in year $t = 2018, \ldots, 2023$. The seasonally unadjusted weekly aggregate SpendingPulse series is $y_{w,\tau,t}$ and $\varnothing_{w,\tau}$ denotes the average turnover in week $w$ of quarter $\tau$ relative to total turnover in quarter $\tau$. $D_{w,\tau,t}$ is the number of days within week $w$ of quarter $\tau$ and $D_\tau$ counts the number of days in quarter $\tau$. Note that the days of a quarter are independent of the year subscript as weeks and quarters are always of similar length across years (except for leap years). Similarly the average is independent of the year subscript even though it is calculated as an expanding window. Concretely, for all four quarters separately, we calculate the historical average share spending in week $w$ has had on total spending in that quarter, scaled by the number of days during the week relative to total days of the quarter. Scaling by the days ratio addresses the varying length of the fourth week of each month. The historic average includes all past data available at week $w$ of quarter $\tau$ in year $t$ where the current quarter is omitted if not yet fully available.

Equation (1) stipulates that we can retrieve a weekly seasonal factor by equally distributing the quarterly factor across the twelve weeks and then correcting for both historic spending patterns across weeks of the quarter and the length of each week. This implies that for weeks within a quarter $\tau$ where spending is regularly higher than in other weeks, the seasonal factor has a dampening effect on the raw series. Aaronson *et al.* (2021) note that this procedure makes two implicit assumptions: First, the weekly seasonal factors aggregated to the quarterly frequency coincide with the seasonal factors from the Federal Statistical Office of Germany. Second, weekly seasonal factors are indeed a function of the quarterly factors. In fact, the weekly seasonal factor is inversely related to the average spending within week $w = 1, \ldots, 12$ of quarter $\tau = 1, \ldots, 4$.

**Final representative weekly consumption series.** Panel (a) of Figure 2 compares the final weekly SpendingPulse series aggregated to a quarterly frequency to the price and seasonally adjusted consumption series published by the Federal Statistical Office of Germany. In terms of dynamics, the series evolve similarly. However, the consumption series is much smoother because of the inclusion of rents with an average share of one-fourth of total expenditures. Usually, expenditures for rents behave stable over time and might not drive or bias our main results. The correlation coefficient between the two quarterly series transformed into growth rates is about 0.60, irrespective of whether the most severe COVID-19 period in 2020 is included or not. In terms of volume, the SpendingPulse-based series captures up to 50% of total household consumption expenditures. Yet, the correlation coefficient on the level of the two price and seasonally adjusted series is at 0.51. Given the large share of rents, we conclude that our final series represents German private consumption expenditures well. Disregarding rents in the official consumption series yields a coverage of our final weekly series of 67% of private consumption expenditures.[4] In our analysis, we work with the weekly series depicted in panel (b) of Figure 2. The weekly series fluctuates quite evenly around zero. Even though we observe some outlier growth rates during the COVID-19 period, overall, weekly spending dynamics do not seem to exhibit a structural break after the onset of the pandemic, nor did the pandemic significantly alter weekly spending behaviour.

**Figure 2:** Consumption Expenditures and SpendingPulse




*Notes:* Panel (a) compares our final weekly SpendingPulse-based consumption series, aggregated to the quarterly frequency, to the official private consumption expenditure series. Panel (b) shows the weekly growth rates of our final weekly SpendingPulse-based consumption series. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany.

[4]In the national accounts, private consumption expenditures are subdivided into 11 expenditure categories. To remove rent expenditures, we calculate consumption expenditures as the sum of all subcategories excluding those on rents, water, electricity, gas and other fuels.

### 3.3 Alternative indicators

Mastercard's SpendingPulse is not the only indicator attempting to track and quantify consumer behaviour. Indeed, there exist some competing indicators, with most of them being of qualitative character and of monthly frequency only. To assess the usefulness and accuracy with which SpendingPulse reflects private consumption expenditures, we compare its performance to a set of alternative indicators, without claiming to give a complete list of all available potential leading indicators.

The European Commission regularly publishes a monthly Consumer Confidence Index that is based on survey questions from the Joint Harmonised EU Programme of Business and Consumer Surveys across European countries, available since the 1970s and it underwent some irregular restructuring to adjust for structural and geographical changes across the EU member states (European Commission, 2023, 2018). This survey-based index aggregates information on households' financial situation and their expectations about future macroeconomic developments. The design and choice of questions used for its construction took into account that research shows that both the individual financial situation and expectations with regard to future economic developments matter for consumption choices (European Commission, 2023).

Germany's largest market research company, the GfK (Growth from Knowledge, formerly known as the Gesellschaft fuer Konsumforschung), provides popular barometers on trends in consumer behaviour at a monthly frequency since the early 2000s. Simultaneously, the GfK is the German data provider for the European Consumer Survey. However, the European Commission treats the raw survey data in other ways than the GfK, thus, both consumer barometers differ from one another. The GfK barometer serves as pivotal signposts for future economic developments, notably those related to household consumption. Households are asked not only about their income and consumption expectations but also about savings and investment decisions. Among others, these information are compiled into two indices summarising the current consumer climate and household's willingness to buy.

Not only surveys on households can provide useful insights into economic developments, also evaluating retailers' and service providers' assessment of their current situation can provide valuable information for analysing consumption patterns. To that end, the ifo Institute asks firms within the retail sector operating in consumption related industries and service providers about their current assessment and future expectations of their economic well-being (see Sauer *et al.*, 2023, for a detailed overview over the ifo survey activities). Since they should at least partially profit from private consumption expenditures in terms of revenue, their assessment should reflect overall tendencies in consumption dynamics. These assessments are provided regularly every month since 1950 (retail trade) and 2005 (service sector), respectively. For the series on economic expectations, we ensure that we match the information accordingly to avoid a mismatch between the horizon under consideration from the survey and the nowcasting quarter.

Finally, since households' consumption decisions are not entirely decoupled from the overall economic well-being, we assess the value of the ifo Institute's flagship indicator, namely the ifo Business Climate Index Germany, that captures the general economic sentiment across German firms and is a well regarded leading indicator for overall economic developments in Germany. An up-to-date literature survey by Lehmann (2023) confirms the accurate predictive power of the ifo Business Climate especially for German GDP growth.

The characteristic shared by all of the previously mentioned indicators is their timely availability by the end or shortly after the end of the month. Having timely information is helpful to closely follow the business cycle and exploiting their long history allows quantifying the relation between these series more precisely. Yet, a drawback is their qualitative nature that sometimes is difficult to translate into concrete figures.[5] In that regard, the retail and hospitality statistics provide valuable information on sales within the respective industries. As opposed to the survey-based data, these come with publication lags between four and six weeks, imposing greater restrictions on a timely analysis of the consumption cycle.

Lastly, the number of new passenger car registrations by private owners regularly feeds into the analysis of household consumption expenditures capturing, among others, households liquidity and financial capacity to make large purchases of non-essential goods. Again, these monthly registration figures come with a publication lag of one week.

# 4 Tracking and Nowcasting Private Consumption

## 4.1 Data Release Schedule

The Federal Statistical Office of Germany typically releases data on private consumption expenditures 55 days after the end of each quarter and concurrently also includes data revisions for previous quarters. Mastercard regularly provides weekly updates of SpendingPulse, releasing data in chunks of a week with a publication delay of about two weeks.

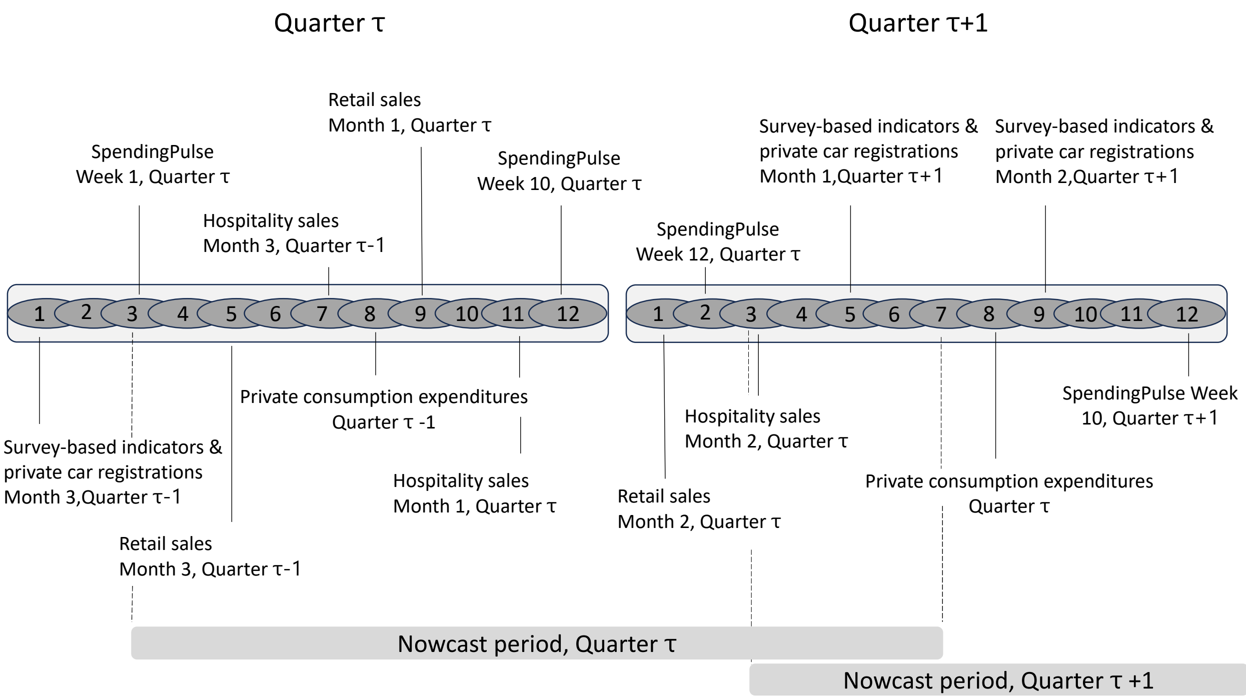
Figure 3 shows the publication schedule of SpendingPulse, the alternative indicators and private consumption expenditures for two generic quarters. Official data for a given quarter are typically published eight weeks into the new quarter. SpendingPulse offers insights into the current quarter from the third week onwards, given the introduced publication lag of two weeks. This means that data is available almost in real-time and data on the quarter of interest are already available by the second week of the next quarter. In addition, the shaded

[5]For the years 2020 until October 2022, Google provides data on mobility trends across various different public spaces. Despite their short time series and less exhaustive coverage of consumption-related spaces, we assessed their nowcasting performance. Since they do not outperform SpendingPulse and their value for analysing future consumption developments is limited, we do not report the results here. Similar results hold true when complementing the analysis with data on table reservations in restaurants provided by OpenTable. The results are, however, available upon request.

areas at the bottom of the figure indicate, for the weekly SpendingPusle series, the weeks where nowcasts and updates thereof are available with more details provided in Section 4.3.

Our alternative indicators are available at a monthly frequency and, except for the sales statistics, published shortly after the end of each month. We classify this as a publication lag of one week after the end of the reporting period. For the sales statistics, in turn, the delay is about six weeks after the end of the month to have all sales series available.

**Figure 3:** Data Release Schedule




*Notes:* Circles refer to the weeks 1 to 12 of the corresponding quarter according to our regular twelve week pattern within each quarter. The shaded areas at the bottom indicate the nowcasting period for each quarter. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany.

## 4.2 A Weekly Consumption Series

Our data at hand to establish a historic series of weekly private consumption expenditures requires an appropriate econometric framework to handle mixed frequencies and different publication schemes. Among others, mixed-frequency vectorautoregressive models have proven to be particularly appealing. We follow Koop *et al.* (2020) who introduce a MF-VAR that does not only allow to link data series of different frequencies but also provides a framework to add additional restrictions to the estimation algorithm of the target series. Their algorithm exploits the idea that there should be a natural relation between the (unobserved) weekly and the (observed) quarterly private consumption series that is, at least partially, captured by the high-frequency indicators in the MF-VAR. Similar to Mariano and Murasawa (2003) and Schorfheide and Song (2015), the model adopts a state space representation. The state equation models a standard VAR at weekly frequency, whereas the measurement equation allows to add an accounting rule ensuring consistency across the estimated weekly and the observed quarterly series of consumption growth. The Kalman filter and smoother is used to interpolate missing values at the weekly frequency.

**Notational conventions.** Our set up strictly follows Koop *et al.* (2020), thus also notation is very similar to their contribution:

- $t = 1, \ldots, T$ denotes the *weekly* target frequency,
- $Y_t^{SPL}$ denotes the observed weekly SpendingPulse series,
- $y_t^{SPL}$ denotes observed weekly seasonally and price adjusted growth in the SpendingPulse series,
- $Y_t^C$ is the (unobserved) weekly private consumption series,
- $y_t^C$ is the weekly consumption growth rate, never observed and to be estimated,
- $Y_t^Q = \sum_{i=1}^{12} Y_{t-i+1}$ is quarterly private consumption, observed only in the twelfth week of each quarter,
- $y_t^Q$ is the quarterly consumption growth rate, observed only in the final (i.e. twelfth) week of a quarter and published by the Federal Statistical Office of Germany.

**State space model.** The MF-VAR is cast into state space form comprising a transition and a measurement equation. The transition Equation (2) models the vector of unobserved weekly consumption growth along with the weekly growth rate in the sales series in SpendingPulse as a standard VAR at the weekly frequency. Where the vector with the weekly SpendingPulse and consumption series, $y_t = (y_t^{SPL}, y_t^C)'$, is of dimension $n$ and assumed to evolve as:

$$y_t = \Phi_0 + \sum_{i=1}^{22} \Phi_i y_{t-i} + u_t \,, \quad u_t \overset{iid}{\sim} N(0, \Sigma) \,. \tag{2}$$

Crucial for this set up is the notion that the weekly SpendingPulse series indeed contains valuable information on the (unobserved) weekly private consumption series. The error term $u_t$ follows a Gaussian mean zero distribution with a time-invariant variance-covariance matrix $\Sigma$. The lag structure is mainly governed by the temporal constraint introduced in the following.

The second ingredient to the state space model is the measurement Equation (3) that ensures consistency across estimated and observed consumption growth rates across time. Following Koop *et al.* (2020), the measurement equation of the state space model reads as:

$$y_t^Q = M_t^Q \Lambda^Q z_t \,, \tag{3}$$

where $z_t = (y_t', \ldots, y_{t-22}')'$. $\Lambda^Q$ holds the weights from the temporal constraint, and $M_t^Q$ is set up to adequately model weekly and quarterly data together. As we observe the quarterly consumption growth rate, $y_t^Q$, only in the twelfth week of a quarter, $M_t^Q$ is set to one for the last week of a quarter and zero otherwise. As Koop *et al.* (2020) note, this matrix is important for the nowcasting exercise, where appropriately selecting the entries equal to one at the end of the sample conveniently handles the "ragged-edge" nature of the data.

The crucial ingredient of the measurement equation is the temporal constraint that governs the estimation of the weekly growth rates. In vein of Mariano and Murasawa (2003) and Schorfheide and Song (2015), the quarterly growth rate of consumption expenditures, $y_t^Q$, can be expressed as the weighted sum of contemporaneous and lagged values of the unobserved weekly growth rates, $y_t^C$:

$$\begin{aligned} y_t^Q = \frac{1}{12}\Big( & y_t^C + 2y_{t-1}^C + 3y_{t-2}^C + 4y_{t-3}^C + 5y_{t-4}^C + 6y_{t-5}^C + 7y_{t-6}^C + 8y_{t-7}^C + 9y_{t-8}^C + 10y_{t-9}^C \\ & + 11y_{t-10}^C + 12y_{t-11}^C + 11y_{t-12}^C + 10y_{t-13}^C + 9y_{t-14}^C + 8y_{t-15}^C + 7y_{t-16}^C + 6y_{t-17}^C \\ & + 5y_{t-18}^C + 4y_{t-19}^C + 3y_{t-20}^C + 2y_{t-21}^C + y_{t-22}^C \Big) . \end{aligned} \tag{4}$$

The measurement Equation (3) together with the temporal constraint in (4) thus constrain the estimation algorithm in a sense that at the end of a quarter, the estimated weekly growth rates, aggregated to a quarterly frequency, coincide with the official publications.

**Prior and posterior simulation.** For estimating the MF-VAR introduced above, we keep following Koop *et al.* (2020) who, in turn, resort to the results of Bhattacharya *et al.* (2015), and use the global-local Dirichlet-Laplace hierarchical prior on the VAR parameters. Bhattacharya *et al.* (2015) show that the Dirichlet-Laplace prior is, from a theoretical perspective, optimal as it induces optimal shrinkage on the parameters in large VARs.

We implement a similar posterior simulation as in Koop *et al.* (2020) to learn about the distribution of the unobserved weekly consumption growth rates. In short, the MCMC algorithm appropriately accounts for the state and measurement equation and is based on a total of 20,000 draws where the first 10,000 draws are discarded. More details on the estimation are available in the Supplementary Material.

## 4.3 Nowcasting Experiment

Mastercard's SpendingPulse might not only be a valuable indicator to construct a historic time series of weekly consumption growth, but might perform satisfactorily as a leading indicator in a nowcasting exercise as well. The SpendingPulse-based MF-VAR, together with the temporal aggregation constraint, is able to simulate such a nowcasting situation. We thus assess its performance against a battery of alternative model specifications and popular alternative indicators.

**Nowcasting set up and information treatment.** Given the short time span of SpendingPulse, starting only in 2018, we restrict all nowcasting models to the same period, allowing for a fair comparison across models and data. We keep the first three years to train our models and evaluate the nowcast accuracy for the period between 2021 and 2022, based on quasi real-time vintages. That is, we use the latest available vintage of all data in our nowcasting experiment as real-time data are not available for all indicators.

When producing the nowcasts, for all data and models, we explicitly account for the "ragged-edge" data structure at the end of the sample that arises due to the asynchronous publication lags across the different data sources. Specifically, irrespective of the indicator or model used, we update our nowcast whenever new data on the indicator become available. For our main model, the MF-VAR, we address data availability at the time the nowcast is made by appropriately choosing the available data via the selection matrix $M_t^Q$ of Equation (3). The release schedule in Figure 3 illustrates how this is done. Since it takes eight weeks into the new quarter until the official statistics are released and SpendingPulse comes with a lag of two weeks, in total, we can produce 17 nowcasts for private consumption growth in each quarter, as indicated by the shaded area. This implies that in weeks three to seven, we produce both updates for the previous and the current quarter. Once SpendingPulse for a quarter is complete, but the national account figures are not published yet, we can nonetheless update our MF-VAR based estimate by profiting from the additional training the Kalman filter gains from adding more data. Since our target series is quarterly consumption growth, we transform our weekly consumption estimate into a quarterly figure using the aggregation constraint in Equation (4). While weekly growth rates unquestionably have their value for different analyses, the quarterlized weekly growth rate provides a first projection of the official statistics. Intuitively, for every week of the quarter where we create a nowcast, we estimate the weekly growth rates and then calculate the quarterly growth rate as the weighted average of the last 22 weekly growth rates. Hence, we effectively compare the evolution in weekly consumption between the last twelve weeks (including the current week) and the set of twelve weeks even before that. Due to the publication delay in SpendingPulse, only starting from the third week of quarter $\tau+1$, do we actually construct a quarterly growth rate of consumption in quarter $\tau$ that aligns with the common calendar quarters. Note that for the nowcast, the temporal constraint is only applied on quarters where the official statistic is already available, while we of course do not condition the nowcast of the current quarter $\tau$ on any official quarterly growth rate as this is the target to be estimated, and hence not yet available.

The literature employs various alternative models to produce nowcasts of macroeconomic aggregates. Here, we consider as competing models a simple autoregressive process of order one, AR(1), of the quarterly consumption series, a standard VAR(1) model of quarterly consumption and the representative consumption series aggregated to the quarterly frequency, and autoregressive distributed lag models (ADL). To quantify the usefulness of SpendingPulse over other data sources, we also provide results based on the alternative indicators. Again, we explicitly take the different release schedules into account by properly choosing only the set of data available whenever a new observation of the indicator variables become available and update the nowcast accordingly. All alternative indicators are only available at a monthly frequency, thus, we assign the release and hence the nowcast update to the corresponding week of the month when comparing model accuracy. Qualitative data are transformed by first differences. With quantitative data we restore to log differences. All models are estimated on an expanding window as new information on either the target series or the indicator series become available. Thus, every additional nowcast requires re-estimating the models.

To evaluate the nowcast accuracy and compare the various models and data sources against each other, we resort to standard evaluation metrices, including the root mean squared forecast errors (RMSFE), the Diebold-Mariano-test (DM-test) of predictive accuracy (Diebold and Mariano, 1995) and the share of correctly predicted signs. For all models and data sources, we calculate these metrices for all weeks where nowcasts or updates thereof are available. In case of the DM-test we always test whether the MF-VAR performs statistically superior compared to all alternative models. Yet, we note that with only few observations available, the performance and power of the DM-test statistic may be limited and results should hence be interpreted carefully.

**Alternative model specifications.** We start by first modelling a simple AR(1) process in log differences of quarterly consumption expenditures. At the beginning of quarter $\tau$, we neither have information from the official statistics on consumption in quarter $\tau-1$ nor on quarter $\tau$. Hence, our first nowcast in the first week of quarter $\tau$ is a two step ahead forecast. We then need to wait until week 8 of that quarter to update our nowcast, this time including information from the previous quarter $\tau-1$.

Second, we evaluate the performance of a vectorautoregressive model of order one, VAR(1), consisting of the official private consumption series and the weekly SpendingPulse series, aggregated to a quarterly frequency in advance. Again, our first nowcast in week 1 of quarter $\tau$ is based on information until quarter $\tau-2$. In week 3, SpendingPulse completes the previous quarter and we can provide a first update of our nowcast. The second update is, as before, available in week 8 of quarter $\tau$.

Third, we estimate two simple ADL models comprising the quarterly consumption series and a "week-to-quarter" representative SpendingPulse series. This version of the SpendingPulse series successively adds the additional information from new data releases to the already available data. Concretely, starting with the first release of SpendingPulse for a quarter, we take this information as representative for the entire quarter and calculate the log difference with respect to the average weekly spending in the previous quarter. As new data becomes available, we take these as representative and calculate average weekly spending in the current quarter relative to the average spending during the previous quarter. We continue to do so until SpendingPulse is complete for the quarter in question. With this model, we handle the asynchronous data releases at the end of the sample by imputing the missing quarterly data as the AR(1) nowcast for weeks where official data on the previous quarter is not yet available. Referring back to the release schedule, we can produce twelve nowcasts for consumption growth in quarter $\tau$, with the first one being produced in the third week of that quarter and the last one in the second week of quarter $\tau + 1$. The first specification models the relation between the two serious including one lag, while the second version chooses the optimal lag length based on the Akaike Information Criterion (AIC).

Fourth, we estimate the same simple OLS-based ADL models including the monthly alternative indicators presented in Section 3.3. With the survey-based indicators and private passenger car registrations becoming available immediately after the end of the reporting period, we can produce nowcasts starting in the fifth week of a quarter and update them in week nine of quarter $\tau$ and week one of quarter $\tau + 1$. Since competing nowcasts based on sales in the retail and hospitality sectors are only available once all data are published, a first nowcast is only available in week 11 of quarter $\tau$, with updates available in week 3 and and 7 of quarter $\tau + 1$.

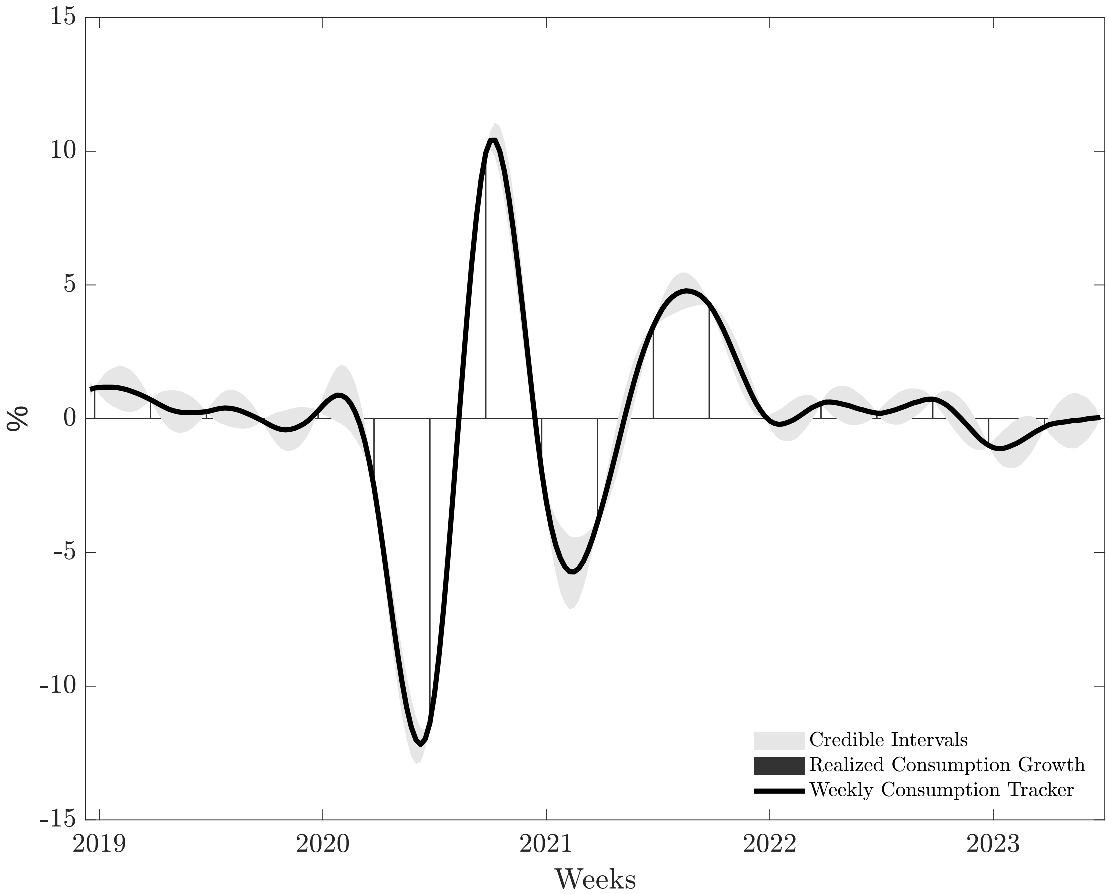
# 5 Results

## 5.1 Weekly Consumption Tracker

The Federal Statistical Office of Germany regularly publishes quarterly figures on private consumption expenditures. Based on these data and the weekly SpendingPulse sales series, Figure 4 presents the weekly series of historic household consumption expenditure growth based on the MF-VAR. Due to the lag structure of the model and the availability of SpendingPulse, the weekly series is available starting in the last quarter of 2018. Concretely, the black line shows our (in-sample) estimate of quarterlized weekly consumption growth where aggregation of the estimated weekly growth rate to a quarterly growth rate follows the introduced temporal aggregation constraint. At the end of each quarter, the weekly consumption series coincides by construction with the small black bars, which carry the quarterly series of household consumption expenditures from the Federal Statistical Office of Germany. The grey shaded areas mark the 84% uncertainty bands that are also subject to the temporal aggregation constraint and hence uncertainty converges to zero in the twelfth week of a quarter, marking the official data release.

Overall, estimation seems to be fairly precise, particularly during the heights of the COVID-19 period. Regularly, the confidence bands tend to widen in the course of the quarter but tighten again from the middle of the quarter. The granular time series smoothly tracks consumption movements within a quarter. While for some quarters, the series exhibits bump or U-shaped patterns, respectively. There are other quarters where the estimates suggest that consumption evolves quite linearly from one quarter to the next. These adjustment dynamics are concealed in the national accounts figures.

**Figure 4:** Weekly Consumption Tracker




*Notes:* The figure shows the historic series of the estimated quarterlized weekly growth rate of private consumption expenditures based on Mastercard's SpendingPulse. The shaded areas represent the 84% equally-tailed posterior probability bands (credible intervals) that collapse to zero by construction at each last week of the quarter as the weekly consumption tracker is designed to match the official figure on realized consumption growth (small black bars).

The weekly consumption series provides insightful information into households' consumption decisions and thus offers use-cases for different applications, ranging from a more granular assessment of the consumption cycle and its turning points to structural analyses of household consumption choices. In structural analyses, the weekly information may hold potential in providing additional insights into the transmission of shocks through the economy and the pace at which households eventually adjust their behaviour. The recent past holds a grand variety of situations that would have profited from a granular understanding of households' behaviour. During the COVID-19 pandemic, the German government did not only impose lockdown measures preventing individuals from pursuing their regular consumption pattern, but concurrently also introduced different support measures designed to help households remain financially stable. Until now, it is still not thoroughly understood to what extent households reacted to these measures and in particular, how long it may take until these measures, imposed on or targeted at the household level, feed into the broader economy. Using quarterly data for this analysis may carry the risk that intra-quarterly dynamics are absent at the lower frequency and interventions might appear to not have had any impact on households at all.

More recently, historically high inflation rates put a strain on households' budget. But when did households precisely start to adjust and cut spending? How and at what pace did households react to the subsequent monetary policy interactions? Particularly central banks may have a great interest in thoroughly understanding the effect their decisions have on the economy. In particular, the time lag with which these measures start impacting inflation rates and, in turn, also household spending, are crucial to understand for properly deciding on an appropriate set of monetary policy measures.

## 5.2 Weekly Nowcasting Results

We quantify and compare the nowcast performance of all models by means of average forecast errors (Table 1) and the share of correctly predicted signs (Table 2). Even in case a model performs poorly in terms of nowcast accuracy, it could still be valuable in indicating whether consumption is heading towards an ascending or descending route. We structure the results by the maximum number of weekly updates we can provide for a given quarter. Week 1 to 12 correspond to the regular weeks of quarter $\tau$ according to our uniform weeks schedule. Weeks 13 to 19 correspond to weeks 1 to 7 of quarter $\tau + 1$. Due to the publication delay in the official statistics, being released only in week 8 of quarter $\tau + 1$ after the end of the reporting period, and the delay in the release of high-frequency indicators, we can provide updates on quarter $\tau$ running already into quarter $\tau + 1$. For indicators at a lower frequency than weekly, we determine the week(s) within the quarter that correspond to their publication day and thus allow us to produce a nowcast or an update thereof and select the appropriate column entries. Empty entries thus represent weeks where no update is feasible.

Overall, the results indicate that SpendingPulse performs at least as good as or significantly better than any alternative indicator in terms of nowcasting accuracy. This becomes especially clear towards the end of the quarter once SpendingPulse becomes more complete. For example, in week ten the MF-VAR produces an average nowcasting error that is almost 60% lower compared to the worst and approximately 10% lower compared to the second-best model. A similar performance is reached in weeks 15 to 19. Even though all models are subject to nowcasting errors, another quality feature is the share of correctly predicted signs across the various model specifications and data sources. Interestingly, all models perform relatively similar with the worst performance observed at the beginning of the quarter. Towards the end of the nowcasting schedule, almost all models reach an accuracy of 50% in terms of getting the sign correct, while the models including the weekly SpendingPulse series eventually reach up to 75% accuracy. The performance of the MF-VAR, instead, stands at a maximum of 88% accuracy, thus, at the end of the nowcasting period it is almost sure that the MF-VAR including SpendingPulse will predict a correct sign.

# 6 Discussion

Private consumption might not only be traced back by means of card expenditures. Adding additional information on household behaviour and spending patterns might enrich the estimation of unobserved weekly dynamics. Even though SpendingPulse captures a great share of individual goods expenditures already, we highlighted before that the share in expenditures on services is only at approximately 15%. Yet, we only have limited additional information on these expenditures and if at all, they are almost exclusively targeted on tourism and travelling activities. Since we focus on high-frequency estimates, ideal candidate series are preferably timely and temporally disaggregated available. We hence include to our baseline MF-VAR specification a weekly series of flight turnover, similar to the one included in the weekly German economic activity index provided by the German Central Bank (see Eraslan and Götz, 2021). Therefore, we aggregate the daily time series provided by Eurocontrol to a weekly level in accordance with our regular week pattern and use the change relative to the previous year to cope with seasonality.[6] Even if the ability to travel is most surely not fully internalised in domestic expenditures, it is at least likely to reflect the general mood about financial resources available for purposes beyond most necessary items.

[6]The daily series of flight turnovers is only available since 2019. Fraport, the operating company of the Frankfurt (Main) airport, provides a similar series at the monthly frequency that shows a strong correlation with the daily series. We thus use the monthly series to extrapolate the daily series aggregated to the weekly frequency back to 2018. The Supplementary Material captures more information on that issue.

**Table 1:** Nowcast Accuracy for Private Consumption Expenditures

| Model | Quarter $\tau$ | | | | | | | | | | | | Quarter $\tau + 1$ | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
| *Quarterly models* | | | | | | | | | | | | | | | | | | | |
| AR(1) | 4.2 | | | | | | | 2.4 | | | | | | | | | | | |
| VAR(1) | 2.5* | | 4.7* | | | | | 4.8 | | | | | | | | | | | |
| *Monthly models* | | | | | | | | | | | | | | | | | | | |
| Retail sales | | | | | | | | | | | 4.1 | | | | 7.9* | | | | 6.9* |
| Cons. confid., EU | | | | | 5.0* | | | | 5.2 | | | | 6.0* | | | | | | |
| Cons. clim., GfK | | | | | 7.4* | | | | 4.0* | | | | 4.0* | | | | | | |
| Maj. purch., GfK | | | | | 4.6* | | | | 2.5* | | | | 2.9 | | | | | | |
| Bus. situat. retail | | | | | 2.1* | | | | 2.5 | | | | 2.5* | | | | | | |
| Bus. expect. retail | | | | | 4.3* | | | | 5.3 | | | | 5.8* | | | | | | |
| Bus. climate index | | | | | 2.6* | | | | 3.1* | | | | 6.7* | | | | | | |
| New car registr. | | | | | 4.8* | | | | 4.6* | | | | 4.5 | | | | | | |
| *Weekly models* | | | | | | | | | | | | | | | | | | | |
| ADL(0) | | | 4.4 | 4.0 | 3.2 | 3.1 | 3.0 | 2.9 | 2.9 | 2.7 | 2.7 | 2.6 | 2.5 | 2.6 | | | | | |
| ADL(AIC) | | | 7.7 | 4.0 | 3.2 | 3.5 | 3.4 | 3.3 | 3.1 | 2.7* | 2.7 | 2.6 | 2.5 | 3.9* | | | | | |
| MF-VAR | | | 4.2 | 3.3 | 3.1 | 3.1 | 3.1 | 2.5 | 2.4 | 2.4 | 2.4 | 2.3 | 4.2 | 4.2 | 2.3 | 2.4 | 2.4 | 2.3 | 2.3 |

*Notes:* The table shows the root mean squared forecast errors from the out-of-sample nowcasting exercise. New car registrations only include numbers for private passenger cars. The autoregressive model of order one, AR(1), comprises the quarterly private consumption series from the Federal Statistical Office of Germany, the vectorautoregressive model of order one, VAR(1), additionally holds a quarterly aggregate of the weekly SpendingPulse-based series. For all monthly models, we apply simple autoregressive distributed lag (ADL) models, where the Akaike Information Criterion (AIC) is used to determine the optimal lag length. With the weekly series, we use the mixed-frequency vectorautoregressive (MF-VAR) model and ADL models. The latter either only consider a contemporaneous relation (0) or the AIC was applied again. The weeks follow the uniform weeks schedule imposed on the data. The weeks 13 to 19 correspond to the weeks 1 to 7 in quarter $t + 1$ before new national accounts figures are released in week 8 for quarter $\tau$. $*$ denotes a statistically significant higher forecast accuracy of the MF-VAR at least to the 10%-level according to the Diebold-Mariano-test. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany, GfK, European Commission, ifo Institute, German Central Bank.

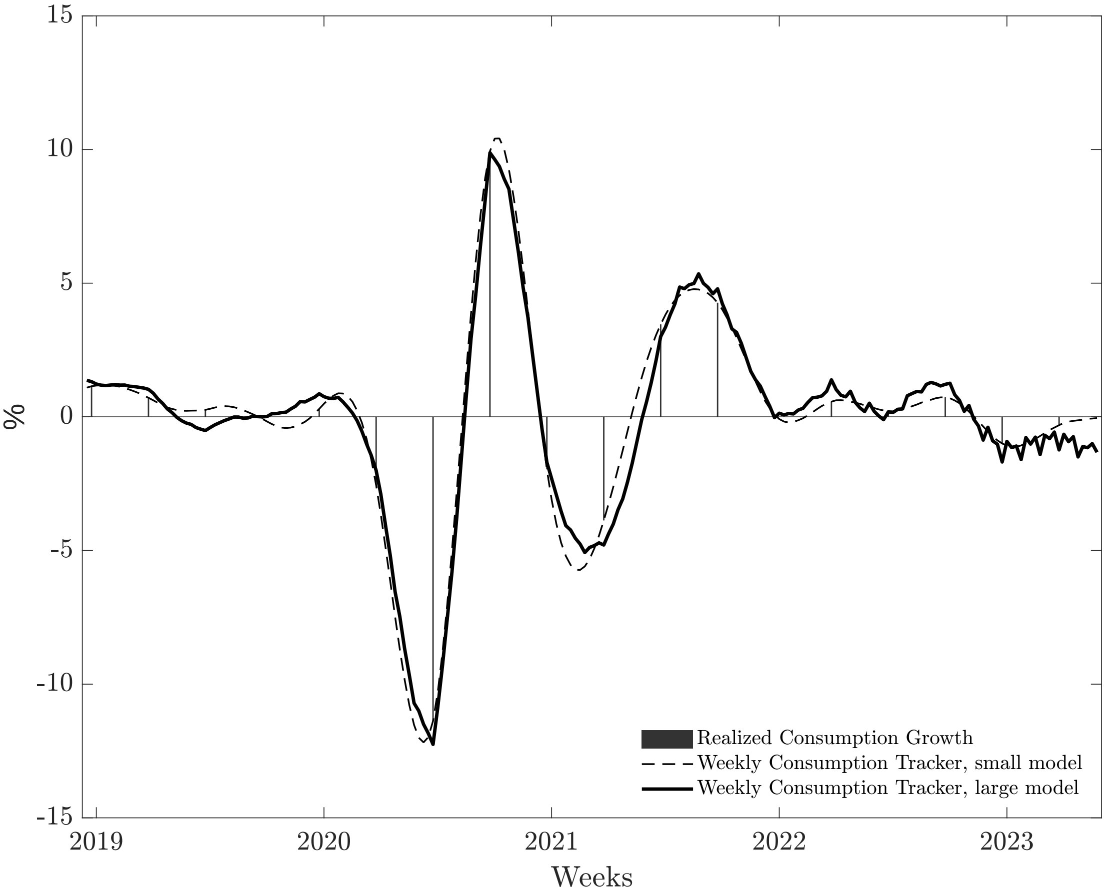
**Table 2:** Share of Correctly Predicted Signs

| Model | Quarter $\tau$ | | | | | | | | | | | | Quarter $\tau+1$ | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
| *Quarterly models* | | | | | | | | | | | | | | | | | | | |
| AR(1) | 63 | | | | | | | 38 | | | | | | | | | | | |
| VAR(1) | 38 | | 25 | | | | | 38 | | | | | | | | | | | |
| *Monthly models* | | | | | | | | | | | | | | | | | | | |
| Retail sales | | | | | | | | | | | 38 | | | | 13 | | | | 38 |
| Cons. confid., EU | | | | | 50 | | | | 38 | | | | 38 | | | | | | |
| Cons. clim., GfK | | | | | 25 | | | | 38 | | | | 38 | | | | | | |
| Maj. purch., GfK | | | | | 38 | | | | 38 | | | | 38 | | | | | | |
| Bus. situat. retail | | | | | 25 | | | | 38 | | | | 38 | | | | | | |
| Bus. expect. retail | | | | | 38 | | | | 50 | | | | 50 | | | | | | |
| Bus. climate index | | | | | 50 | | | | 50 | | | | 50 | | | | | | |
| New car registr. | | | | | 38 | | | | 13 | | | | 38 | | | | | | |
| *Weekly models* | | | | | | | | | | | | | | | | | | | |
| ADL(0) | | | 50 | 63 | 75 | 75 | 75 | 75 | 75 | 75 | 63 | 63 | 75 | 75 | | | | | |
| ADL(AIC) | | | 38 | 63 | 75 | 75 | 75 | 75 | 75 | 75 | 63 | 63 | 75 | 50 | | | | | |
| MF-VAR | | | 38 | 50 | 50 | 63 | 63 | 50 | 63 | 63 | 63 | 75 | 75 | 75 | 63 | 75 | 88 | 88 | 88 |

*Notes:* The table shows the share of correctly predicted signs (in %) from the out-of-sample nowcasting exercise. New car registrations only include numbers for private passenger cars. The autoregressive model of order one, AR(1), comprises the quarterly private consumption series from the Federal Statistical Office of Germany, the vectoroautoregressive model of order one, VAR(1), additionally holds a quarterly aggregate of the weekly SpendingPulse-based series. For all monthly models, we apply simple autoregressive distributed lag (ADL) models, where the Akaike Information Criterion (AIC) is used to determine the optimal lag length. With the weekly series, we use the mixed-frequency vectorautoregressive (MF-VAR) model and ADL models. The latter either only consider a contemporaneous relation (0) or the AIC was applied again. The weeks follow the uniform weeks schedule imposed on the data. The weeks 13 to 19 correspond to the weeks 1 to 7 in quarter $t+1$ before new national accounts figures are released in week 8 for quarter $\tau$. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany, GfK, European Commission, ifo Institute, German Central Bank.

We also include the set of alternative monthly indicators from the nowcasting experiment by extending the model to cope with weekly, monthly and quarterly time series simultaneously (see the Supplemetary Material for more details). Figure 5 contrasts the baseline MF-VAR including only the weekly SpendingPulse series along with the quarterly consumption series (dashed line) to the weekly consumption estimate from the MF-VAR extended to hold several more indicators at monthly and weekly frequency (solid line). Overall, the median estimates are very close and show very similar patterns. Some differences strike out especially during the midst of the COVID-19 period (for example, the first quarter of 2021) and at the current end of the sample. While during the COVID-19 period, the extended model suggests that consumption did not suffer as much as suggested by only including Mastercard's SpendingPulse, the extended MF-VAR estimate shows more fluctuations in weekly consumption at the current end, possibly related to quite stronger fluctuations especially in the monthly indicators. In the end, we conclude that Mastercard's transaction data have a high in-sample power to estimate unobserved weekly consumption patterns in Germany.

**Figure 5:** Weekly Consumption Tracker, small vs. large Model




*Notes:* The figure shows the historic series of the estimated quarterlized weekly growth rate of private consumption expenditures based on Mastercard's SpendingPulse (small model, dashed line) and compares it to the estimate realized from a larger model including alternative indicators. The official figures on realized consumption growth are indicated by the small black bars.

# 7 Conclusion

Little do we know about private consumption expenditures in Germany ahead of the release of quarterly national accounts figures that come along with publication lags of several weeks. Alternative data sources of higher frequency become more popular in the course of the years. We show that the spending patterns tracked in Mastercard's SpendingPulse provide useful information on German consumption expenditures in real-time. Based on these data, we uncover weekly consumption patterns, where our applied framework ensures consistency with the official quarterly series. SpendingPulse accounts for up to 67% of private consumption expenditures what makes it a promising complementary data source for Germany. Our results are twofold. After a thorough cleaning procedure, we are first able to produce a weekly series of quarterlized consumption growth that allows to track consumers more closely and going forward, this series might offer services to analyze consumer behaviour or assess policy interventions, such as changes in the monetary policy course of the European Central Bank, with more temporal granularity. Second, we find that in a nowcasting experiment, a mixed-frequency vectorautoregressive model based on SpendingPulse outperforms various alternative data and model specifications, thus, making our weekly consumption series a reliable leading indicator for private consumption expenditures in Germany.

In the future, we regularly want to publish this weekly consumption series and thereby tracking private consumption expenditures in Germany in real-time. Our analyses might initiate future research activities in two strands of the existing forecasting literature. First, additional sources for alternative high-frequency indicators can be used to forecast other very prominent parts of gross domestic product such as exports or investments in equipment. Second, possible extensions in this first strand of the literature might initiate future research on the question whether it is preferable to forecast gross domestic product directly or by summing up the nowcasts of its single components, either on the expenditure or the production side calculation. Given the latest methodological improvements together with new data sources puts a spotlight on this important issue.

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# From Shopping to Statistics: Tracking and Nowcasting Private Consumption Expenditures in Real-Time*

**– Supplementary Material –**

Friederike Fourné Robert Lehmann

This is the Supplementary Material to the article "From Shopping to Statistics: Tracking and Nowcasting Private Consumption Expenditures in Real-Time". It contains additional information referenced in the main paper. In particular, it includes further information on credit card and transaction data, Mastercard SpendingPulse$^{TM}$, data mapping issues, the alternative indicators applied in the nowcasting exercise, and the Bayesian estimation.

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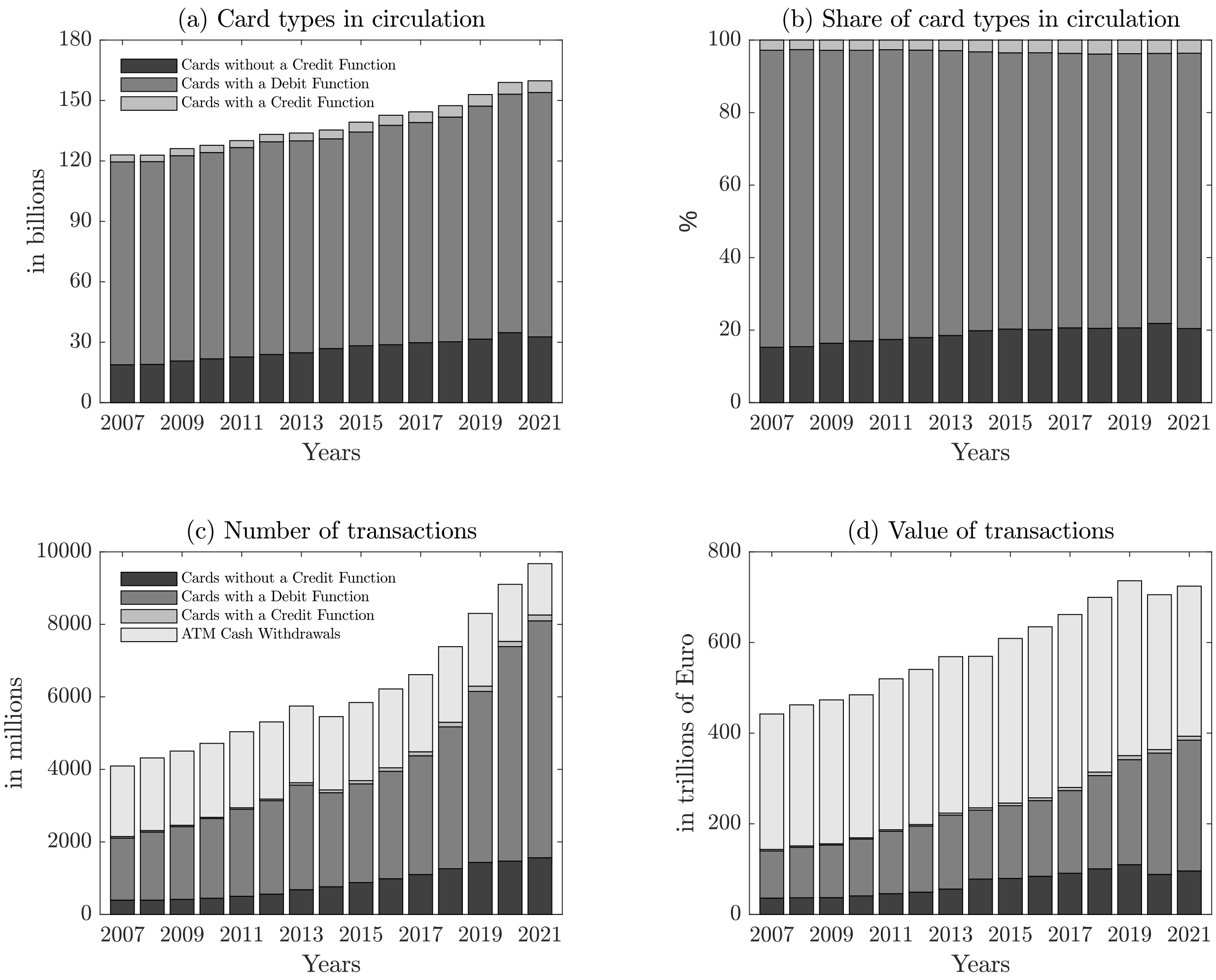
# A. Credit Card and Transaction Data

Figure A1 shows some stylized facts from the Payments and Settlement Systems Statistics (PSS) of the European Central Bank on the evolution of cash and card transactions in Germany. These graphs substantiate the main message of a growing importance of cashless transactions in Germany, with cash still keeping a prominent role overall.

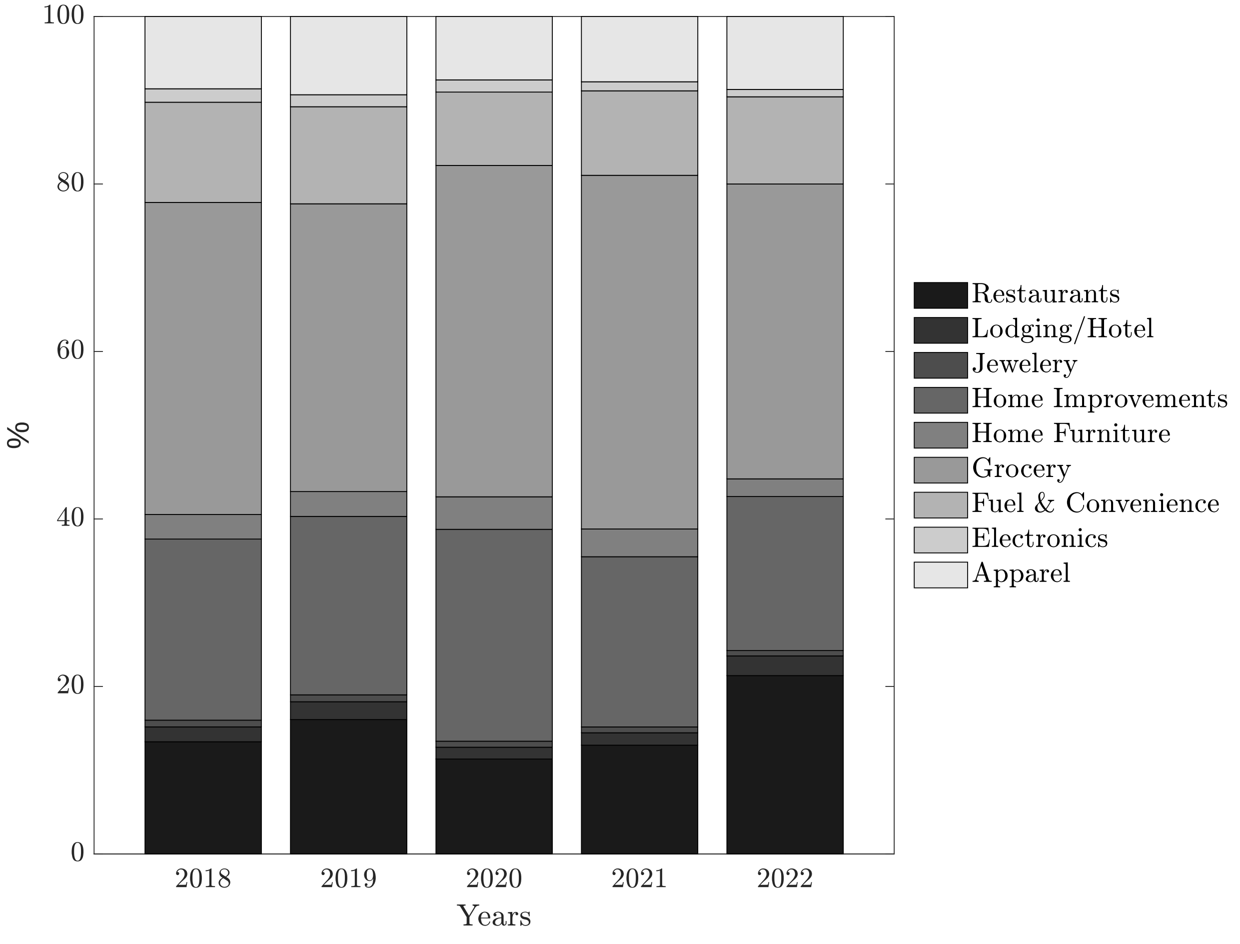
**Figure A1:** Developments in Cash and Card Transactions in Germany




*Notes:* The graphs show the evolution of cash (ATM) and card payments in terms of the evolution of number and value of transactions. Card payments are separately reported for debit cards and credit cards with and without a credit function. Panel (a) shows the absolute and panel (b) the relative number of card types in circulation. In panel (c), the absolute number of transactions is displayed, with the corresponding values in panel (d). *Sources:* Payments and Settlement Systems Statistics.

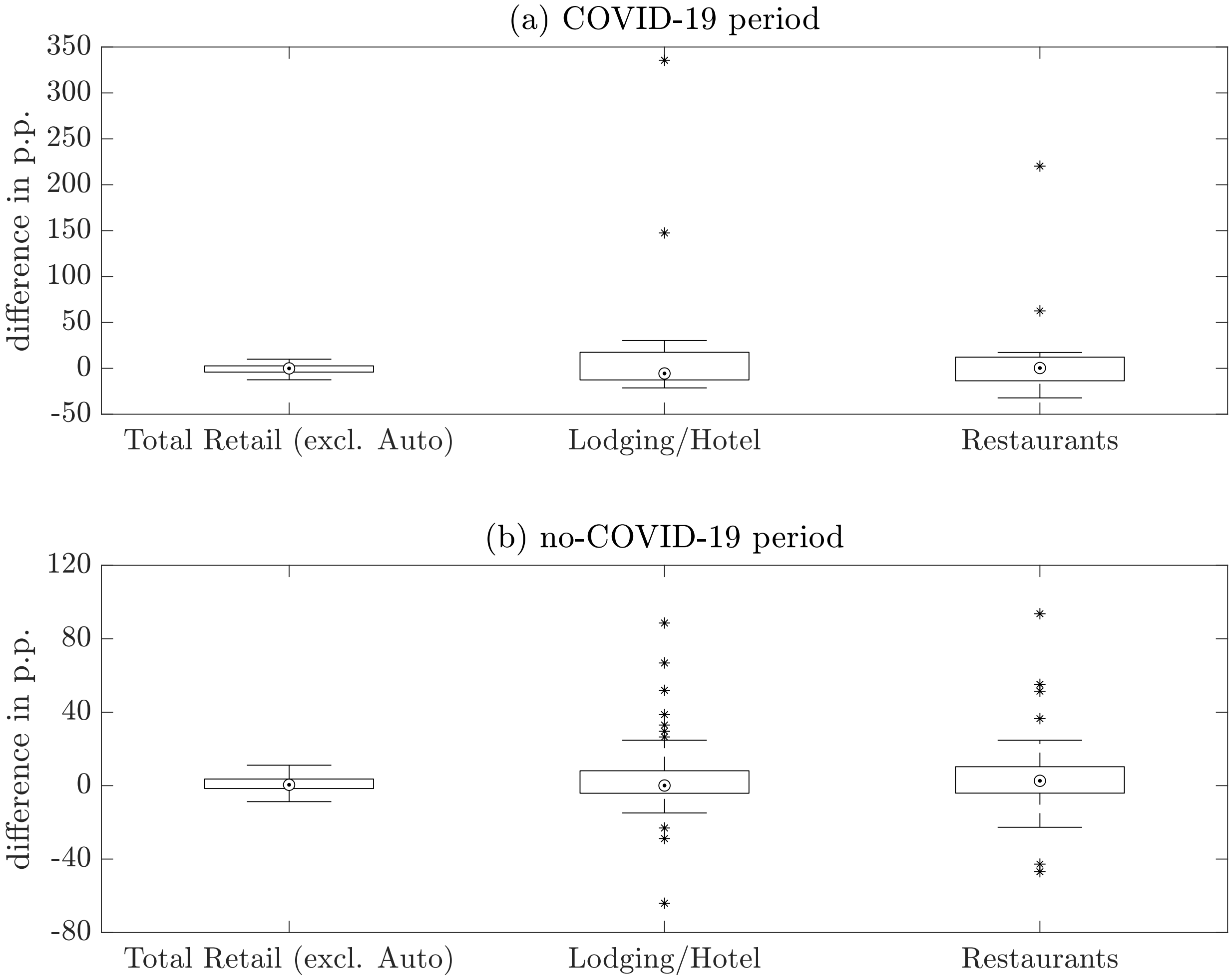
Figure A2 shows the sector coverage of sales in Mastercard's SpendingPulse. Overall, sales in the retail sector make up the largest share relative to those within the hospitality industry. Within the latter, restaurant turnover dominates with a rather stable distribution over the years. The largest category within the retail sector is grocery. Figure A3 shows the distribution of the differences between monthly growth rates based on the raw SpendingPulse series and the nominal and seasonally unadjusted sales statistics from official statistics.

**Figure A2:** Turnover Shares by Sector in Mastercard's SpendingPulse




*Notes:* The figure shows the share of sector sales relative to total turnover in Mastercard's SpendingPulse. All data are neither price nor seasonally adjusted. *Sources:* Mastercard's SpendingPulse.

**Figure A3:** Differences between SpendingPulse and official Statistics




*Notes:* The figures shows the distributions of differences between the monthly growth rates in SpendingPulse and the corresponding series from official statistics. The medians are marked by a dot-circle-combination and outliers by asterisks. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany.

# B. Data Preparation

## B.1. Data Mapping

Tables B1 and B2 match SpendingPulse to the official series. Aggregation is done by summing up multiple series. This might, however, not be the cleanest approach but since exact weights are not available, it is a good approximation.

**Table B1:** Matching SpendingPulse with Retail Sales Statistics

| **SpendingPulse sector** | **Official classification, WZ08** | **RPI/CPI** |
|---|---|---|
| Total Retail (excl. auto) | 47 – Total retail (excl. automobile) | Retail price index (RPI), retail trade (excl. vehicle trade) |
| Apparel | 47.71 – Retail sale of inform. and communic. equip. in special. stores | RPI, retail sale of clothing |
| Electronics | 47.4 – Retail sale of inform. and communic. equip. in special. stores | RPI, retail sale of inform. and communic. equip. |
| Fuel & Convenience | 47.3 – Retail sale of automotive fuel in special. stores | RPI, retail sale of autom. fuel |
| Grocery | 47.1 – Retail sale in non-special. stores, 47.2 – Retail sale of food, bever. and tobac. in special. stores | RPI, retail sale in non-special. stores, retail sale of food, bever. and tobac. |
| Home Furniture | 47.59 – Retail sale of furniture, lighting equip. and other household articles in special. stores | RPI, retail sale of furniture, lighting equip. etc. |
| Home Improvement | 47.52 – Retail sale of hardware, paints and glass in special. stores | RPI, retail sale of hardware, paints and glass |
| Jewelry | 47.77 – Retail sale of watches and jewelry in special. stores | RPI, retail sale of watches and jewellery |
| Lodging/Hotels | 55 – Accommodation | CC13-112 overnight stays |
| Restaurants | 56 – Food and bev. service activities | CC13-111 restaurant services |

*Notes:* The table shows the matching between the SpendingPulse sectors and the official classification system for German statistics (German Classification of Economic Activities, Edition 2008 – WZ08). The numbers represent the 2-digit or lower code in economic activities and CC13 stands for a specific category in the German classification for the consumer price index (CPI). The retail price index (RPI) always includes value added tax. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany.

**Table B2:** Matching SpendingPulse with Household Consumption Statistics

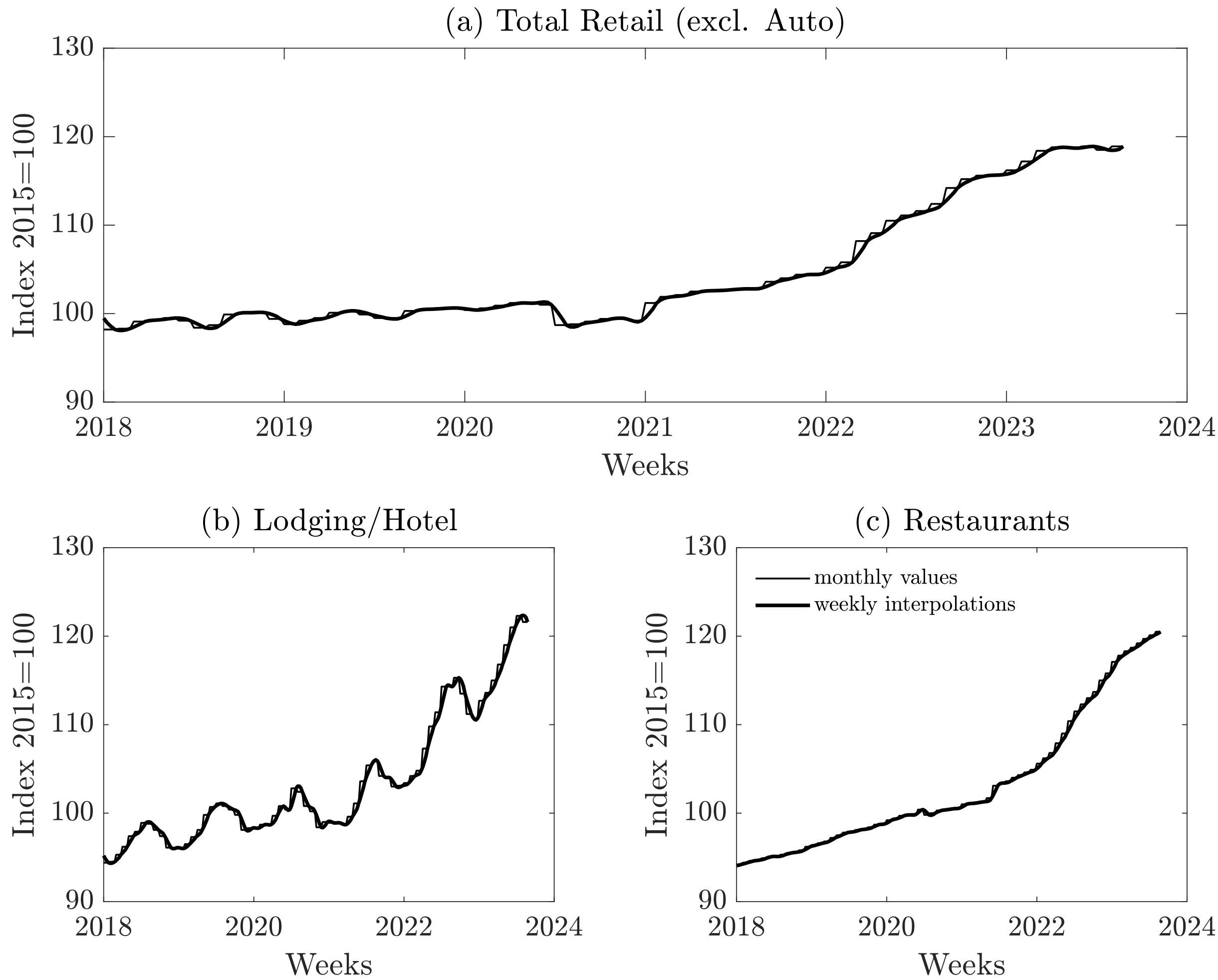
| **Consumption category** | **SpendingPulse sector** |
|---|---|
| Transport and Communication | Electronics |
| Recreation and Culture | no match |
| Rent, Water, Electricity, Gas i.a. Fuels | Fuel & Convenience |
| Food, Beverages and Tobacco | Grocery |
| Clothing and Footwear | Apparel, Jewelry |
| Furnishings for Households | Home Furniture, Home Improvement |
| Accommodation and Catering Services | Restaurants, Lodging/Hotels |
| Other Purposes | no match |
| Total | all sectors |

*Notes:* The table shows the matching between the SpendingPulse sectors and final consumption expenditures for households (plus non-profit institutions serving households). *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany.

## B.2. Weekly Price Indices

Official statistics in Germany publish price indices at a monthly frequency. We construct weekly price indices as cubic spline interpolations of either the monthly producer price index (retail sales) or consumer price indices (hospitality industry). The cubic spline interpolation models the (unobserved) weekly values of the monthly price indices as piece-wise cubic polynomials bounded by the preceding and current monthly values (see, e.g., Forsythe *et al.*, 1977), thus, ensuring that monthly values published by the Federal Statistical Office of Germany are binding. Furthermore, the weekly series transitions smoothly across the months. Figure B1 shows the weekly price indices together with the monthly values.

**Figure B1:** Weekly Price Indices




*Notes:* The figures show the monthly price indices from official statistics (step function, thin lines) along with their weekly series obtained from a cubic interpolation of the monthly values (thick lines). *Sources:* Authors' calculations based on data from the Federal Statistical Office of Germany.

## B.3. Final Weekly Consumption Series

The final weekly series, meant to capture consumption dynamics registered in SpendingPulse, exhibits high correlations with the dynamics in the official statistics after aggregating it to a quarterly frequency. Table B3 shows the correlation coefficients between the two series both including and excluding quarters in 2020 that were particularly hit by lockdown restrictions in response to the COVID-19 crisis. The first part of the table looks at the correlation between the raw data, the second part shows the correlation among the price and seasonally adjusted series. Despite the form of transformation, our consumption series resulting from SpendingPulse is always highly connected to the figures from German national accounts, thus, making our weekly series a valuable indicator in real-time.

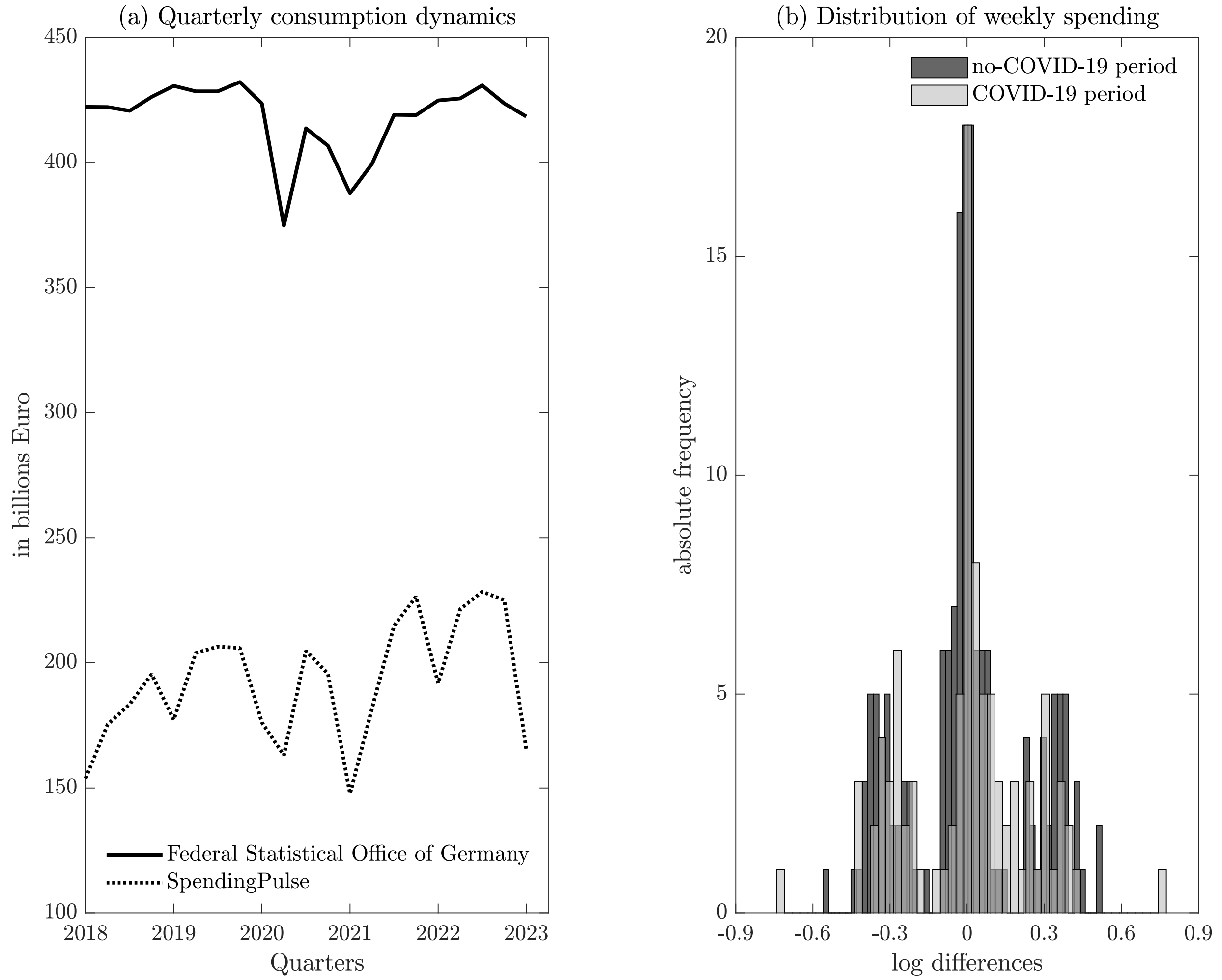
**Table B3:** Correlation between SpendingPulse and Private Consumption

| | **nominal, unadjusted** | **price and seasonally adjusted** |
|---|---|---|
| | *Levels* | |
| total period | 0.92*** | 0.51** |
| excl. COVID-19 | 0.95*** | 0.52** |
| | *Growth rates* | |
| total period | 0.85*** | 0.60*** |
| excl. COVID-19 | 0.90*** | 0.60** |

*Notes:* The table shows the Pearson correlation coefficients between the to a quarterly frequency aggregated SpendingPulse series and the private consumption figures from German national accounts. The second column considers nominal and seasonally unadjusted data. The third column shows correlations between the price and seasonally adjusted series. ***, **, * denote correlation coefficients that are statistically different from zero to the 1%, 5% or 10% confidence level. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany.

In addition to the figures presented in the main text, panel (a) in Figure B2 visualizes to what extent the weekly series, aggregated to the quarterly frequency, can track actual consumption volumes. Overall, the dynamics are similar, yet, in terms of volume our SpendingPulse series represents approximately 50% of total private consumption expenditures. As discussed in the main text, if we exclude rents then SpendingPulse can explain 67% of the consumption aggregate. Panel (b) in Figure B2 shows the distribution of weekly spending. Overall, the weekly dynamics did not suffer a tremendous downfall during the COVID-19 pandemic, and results do not suggest a severe structural break.

**Figure B2:** Characteristics of the Weekly Consumption Series




*Notes:* Panel (a) shows the weekly series aggregated to the quarterly frequency in comparison to private consumption expenditures from German national accounts. Panel (b) plots the distribution of weekly consumption spending (in log differences) in the course of the weeks, divided into the COVID-19 period and the remaining weeks. *Sources:* Mastercard's SpendingPulse, Federal Statistical Office of Germany.

# C. Tracking and Nowcasting Private Consumption

## C.1. Alternative indicators

There exist other, popular indicators attempting to track or mirror household consumption behaviour. As detailed in the main text, these range from sales statistics, to firm and household survey-based indices and private passenger car registrations. Table C1 presents all alternative indicators, together with some description, the original source and the monthly publication lags. Additionally, Table C2 presents some descriptive statistics and Figure C1 plots their development over time.

**Table C1:** Details on the Alternative Indicators

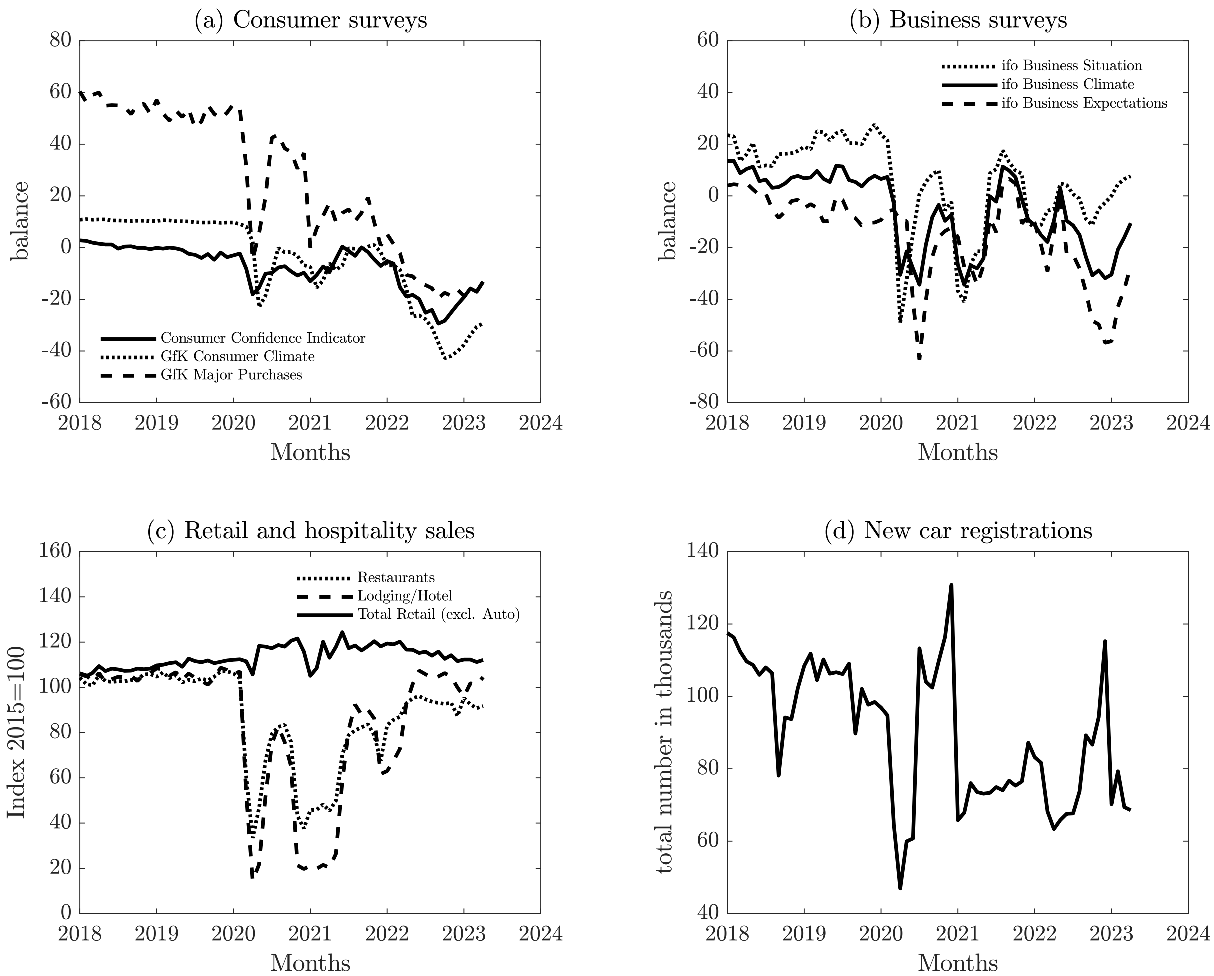
| **Indicator** | **Description** | **Source** | **Lag** |
|---|---|---|---|
| | *Survey-based Indicators* | | |
| Consumer Confidence Indicator | Arithmetic average of the survey questions on households' financial situation (past and expected), expectations on the general economic situation and future major purchases (over the next 12 months), monthly, seasonally adjusted, balances. | European Commission | 0 months |
| GfK Consumer Climate | Average of the survey questions on households' income expectations, willingness to buy and savings, monthly, seasonally adjusted, balances. | GfK | 0 months |
| GfK Major Purchases | Question on consumers' willingness to buy, monthly, seasonally adjusted, balances. | GfK | 0 months |
| ifo Business Situation Retail Trade | Question on retailers' current business situation, monthly, seasonally adjusted, balances. **Question:** 'We assess our current business situation as [...]' **Answer:** (+) good, (=) satisfactory, or (–) bad. | ifo Institute | 0 months |
| ifo Business Expectations Retail Trade | Question on retailers' expectations on business development (over the next 6 months), monthly, seasonally adjusted, balances. **Question:** 'In the next 6 months, our business situation will be [...]' **Answer:** (+) rather favorable, (=) rather stay the same, or (–) rather unfavorable. | ifo Institute | 0 months |
| ifo Business Climate Retail Trade | Geometric average of retailers' business situation and business expectations, monthly, seasonally adjusted, balances. | ifo Institute | 0 months |
| | *Quantitative Indicators* | | |
| Retail Sales | Total turnover in retail trade, monthly, price and seasonally adjusted, log-differences. | Federal Statistical Office of Germany | 1 month |
| New Car Registrations | Total number of newly registered cars by private owners, monthly, seasonally adjusted, log-differences. | German Central Bank | 0 months |

**Table C2:** Descriptive Statistics for the Alternative Indicators

| **Indicator** | **Mean** | **STD** | **Min** | **Max** |
|---|---|---|---|---|
| Consumer Confidence Indicator | -7.9 | 8.4 | -29.4 | 2.8 |
| GfK Consumer Climate | -5.5 | 16.9 | -42.8 | 11.0 |
| GfK Major Purchases | 23.3 | 28.9 | -19.5 | 60.4 |
| ifo Business Situation | 4.7 | 17.2 | -49.1 | 27.6 |
| ifo Business Expectations | -15.5 | 16.7 | -63.3 | 6.6 |
| ifo Business Climate | -5.8 | 14.7 | -34.4 | 13.5 |
| Retail Sales (in %) | 0.2 | 3.1 | -9.2 | 11.9 |
| New Car Registrations (in %) | 0.6 | 17.1 | -49.7 | 86.5 |

*Notes:* The table shows some descriptive statistics for the alternative indicators including the mean, the standard deviation (STD), the minimum and the maximum value. The statistics are calculated for the whole forecasting period. *Sources:* European Commission, Growth from Knowledge, ifo Institute, Federal Statistical Office of Germany, German Central Bank.

**Figure C1:** Development of the Alternative Indicators




*Notes:* Panels (a) and (b) show the monthly indicators either from consumer or business survey results. Panel (c) plots the series of sales in the retail and hospitality industries based on official statistics. Panel (d) shows the number of new private passenger car registrations. *Sources:* European Commission, Growth from Knowledge, ifo Institute, Federal Statistical Office of Germany, German Central Bank.

## C.2. A Weekly Consumption Series

The choice of the prior for estimating the MF-VAR keeps in mind the computational effort to estimate the numerous parameters of the model. Following Koop *et al.* (2020), we use a global local Dirichlet-Laplace prior. The VAR model from the main text can be expressed as a multivariate regression problem, $\mathbf{y_t} = \mathbf{X_t}\beta + \epsilon_t$, with $\epsilon_t \sim \mathcal{N}(0, \Sigma)$, $\mathbf{X_t} = I_n \otimes [1, \mathbf{y}'_{t-1}, \ldots, \mathbf{y}'_{t-22}]$ and the $k$-dimensional coefficient vector $\beta = vec([\phi_0, \phi_1, \ldots, \phi_{22}]')$. The Dirichlet-Laplace prior is imposed on the coefficient vector defined as $\beta = (\beta_1, \ldots, \beta_{22})$, such that priors on individual coefficients are independent from each other and given as:

$$\beta_j \sim \mathcal{N}(0, \psi_j^\beta, \phi_{j,\beta}^2, \tau_\beta^2)\,, \tag{1}$$

$$\psi_j^\beta \sim exp(\frac{1}{2})\,, \tag{2}$$

$$\phi_{j,\beta} \sim dir(\alpha_\beta, \ldots, \alpha_\beta)\,, \tag{3}$$

$$\tau_\beta \sim G(k\alpha_\beta, \frac{1}{2}), \tag{4}$$

The parameters in Equations (2) to (4) shape the prior variance but need to be estimated. The algorithm chooses them automatically and thereby decides how much shrinkage on each coefficient is allowed. The Dirichlet-Laplace prior is hierarchical in a sense that the prior on the coefficients in Equation (1) involves unknown parameters that, in turn, require their own priors. The parameters on the variance include a global term in Equation (4) that is the same across all coefficients, and a local term in Equation (2) that is different for each coefficient $\beta_j$. Adding Equation (3), Bhattacharya *et al.* (2015) show that the Dirichlet-Laplace prior yields a posterior on the coefficients that optimally contracts to its true values. The Dirichlet-Laplace prior requires only one hyperparameter, $\alpha_\beta$. We set the hyperparameter $\alpha_\beta = \frac{1}{2}$. To initialise the algorithm, we set the starting values for the Dirichlet-Laplace prior to $\psi_j^\beta = \phi_{j,\beta} = \tau_\beta = 0.1$.

## C.3. A Weekly Consumption Series with Multiple Frequencies

To enrich the information set beyond those incorporated in the weekly SpendingPulse series, we add further monthly indicators to the MF-VAR. The main functioning and setup of the model remains unchanged. To allow for three frequencies, we only need to redefine the state space representation and add an additional temporal constraint. Similar to the MF-VAR set out in Koop *et al.* (2020), the weekly VAR reads as:

$$\begin{bmatrix} y_t^{SPL} \\ y_t^1 \\ y_t^2 \\ y_t^C \end{bmatrix} = \begin{bmatrix} \Phi_{wc} \\ \Phi_{mc} \\ \Phi_{qc} \end{bmatrix} + \underbrace{\begin{bmatrix} \Phi_{ww,1}\Phi_{wm,1}\Phi_{wq,1} \\ \Phi_{mw,1}\Phi_{mm,1}\Phi_{mq,1} \\ \Phi_{qw,1}\Phi_{qm,1}\Phi_{qq,1} \end{bmatrix}}_{A_1} \begin{bmatrix} y_{t-1}^{SPL} \\ y_{t-1}^1 \\ y_{t-1}^2 \\ y_{t-1}^C \end{bmatrix} + \cdots + A_{22} \begin{bmatrix} y_{t-22}^{SPL} \\ y_{t-22}^1 \\ y_{t-22}^2 \\ y_{t-22}^C \end{bmatrix} + \epsilon_t, \tag{5}$$

where we restrict the set of monthly indicators to two series ($nm = 2$, $y_t^1$, $y_t^2$) for notational convenience. $\Phi_{(w,m,q)c}$ denote the constant terms associated with the weekly, monthly and quarterly series, respectively. $\Phi_{ww,(1,\ldots,22)}$, $\Phi_{wm,(1,\ldots,22)}$, $\Phi_{wq,(1,\ldots,22)}$ hold the VAR coefficients of the weekly SpendingPulse series onto the weekly ($ww$), monthly ($wm$) and quarterly ($wq$) series and their corresponding lags. Analogous notation holds for the monthly and quarterly indicators. Note that for the monthly indicators, the matrices $\Phi_{mx,x}$ hold the coefficients on both monthly series. As with the two frequency model, grouping the VAR coefficients into

$$\begin{aligned}
\Phi_{ww} &= \left[\Phi_{ww,1}\Phi_{ww,2}\ldots\Phi_{ww,22}\right], \\
\Phi_{wm} &= \left[\Phi_{wm,1}\Phi_{wm,2}\ldots\Phi_{wm,22}\right], \\
\Phi_{wq} &= \left[\Phi_{wq,1}\Phi_{wq,2}\ldots\Phi_{wq,22}\right], \\
\Phi_{mw} &= \left[\Phi_{mw,1}\Phi_{mw,2}\ldots\Phi_{mw,22}\right], \\
\Phi_{mm} &= \left[\Phi_{mm,1}\Phi_{mm,2}\ldots\Phi_{mm,22}\right], \\
\Phi_{mq} &= \left[\Phi_{mq,1}\Phi_{mq,2}\ldots\Phi_{mq,22}\right], \\
\Phi_{qw} &= \left[\Phi_{qw,1}\Phi_{qw,2}\ldots\Phi_{qw,22}\right], \\
\Phi_{qm} &= \left[\Phi_{qm,1}\Phi_{qm,2}\ldots\Phi_{qm,22}\right], \\
\Phi_{qq} &= \left[\Phi_{qq,1}\Phi_{qm,2}\ldots\Phi_{qq,22}\right],
\end{aligned}$$

allows to write the state equation as:

$$\mathbf{s_t} = \Gamma_s \mathbf{s}_{t-1} + \Gamma_z \mathbf{y}_{t-p:t-1}^{SPL} + \Gamma_c + \Gamma_u u_t\,, \tag{6}$$

where $\mathbf{s_t} = \left(y_t^1, y_t^2, y_{t-1}^1, y_{t-1}^2, \ldots, y_{t-22}^1, y_{t-22}^2, y_t^C, y_{t-1}^C, \ldots, y_{t-22}^C\right)'$ is a $z \times 1$ vector holding the monthly and quarterly variables and their lags, where the monthly indicators are ordered first. $\mathbf{y}_{t-p:t-1}^{SPL}$ comprises the weekly SpendingPulse series. The coefficient matrices in (6) are defined as:

$$\Gamma_s = \begin{bmatrix} \Phi_{mm} & 0 & \Phi_{mq} & 0 \\ \mathbf{I} & & \mathbf{0} & \\ \Phi_{qm} & 0 & \Phi_{qq} & 0 \\ \mathbf{0} & \mathbf{I} & \mathbf{0} & \end{bmatrix}_{z\times z}, \Gamma_z = \begin{bmatrix} \Phi_{mw} \\ 0 \\ \Phi_{qw} \\ 0 \end{bmatrix}_{z\times p}, \Gamma_c = \begin{bmatrix} \Phi_{mc} \\ 0 \\ \Phi_{qc} \\ 0 \end{bmatrix}_{z\times 1}, \tag{7}$$

To close the model, we have three variants of the measurement equation depending on the data availability that incorporate the temporal constraints on the monthly and quarterly variables. Analogously to the temporal constraint on the quarterly series, the monthly constraint can be expressed as:

$$y_t^M = \frac{1}{4}\Big(y_t + 2y_{t-1} + 3y_{t-2} + 4y_{t-3} + 3y_{t-4} + 2y_{t-5} + y_{t-6}\Big), \tag{8}$$

Accordingly, in weeks where we only observe the weekly series, the measurement equation is given by:

$$y_t^{SPL} = \Lambda_{qs}\mathbf{s_t} + \Phi_{ww}\mathbf{y}_{t-p:t-1}^{SPL} + \Phi_{wc} + u_{w,t}, \tag{9}$$

with

$$\Lambda_{qs} = \begin{bmatrix} 0 & 0 & \Phi_{wm} & 0 & \Phi_{wq} \end{bmatrix}, \tag{10}$$

In weeks four and eight we observe both the weekly and the monthly series while the quarterly series is not yet available. Hence, the measurement equation reads as:

$$\begin{bmatrix} y_t^{SPL} \\ y_t^{mthl,1} \\ y_t^{mthl,2} \end{bmatrix} = \Lambda_{ms}\mathbf{s}_t + \Lambda_z y_{t-p:t-1}^{SPL} + \begin{bmatrix} \Phi_{wc} \\ \Phi_{mc} \end{bmatrix}, \tag{11}$$

with

$$\Lambda_{ms} = \begin{bmatrix} 0 & 0 & \Phi_{wm} & 0 & \Phi_{wq} \\ & & M_m & & \end{bmatrix}, \Lambda_z = \begin{bmatrix} \Phi_{ww} \\ 0 \\ 0 \end{bmatrix}, \tag{12}$$

$$M_m = \begin{bmatrix} \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & \mathbf{0}_{1\times 32} & \mathbf{0}_{1\times 23} \\ 0 & \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & \mathbf{0}_{1\times 32} & \mathbf{0}_{1\times 23} \end{bmatrix}.$$

In the last week of each quarter, when all series are available, the measurement equation also incorporates the temporal constraint on the quarterly indicator, given by:

$$\begin{bmatrix} y_t^{SPL} \\ y_t^1 \\ y_t^2 \\ y_t^C \end{bmatrix} = \Lambda_{qs}\mathbf{s}_t + \Lambda_z y_{t-p:t-1}^{SPL} + \begin{bmatrix} \Phi_{wc} \\ \Phi_{mc} \\ \Phi_{qc} \end{bmatrix}, \tag{13}$$

where

$$\Lambda_{qs} = \begin{bmatrix} 0 & 0 & \Phi_{wm} & 0 & \Phi_{wq} \\ & & M_q & & \end{bmatrix}, \Lambda_z = \begin{bmatrix} \Phi_{ww} \\ 0 \\ 0 \\ 0 \end{bmatrix}, \tag{14}$$

$$M_q = \begin{bmatrix} \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & 0 & \mathbf{0}_{1\times 32} & \mathbf{0}_{1\times 23} \\ 0 & \frac{1}{4} & 0 & \frac{1}{2} & 0 & \frac{3}{4} & 0 & 1 & 0 & \frac{3}{4} & 0 & \frac{1}{2} & 0 & \frac{1}{4} & \mathbf{0}_{1\times 32} & \mathbf{0}_{1\times 23} \\ & & & & & & \mathbf{0}_{1\times 14} & & & & & & & & \mathbf{0}_{1\times 32} & \mathbf{\Upsilon}_{1\times 23} \end{bmatrix}.$$

$\mathbf{\Upsilon}$ holds the temporal constraint (4) from the main paper for the quarterly series, i.e.,

$$\Upsilon = \begin{pmatrix} \frac{1}{12} & \frac{2}{12} & \frac{3}{12} & \frac{4}{12} & \frac{5}{12} & \frac{6}{12} & \frac{7}{12} & \frac{8}{12} & \frac{9}{12} & \frac{10}{12} & \frac{11}{12} & 1 & \dots \\ \frac{11}{12} & \frac{10}{12} & \frac{9}{12} & \frac{8}{12} & \frac{7}{12} & \frac{6}{12} & \frac{5}{12} & \frac{4}{12} & \frac{3}{12} & \frac{2}{12} & \frac{1}{12} \end{pmatrix}.$$

## C.4. Alternative Model Specifications

We compare the model performance of our MF-VAR against various alternative model and data specifications. Unless indicated differently, notation follows the specification in the main document. We first specify an AR(1) model of quarterly consumption growth as:

$$y_\tau^Q = \alpha y_{\tau-1}^Q + \epsilon_\tau. \tag{15}$$

Due to the publication lags, in week 1 of quarter $\tau$ the last available data on consumption is from quarter $\tau - 2$, wherefore we specify a two step ahead forecast in week 1 of quarter $\tau$. Once quarter $\tau - 1$ becomes available in week eight of quarter $\tau$, we run the direct forecast as in Equation (15).

Second, we specify a VAR(1) at the quarterly frequency including the consumption growth rate and the consumption series based on SpendingPulse aggregated to the quarterly frequency:

$$\mathbf{y}_\tau = \alpha \mathbf{y}_{\tau-1} + \epsilon_\tau, \tag{16}$$

where $\mathbf{y}_\tau$ holds the two series on consumption growth and $\alpha$ collects the regression coefficients. The first nowcast in week one of quarter $\tau$ is based on information until quarter $\tau - 2$. In week three, SpendingPulse completes the previous quarter and we can provide a first update of our nowcast. The second update is available in week eight of quarter $\tau$.

Third, we estimate two simple autoregressive distributed lag (ADL) models including the log-differenced quarterly consumption series and a "week-to-quarter" representative SpendingPulse series in log differences, described in the main text. Once, we focus on a model exclusively exploiting the contemporaneous relation between consumption and SpendingPulse,

$$y^Q_{t,\tau} = \alpha y^{SPL}_{t,\tau^*} + \epsilon_\tau \quad t \in (1, \ldots, 12), \tag{17}$$

where $y^{SPL}_{t,\tau^*}$, denotes the log difference of the representative SpendingPulse series for quarter $\tau$ in week $t$. In addition, we modify the model and choose a lag structure according to the Akaike Information Criterion,

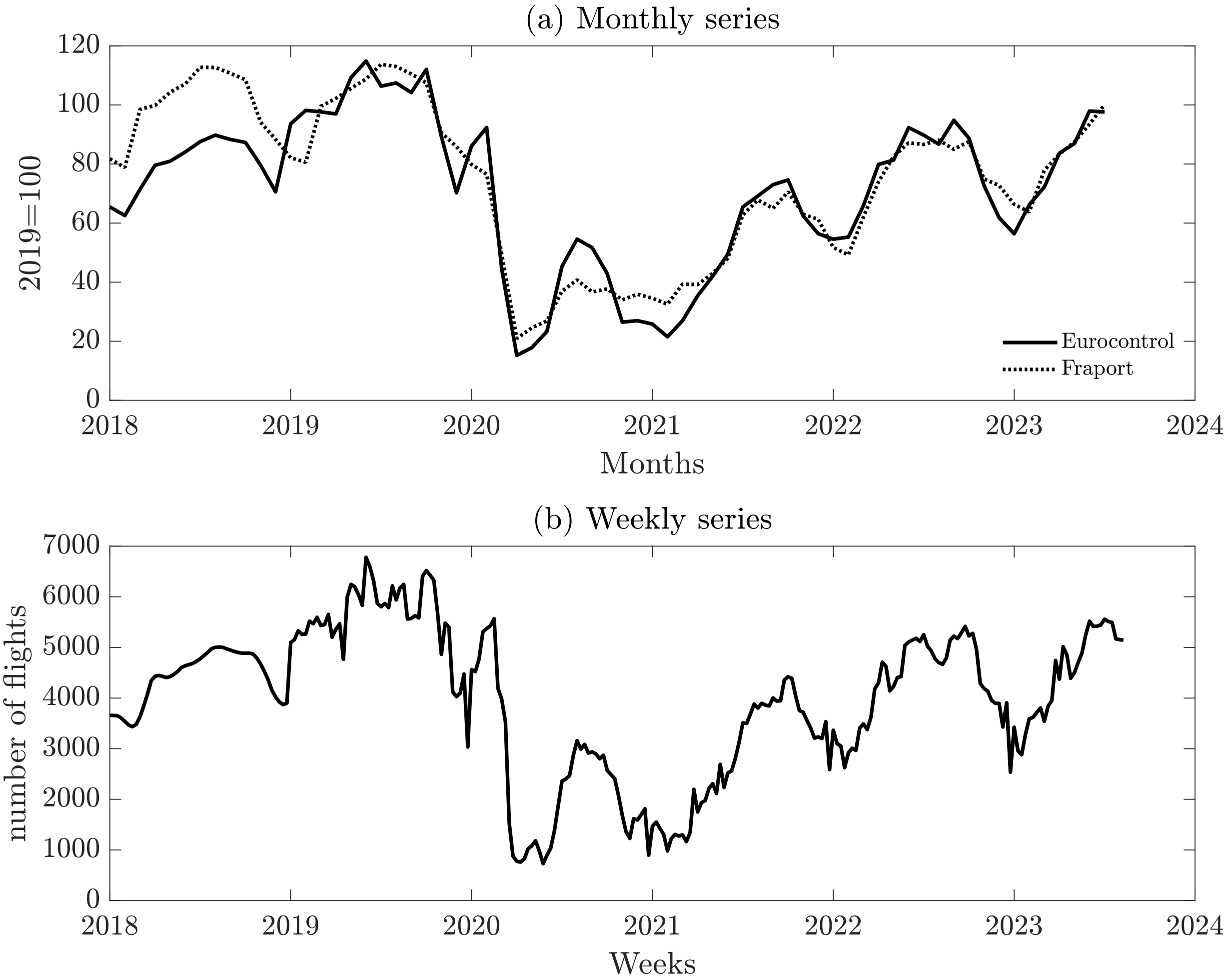
$$y^Q_{t,\tau} = \alpha \sum_{i=0}^{p*} y^{SPL}_{t-i,\tau^*} + \epsilon_\tau \quad t \in (1, \ldots, 12), \tag{18}$$

where $p^*$ is the optimal lag length. Lastly, we estimate model (17) replacing the SpendingPulse series with all alternative indicators introduced before.

# D. A Weekly Flight Turnover Series

Eurocontrol provides a daily time series on flight turnovers in Germany going back to late December 2018. In principle, the model could cope with time series of different length, however, Fraport, the operating company of the Frankfurt (Main) airport, provides a similar series — focusing on flight turnovers in Frankfurt (Main) only — at the monthly frequency dating back to 2016. At the monthly frequency, both series show very similar dynamics with a correlation of about 0.96. We hence use the monthly series to extrapolate the daily series, first aggregated to a weekly frequency according to our weekly schedule introduced in the main text, back to January 2018 using the Kalman filter. Panel (a) in Figure D1 plots the monthly time series from Fraport along with the monthly aggregate of the daily time series, where visual inspection fosters the close co-movement between the two series. Panel (b) in Figure D1 shows the underlying weekly time series, where the dotted line marks the extrapolated time series, aggregated to the monthly frequency. Since no seasonal adjustment is provided from official sources, we use the annual growth rate as in Baumeister *et al.* (2022) to address seasonality.

**Figure D1:** Flight Turnovers




*Notes:* Panel (a) shows the monthly series of flight turnovers from Eurocontrol and Fraport. The underlying daily time series of Eurocontrol is backcasted into 2018 based on the monthly Fraport series using the Kalman filter. Panel (b) plots the weekly flight turnover series based on the Eurocontrol series aggregated in accordance with our weekly time schedule. *Sources:* Eurocontrol, Fraport.

## References

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