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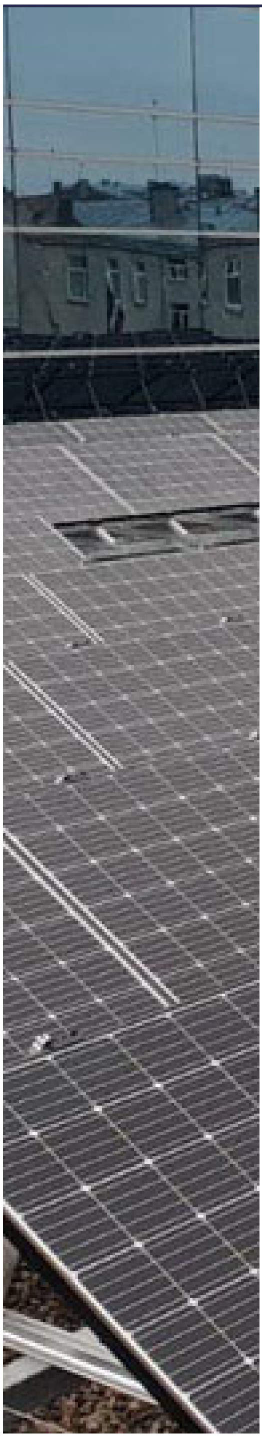

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Consumer Spending in the Covid-19 Pandemic: Evidence from Card Transactions in Latvia

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Abstract

We use a novel card transaction data from the Latvijas Banka to study the consumption response to the Covid-19 pandemic in Latvia throughout three separate waves of the pandemic. We find that card transaction activity fell similarly in all three waves. There is also some suggestive evidence that during the second and third waves of the pandemic, the consumption response was largely caused by the containment measures instead of the behavioural adjustment of consumers. The consumption response varied greatly across different sectors with the Airlines and Entertainment sectors faring the worst. However, the situation was not homogeneous during the three waves of the pandemic, given the changing composition of the containment measures. We show that merchants with a higher share of online transactions in the prepandemic period fared better than others during the second and the third waves of the pandemic. Similarly, we also find evidence that investment in online platforms during the initial phases of the pandemic seems to have resulted in better resilience in the following waves. Finally, we show that the nowcasting model with card transaction data outperforms all benchmark models when it comes to retail nowcasting and yields a notable improvement in forecasting metrics.

Keywords: card transactions, consumer spending, Covid-19, retail trade nowcasting

JEL Codes: E21, E27, C32, C53

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1 Introduction

The Covid-19 pandemic and the related public health interventions have caused a severe disruption to economic activity around the world. In 2020, according to the International Monetary Fund's World Economic Outlook, the world output fell by 3.1% and in the case of euro area - by staggering 6.3% (International Monetary Fund, 2021). Containment measures (CMs) introduced by governments and behavioural adjustment of individuals led to a sharp drop in private consumption, which was the largest contributor to lower levels of economic activity. The speed at which consumers altered their consumption behaviour was unprecedented and the standard economic indicators, which become available with a delay of several weeks or even months, were ill-suited for a timely assessment of the size and the scope of economic damage. This, in turn, made it difficult for economic policy makers to design a targeted fiscal stimulus to households and businesses. Therefore, policymakers and economists alike are looking for high frequency indicators that provide a more timely insight into the state of the economy, particularly in times of crisis.

This study investigates the consumption response to the Covid-19 pandemic in Latvia, using a novel card transaction data from Latvijas Banka. The data set is comprised of daily card transactions for four major commercial banks in Latvia and covers approximately 98% of all domestic card transactions. There are several advantages of using transaction data over more traditional indicators of economic activity when it comes to grasping the size and the scope of consumption response. First, information on card transactions is available with a lag of only a few days compared to weeks and months in the case of more traditional economic indicators. Second, the card transaction data is available at daily and weekly frequencies opposed to monthly or even quarterly frequencies of key economic statistics, e.g. national accounts. This is particularly important in the times of crisis when events unfold quickly. Third, our data provides a detailed information on consumption patterns across different merchant categories and different methods of payment (online vs. in-store).

We use this novel data set to uncover the magnitude of the consumption response to the Covid-19 pandemic in Latvia. Our data set encompasses approximately 21 months of the Covid-19 pandemic and covers three separate outbreaks of the virus and the related waves of the CMs. Previous studies have mostly focused only on the first few months of the pandemic (see, for example, Andersen et al. 2020, Sheridan et al. 2020, Chen et al. 2021). We contribute to the literature by covering also the second outbreak (which started in the 4th quarter of 2020 and lasted until the end of the 1st quarter of 2021) as well as the third outbreak of the pandemic (the

4th quarter of 2021). Next, we explore the heterogeneity of the consumption response across different merchant categories. The data set includes detailed information on 286 merchant category codes (MCC).[1] Moreover, we can distinguish between online transactions and offline (in-store) transactions. Therefore, we also investigate whether online platforms helped merchants to mitigate the drop in offline transaction activity. Finally, we explore whether card transaction data improve the forecast accuracy of standard nowcasting models.

Our main findings are as follows. First, the card transaction activity fell noticeably during the three waves of the pandemic. Moreover, there is some indicative evidence that during the second and the third waves of the pandemic, the consumption response was largely caused by the CMs instead of voluntary behavioural adjustment of consumers. Second, the consumption response to the Covid-19 pandemic varied greatly across different sectors. However, the situation was not homogeneous in all three waves of the pandemic, given the changing composition of the CMs. Third, we find that merchants with a higher share of online transactions in the prepandemic period fared better than others during the second and the third waves of the pandemic. Similarly, we also find evidence that investment in online platforms during the initial phases of the pandemic seems to have resulted in better resilience in the future waves. Finally, we verify the usefulness of card transaction data for nowcasting retail trade turnover in Latvia. In doing so, we capitalise on the fact that the card transaction data becomes available to us about two to three weeks before the official release of the retail trade statistics. Given these differences in release timings, we demonstrate that the model augmented with card transaction data outperforms all benchmark models in out-of-sample nowcasting competition and yields a notable reduction in forecasting metrics.

The remainder of the study is structured as follows. Section 2 reviews the related literature. Section 3 provides a brief overview of the Covid-19 pandemic and the related CMs and introduces our data set. Section 4 and Section 5 discuss the main findings of the study. Section 6 concludes.

2 Literature Review

Our study relates to a strand of literature investigating the economic consequences of the Covid-19 pandemic. Previous studies have shown that the Covid-19 shock severely affected labour markets (Baek et al. 2021, Coibion et al. 2020b), stock exchange (Cox et al. 2020, Xu 2021),

[1] 262 after grouping together individual companies into broader Airlines (MCCs 3000–3299), Car rentals (MCCs 3300–3499) and Lodging (MCCs 3500–3999) categories.

individual mobility (Anke et al. 2021) and economic activity in general (Maloney and Taskin 2020). The Covid-19 crisis has also considerably altered private consumption through at least two channels (Horvath et al. 2021). First, it has changed consumer behaviour due to concerns about the health risks of visiting restaurants, shops and other public spaces. Second, the CMs introduced to limit the spread of Covid-19, such as the closure of non-essential businesses, have directly removed some consumption possibilities. Therefore, several studies have tried to grasp the size and the scope of the consumption response to the Covid-19 pandemic. For example, Coibion et al. (2020a) use several waves of a customized household survey to measure consumer spending in the US before and after the initial shock of the Covid-19 crisis. They find that overall spending droped by nearly a third between January and April 2020. Similarly, Hodbod et al. (2021) use household survey data to document the drivers of the consumption changes during the first wave of the Covid-19 pandemic in France, Germany, Italy, the Netherlands, and Spain. They find that a large proportion of households report to consume less than before, particularly when it comes to spending on tourism, hospitality and public transport. Furthermore, countries that were harder hit by the pandemic were generally those that also saw a bigger drop in the reported consumption.

More specifically, our study contributes to rapidly growing literature which uses novel financial data to gauge the economic impact of the Covid-19 pandemic.[2] Baker et al. (2020) use transaction-level data from a non-profit Fintech in the US which obtains information from individuals' bank accounts and aids them in personal financial decision-making. They find that consumer spending increased in late February and in early March 2020, but fell sharply afterwards. Similarly, Chronopoulos et al. (2020) collect data from a popular personal finance application in the UK and find that consumer spending declined markedly in late February 2020, when a government-imposed lockdown became imminent, and continued to decline throughout the lockdown.

Other studies have relied on card transaction data from individual banks. Andersen et al. (2020) use customer transaction data from the largest bank in Denmark (Danske Bank) to estimate how aggregate spending changed in early phases of the Covid-19 pandemic. They find that consumer spending dropped by approximately 27% once the CMs were imposed. In a related study, Sheridan et al. (2020) use transaction data from Danske Bank to compare the consumption response in Denmark and Sweden. Both countries were similarly exposed to the Covid-19

[2] The use of non-traditional data is not limited to the consumption response only. For example, some studies have relied on smartphone location data to identify the determinants of social distancing during the 2020 Covid-19 outbreak (Maloney and Taskin 2020), while others explore how political partisanship affects risk perceptions related to Covid-19 (Barrios and Hochberg 2020).

pandemic, but the CMs in Denmark were much more stringent than in Sweden. Nevertheless, they find that both countries experienced a rather similar drop in consumer spending (25% and 29%, respectively) and conclude that most of the economic disruption is caused by the pandemic itself. Chen et al. (2021) use an offline transaction data from the largest payment service provider in China and show that consumer spending fell by 32% in early 2020. The drop was more than double the size in the epicentre of the pandemic, Wuhan. Bounie et al. (2020) use transaction data from the French consortium of card providers and show that in France card transaction expenditures declined by about 50% during the spring 2020 and then strongly recovered in the summer, before faltering again in late September.

One of the advantages of our data set is its broad coverage. It is comprised of daily card transactions made in four major commercial banks in Latvia and covers approximately 98% of all domestic card transactions. There are few studies which, similarly to this paper, use central bank data sets covering transactions of more than one bank. Kantur and Özcan (2021) use weekly card transaction data, which the Central Bank of the Republic of Turkey collects from all the banks operating in Turkey. Their findings show that the card spending in Turkey declined noticeably in the early stages of the pandemic. Horvath et al. (2021) use monthly account-level data on consumer credit cards from the Federal Reserve Board's FR Y-14M reports to study the impact of the Covid-19 pandemic on the use of consumer credit in the US. They find a sharp drop in the consumer credit use in the initial stages of the pandemic. Credit card spending fell by 50% year-on-year in March to April 2020 but then gradually recovered. They also provide evidence that the drop in credit card use, at least initially, was largely caused by the fear of the virus and not necessarily by the CMs. Camara et al. (2020) use very detailed information on credit card payments from Cartes Bancaires in France. The information on timing and location of the transaction, the nature of the merchant, and the type of purchase (i.e. online or offline) allowed them to contrast consumption patterns along the geographical and technological (online/offline) dimensions. Similarly to Camara et al. (2020), we examine substitution between offline and online payments using the difference-in-difference approach.

Previous studies have also shown that the Covid-19 shock has had a heterogeneous impact on consumer spending across different types of goods and services. Generally, studies find that the spending on non-discretionary goods and services, such as groceries, medical expenses and utilities, remained unaffected or even increased during the Covid-19 pandemic, whereas spending on air travel, restaurants, etc. declined dramatically (Andersen et al. 2020, Baker et al. 2020, Chen et al. 2021, Chronopoulos et al. 2020, Coibion et al. 2020a, Kantur and Özcan

2021). These conclusions, however, are mostly drawn from the first few months of the Covid-19 pandemic. We contribute to this literature by providing evidence on how consumer spending across different merchant groups has varied over 21 months since the outbreak of the Covid-19 pandemic, covering three separate waves of the infection and CMs.

Finally, previous studies have used card transaction data to forecast traditional economic indicators. the indicators maintained and published by national statistical agencies, such as national accounts or retail trade indices, are usually made available with a considerable lag, so access to high frequency data provides an opportunity to assess the current state of the economy in a timelier manner, especially during the times of crisis. Naturally, many studies have found that card transaction data contains useful information when forecasting different economic variables (Duarte et al. 2017, García et al. 2021). However, only a few studies focus on forecasting economic indicators during the Covid-19 crisis. One such example is Chapman and Desai (2021) who show that models containing Canadian retail transaction data provide major gains in forecasting accuracy of several macroeconomic variables, such as GDP, inflation and unemployment. We contribute to the literature by considering a different variable of interest, namely retail trade turnover, and by performing the forecasting exercise over the full span of Covid-19 which includes the onset as well as the consecutive waves and recovery phases of the pandemic.

3 Background and Data Description

3.1 A Brief Overview of Covid-19 and the CMs in Latvia: 2020-2021

The Covid-19 pandemic struck Latvia a couple of weeks later than most other European countries. The first Covid-19 case in Latvia was confirmed on 2 March 2020 triggering a swift policy response. On 12 March a state of emergency was declared for a month (until 14 April) and numerous containment and closure policies were introduced (see Figure 1). Public events were cancelled or postponed, recreational activities, including culture, sports and nightclubs were largely prohibited. Most of in-person classes and lectures in educational establishments were cancelled and transferred to an online environment. In the upcoming weeks, the restrictions were further strengthened. By the end of March 2020, a ban on international travel was imposed, all private gatherings of more than one household were prohibited, and additional restrictions were imposed on shopping centres. The state of emergency was extended twice. First, in early April it was prolonged until 12 May, with containment and closure measures remaining broadly unchanged. In May the state of emergency was further extended until 9 June, however, restrictions on public and private events were eased and the ban on international travel was lifted.

The swift policy response in the first wave of the Covid-19 pandemic was possibly one of the reasons why Latvia was relatively more successful in containing the spread of Covid-19 than most other European countries. On 9 June the total number of Covid-19 cases stood at 1089 and overall 26 people had died from the virus (approximately 0.06% and 0.001% of the population). Furthermore, there was little evidence that new infections would increase notably after the restrictions were lifted. The daily average of new Covid-19 infections in June stood at 1.7.

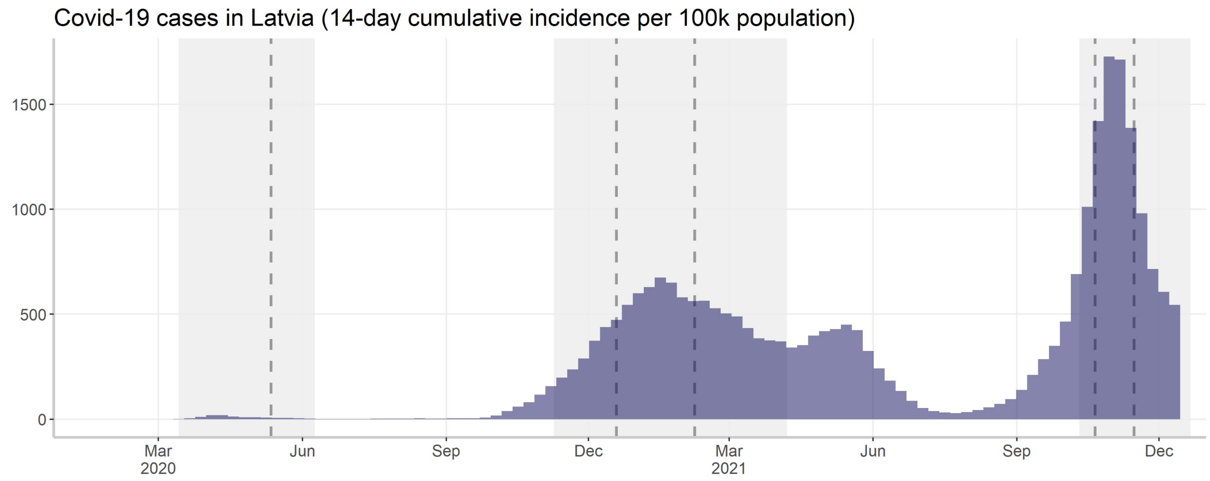

Figure 1: The evolution of the Covid-19 pandemic in Latvia

Notes: Gray areas represent the periods when the state of emergency was in place. Vertical dashed lines indicate important dates in which CMs were significantly altered within the state of emergency period (left to right): 12 May 2020 (the state of emergency was prolonged until 9 June, but restrictions were eased); 19 December 2020 (only essential stores could operate in-person; curfew was imposed on weekends and holidays); 7 February 2021 (the state of emergency was prolonged until 6 April, but curfew was lifted and restrictions were eased); 21 October 2021 (all non-essential shops had to be closed; curfew was imposed from 8pm until 5am.); 16 November 2021 (most of the CMs were eased for the vaccinated individuals).
Source: Latvia's open data portal: https://data.gov.lv/eng

The successful containment of the virus, however, came at a price. Economic activity shrunk markedly. In Q2 2020 real GDP fell by 7.3% compared to Q1 (-8.4% year-on-year). Due to the imposed restrictions and general precaution, the largest contribution to the decline in economic activity came from private consumption which fell by 20.4% (-19.6% year-on-year).

The second wave of infections came in late September and early October 2020. Despite the rapid increase in new infections, CMs were introduced in a more gradual manner than in the spring. First, restrictions were imposed in certain municipalities with high infection rates, but given that the number of municipalities conforming with this criterion grew rapidly, by the end of October restrictions on public and private events were imposed at national level. On 9 November

2020 a state of emergency was declared until 6 December. As in spring, public (and later also private) events had to be cancelled, recreational activities, including culture and sports, were again largely prohibited, restaurants were limited to take-away services, and only essential stores were allowed to be open within shopping malls. The restrictions on education were somewhat milder than in spring, since kindergartens and primary schools could operate in-person, however, with social distancing measures in place. In early December the state of emergency was further prolonged until 11 January 2021, and additional restrictions were imposed. Importantly, all non-essential stores had to be closed on weekends. Nevertheless, the epidemiological situation kept getting worse. Therefore, in the last weeks of December the state of emergency was once again extended (until 7 February) and restrictions were further tightened. Only essential stores could operate in-person, school holidays were extended and a curfew from 10pm until 8am was imposed on weekends and holidays. In February 2021 the state of emergency was prolonged until 6 April, but curfew was lifted and restrictions were gradually eased. The number of new Covid-19 infections remained at elevated levels throughout the spring 2021.

In May most of the remaining restrictions were lifted for fully vaccinated individuals or those who had recently recovered from Covid-19. Despite the fact that vaccines were already freely available to every adult in May, the vaccination rates were among the lowest in the European Union. In early September 2021, when daily infections started to increase, only 40% of the population were fully vaccinated, compared to 61% in Germany and 64% in the UK.

As a result, in early autumn 2021 Latvia was among the few countries experiencing a rapid increase in the number of new infections and Covid-19 related deaths. In early October the cumulative incidence of Covid-19 cases was nearly three times higher than at the peak of the second wave. On 11 October a state of emergency was announced for the third time. Initially, the restrictions primarily concerned the unvaccinated part of the population. However, with the number of new cases growing rapidly, stringent CMs applicable to everybody irrespective of their vaccination status were introduced on 21 October. For four weeks (until 15 November) all non-essential shops had to be closed, public and private events were cancelled, recreational activities were prohibited and curfew was imposed from 8pm until 5am. From 16 November most of the restrictions were lifted for fully vaccinated individuals and those who had recovered from Covid-19 within last 180 days.

3.2 Data Sample

For the empirical part of this study, we use a novel card transaction data from Latvijas Banka. Each week commercial banks with a transaction market share of at least 5% submit daily card (credit and debit) transaction data covering the previous week. Our sample contains information on four major commercial banks and covers approximately 98% of all domestic card transactions in Latvia. For the purpose of this study, we limit the data sample to the transactions made within Latvia and exclude ATM withdrawals. Nevertheless, the coverage of our sample is noteworthy, capturing a noticeable proportion of all consumer spending. In 2020, the total card transaction volume in our data sample accounted for roughly 28% of Latvia's private consumption expenditure.

Since a portion of payments made over the weekend or holidays appears in the statistics on the following working day, we aggregate data into weekly frequency. Our data covers 105 weeks over the period from January 2020 to December 2021. The data sample therefore includes three waves of the pandemic: the first wave (12 March 2020 – 6 June 2020), the second wave (9 November 2020 – 6 April 2021) and the third wave (21 October 2021 until the end of the sample period).[3] The weekly transaction amounts range from 70M to 125M EUR.

Our data set contains information on card transactions for 17 broad and 262 narrow MCC categories.[4] For example, broad MCC category Clothing stores (MCCs 5600-5699) can be broken down into 12 unique narrow categories. Moreover, we distinguish between online transactions and offline (in-store) transactions (Table 1 presents summary statistics for the broad categories).

4 Results

4.1 Card Transactions During the Covid-19 Pandemic

Figure 2 shows the aggregate weekly card spending in Latvia. Over January and February 2020 the weekly card transaction amounts fluctuated between 80M–88M EUR. There was a sharp increase in transaction volumes in early March, just before the government declared a state of emergency as a response to the pandemic and introduced CMs to reduce the spread of the virus. The initial increase was followed by a swift drop afterwards. The weekly card spending fell to approximately 70M EUR by the end of March (15% lower than in the period from 1 January to

[3] The end date of the the third wave of pandemic is assumed to be 28 February 2022, which at the time of writing, was the envisaged end date of the state of emergency.

[4] We do not consider narrow categories in the case of Airlines (MCCs 3000–3299), Car Rentals (MCCs 3300–3499) and Lodging (MCCs 3500–3999) because they identify individual companies.

Table 1: Descriptive statistics of weekly card transactions by broad MCC categories

MCC group		Sum of card payments in a week Mean	St.Dev.	Mean transaction amount	Number of payments	Share of online payments (amount)
		EUR	EUR	EUR	count	%
0700-0999	Agricultural services	225,130	50,765	18	10,541	0.29
1500-2999	Sub-contractor services	58,624	19,041	89	683	7.34
3000-3299	Airlines	410,718	360,939	135	3,055	98.53
3300-3499	Car rentals	48,119	19,863	128	991	15.52
3500-3999	Lodging	315,802	167,617	64	7,095	2.84
4000-4799	Transportation services	3,720,091	740,614	34	159,330	34.08
4800-4999	Utility services	886,392	213,065	39	19,998	27.00
5000-5499	Supermarkets and department stores	45,821,939	7,049,812	36	3,590,561	1.09
5500-5599	Vehicles and fuel	9,338,556	2,113,395	79	515,070	1.41
5600-5699	Clothing stores	4,065,313	1,886,233	41	110,807	23.99
5700-5999	Miscellaneous stores	19,495,399	4,354,518	38	1,270,723	4.35
6000-7299	Financial services	781,724	202,875	45	24,711	19.95
7300-7529	Business services	405,872	100,990	26	73,311	53.26
7530-7799	Repair services	649,921	152,242	54	13,929	0.43
7800-7999	Entertainment	1,607,178	721,463	19	70,582	61.35
8000-8999	Professional services	3,150,636	835,732	50	72,272	3.94
9200-9402	Government services	1,040,429	268,376	44	30,529	3.84

Note: A negative value for weekly transactions is possible when refunds exceed outgoing transactions.

11 March) and remained at depressed levels for several weeks. In mid-May, despite the state of emergency being still in force, restrictions were somewhat eased, and card transaction activity also recovered. It continued to increase during the summer and early autumn 2020 against the background of low infection figures and relatively loose restrictions.

Transaction activity did not fall noticeably when the state of emergency was announced for the second time in early November 2020. Although public and private events were largely prohibited, and only the essential stores were allowed to be open within shopping malls, weekly card spending was close to the levels observed in October. Card spending did not fall even after all non-essential stores had to be closed on weekends starting from early December. In fact, with the epidemiological situation getting worse and tougher restrictions becoming inevitable, spending amounts increased sharply in the week before Christmas. The increase was followed by a large drop afterwards. Starting from 19 December CMs were strengthened and only the essential stores could operate in-person. As a result, weekly card spending fell to 70M–75M EUR and remained practically unchanged until February 2021 when restrictions were gradually lifted.

Weekly card spending recovered gradually in the spring 2021 before peaking at 115M–125M EUR in June and July, when the majority of the remaining restrictions were abandoned. It then leveled off in August and decreased somewhat in September against the background of rapidly increasing infection rates. Nevertheless, the transaction amounts remained at relatively high levels (approximately at 110M EUR) even after a state of emergency was announced for the

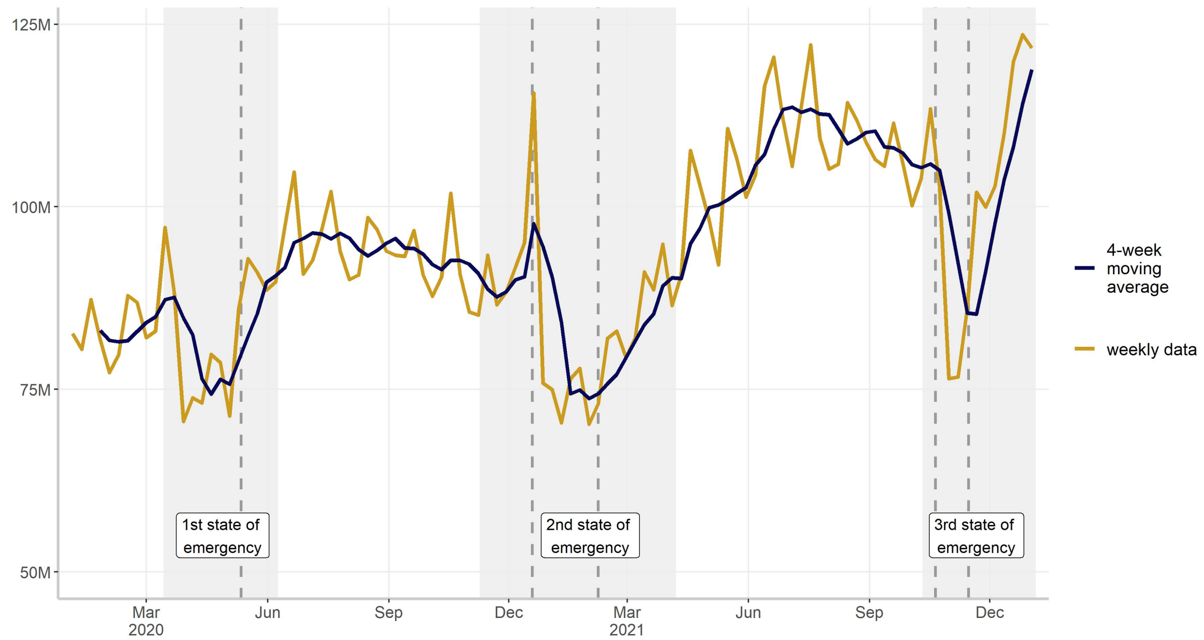

Figure 2: Weekly payment card transactions (M EUR)

Note: Gray areas represent the periods when the state of emergency was in place. Vertical dashed lines indicate important dates in which CMs were significantly altered within the state of emergency period (left to right): 12 May 2020 (the state of emergency was prolonged until 9 June, but restrictions were eased); 19 December 2020 (only essential stores could operate in-person; curfew was imposed on weekends and holidays); 7 February 2021 (the state of emergency was prolonged until 6 April, but curfew was lifted and restrictions were eased); 21 October 2021 (all non-essential shops had to be closed; curfew was imposed from 8pm until 5am.); 16 November 2021 (most of the CMs were eased for the vaccinated individuals).

third time on 11 October, and CMs were again imposed (although they mostly applied to the unvaccinated individuals). The situation changed dramatically on 21 October when CMs were further tightened and extended to everybody irrespective of their vaccination status. Weekly card spending dropped to 75M EUR and remained at depressed levels until the restrictions were eased in mid-November.

Overall, our data provides some indicative evidence that during the second and the third waves of the pandemic, the consumption response was largely caused by the CMs instead of voluntary behavioural adjustment of consumers. In both waves, consumer card spending did not react noticeably to the worsening epidemiological situation and the introduction of a state of emergency, and fell only after stringent CMs were imposed.

There is a considerable heterogeneity in card transaction dynamics across merchant categories (Figure 3). While the initial drop in transaction volumes during the first state of emergency is evident in nearly all categories, Airlines (MCCs 3000–3299) and Entertainment (MCCs 7800–7999) were hit the hardest. The weekly card transaction volumes in both categories fell practically to zero. In fact, in the case of Airlines, the transaction volumes even became negative, because the refunds for unused tickets exceeded the new purchases. Noteworthy, a decrease in

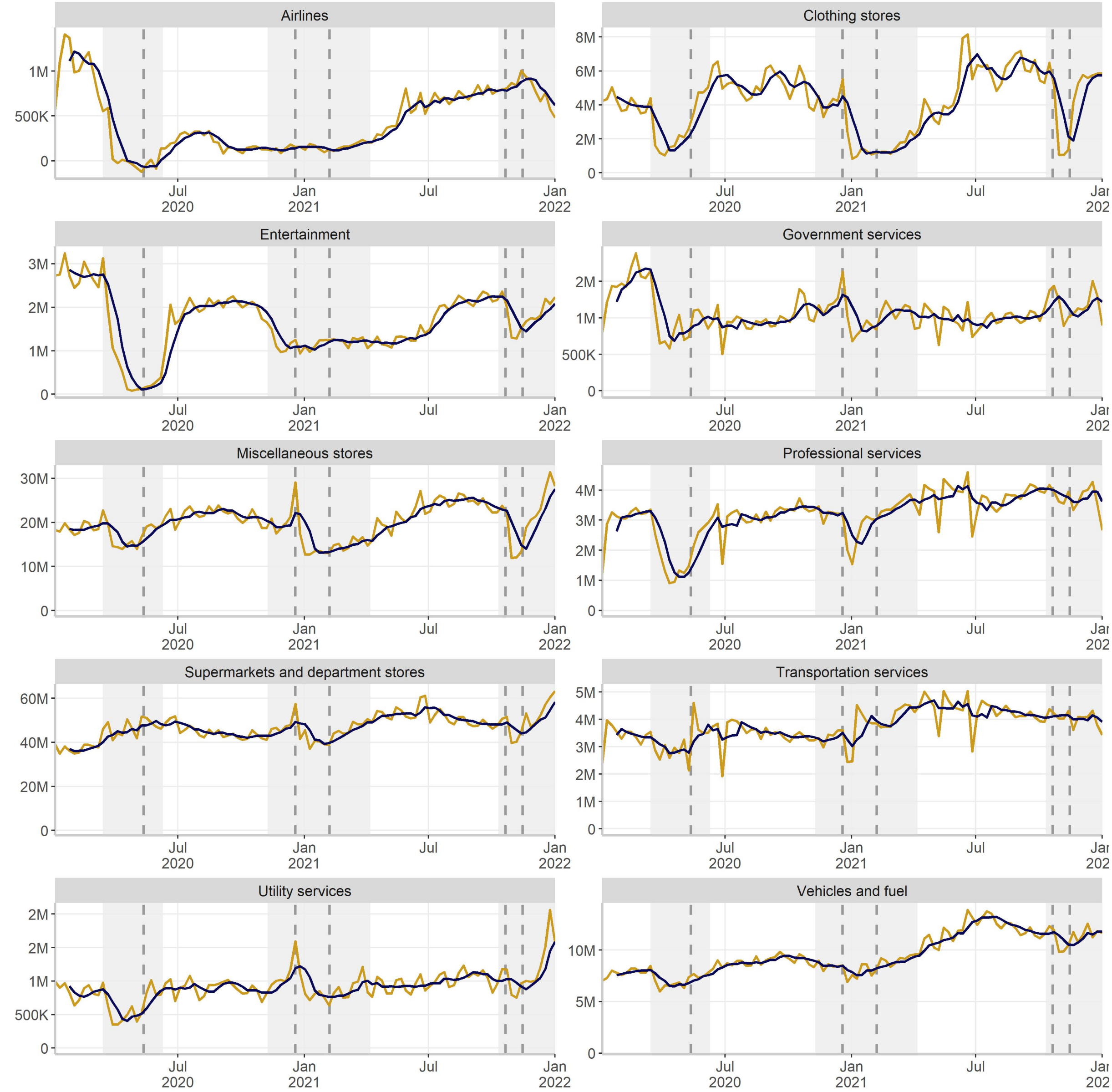

Figure 3: Weekly payment card transactions in selected merchant categories (EUR)

Note: Only MCC groups with maximum weekly card transaction volumes larger than 1M EUR are depicted. Gray areas represent the periods when the state of emergency was in place. Vertical dashed lines indicate important dates in which CMs were significantly altered within the state of emergency period (left to right): 12 May 2020 (the state of emergency was prolonged until 9 June, but restrictions were eased); 19 December 2020 (only essential stores could operate in-person; curfew was imposed on weekends and holidays); 7 February 2021 (the state of emergency was prolonged until 6 April, but curfew was lifted and restrictions were eased); 21 October 2021 (all non-essential shops had to be closed; curfew was imposed from 8pm until 5am.); 16 November 2021 (most of the CMs were eased for the vaccinated individuals).

card spending was also evident in Clothing stores (–75% lower than in the period from 1 January to 11 March) and Miscellaneous stores (–25%), both of which suffered due to the restrictions imposed on shopping centres as well as in Professional services (–70%) and Government services (–60%). In turn, card spending actually increased in the case of Supermarkets and department stores which were allowed to operate without major restrictions. Overall, this is consistent with the findings of previous studies which show that the initial impact of the Covid-19 pandemic varied greatly across different sectors (Andersen et al. 2020, Baker et al. 2020, Chen et al. 2021, Chronopoulos et al. 2020, Coibion et al. 2020a, Kantur and Özcan 2021).

Also, the recovery paths during the summer months of 2021 and the response to the second wave of the pandemic (and the ensuing state of emergency) differed considerably across merchant categories. Card spending on Airlines remained at depressed levels (20% of the prepandemic level) until the summer 2021 when vaccines became freely available and the European Union Digital Certificate was introduced to facilitate international travel. Similarly, spending on Entertainment also recovered only partially during the summer 2021 and fell again to approximately 30% of the prepandemic level during the second wave. In turn, card spending on other categories, such as Clothing stores, Miscellaneous stores and Professional services, rapidly recovered to the prepandemic level after the CMs were eased in May and June 2020. However, once strict restrictions were again imposed in December 2020, it sharply fell to the levels seen in the spring 2020. The fact that card spending on these categories did not fall noticeably during the autumn 2020, when CMs were relatively modest and the number of new infections grew rapidly, suggests that at least during the second wave of the pandemic the economic disruption was caused by the CMs rather than behavioural adjustment of consumers.

The CMs were gradually eased starting from February 2021, and the card spending slowly recovered in nearly all categories. In the summer 2021 only spending on Airlines and Entertainment were below the prepandemic level. For most other categories, the card spending reached the highest values in the sample period. The transaction volumes remained at elevated even after the third state of emergency was announced in early October 2021 when the number of new Covid-19 infections skyrocketed. The situation, however, changed dramatically after 21 October, when strict CMs were once again imposed and, as a result, card spending for most of the categories returned to the levels seen during the first and the second waves of the pandemic. A noticeable exception is spending on Airlines, which actually increased during this period.

To summarize, our data suggest that indeed the consumption response to the Covid-19 pandemic varied greatly across different sectors. However, the situation was not homogeneous in all three waves of the pandemic, given the changing composition of the CMs.

Overall, card transaction data seem to be a valuable source of information when it comes to gauging the economic activity across different sectors. Furthermore, it becomes available several weeks before comparable more traditional economic indicators, such as retail trade turnover , are released (for more granular data the time difference is even larger). This is particularly important in the times of crisis when the availability of representative and timely data is crucial for tailoring a well-targeted policy response.

4.2 Online vs. offline payments

Our data set contains an indicator of payment method, i.e. whether a card transaction took place offline (in-store) or online. Figure 4 displays the total card spending over the pandemic for both types of transaction methods. In the prepandemic period of 2020, the weekly value of online payments with domestically issued cards was slightly below 5M EUR, or approximately 5% of total payments (see the left panel of Figure A1 in Appendix).

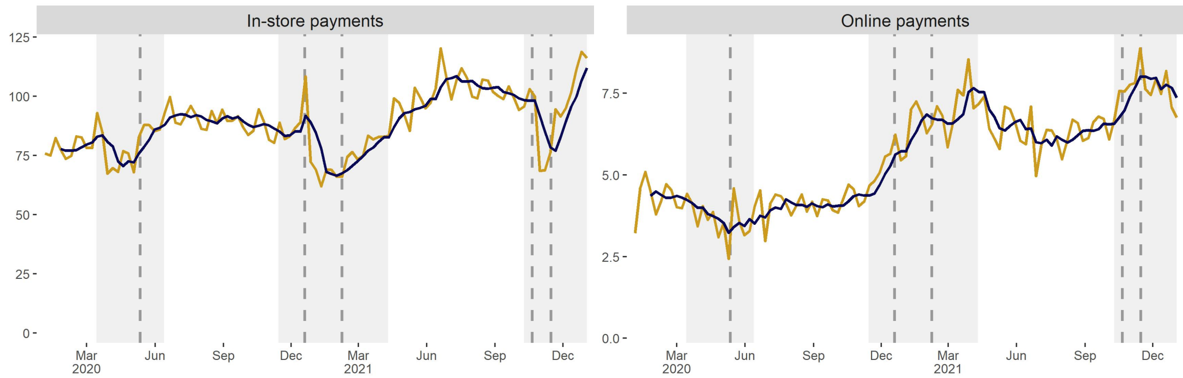

Figure 4: In-store and online weekly payment card transactions (M EUR)

Notes: The yellow line represents weekly payment card transactions and the black line shows a 4-week moving average. Gray areas represent the periods when the state of emergency was in place. Vertical dashed lines indicate important dates in which CMs were significantly altered within the state of emergency period.

During the first wave of the Covid-19 pandemic, a fall in card transaction activity was observed in both online and offline payments. The decline in online payments was attributed to the sharp drop in spending on Entertainment and Airlines (see the right panel of Figure A1 in Appendix) both of which are heavily reliant on online transactions. Despite the drop in aggregate figures, the online transaction (volume) share increased during the first wave of the pandemic for nearly all MCC groups (see Figure 5). The substitution towards online payments was made possible by the adjustment on both the supply (technical availability of online platforms) and the demand (change in consumer behaviour) sides. In fact, for most MCC groups, the share of online transactions remained above the prepandemic levels even during the recovery phase in the summer 2020, when most of the CMs were abandoned.

The online transaction share increased even more during the the second wave of the pandemic. At its peak, online transactions accounted for nearly 10% of all card spending, nearly twice as much as before the pandemic (see Figure A1). Figure A2 shows that category-wise the largest increase in the online payment share was observed in the case of Clothing stores, with online

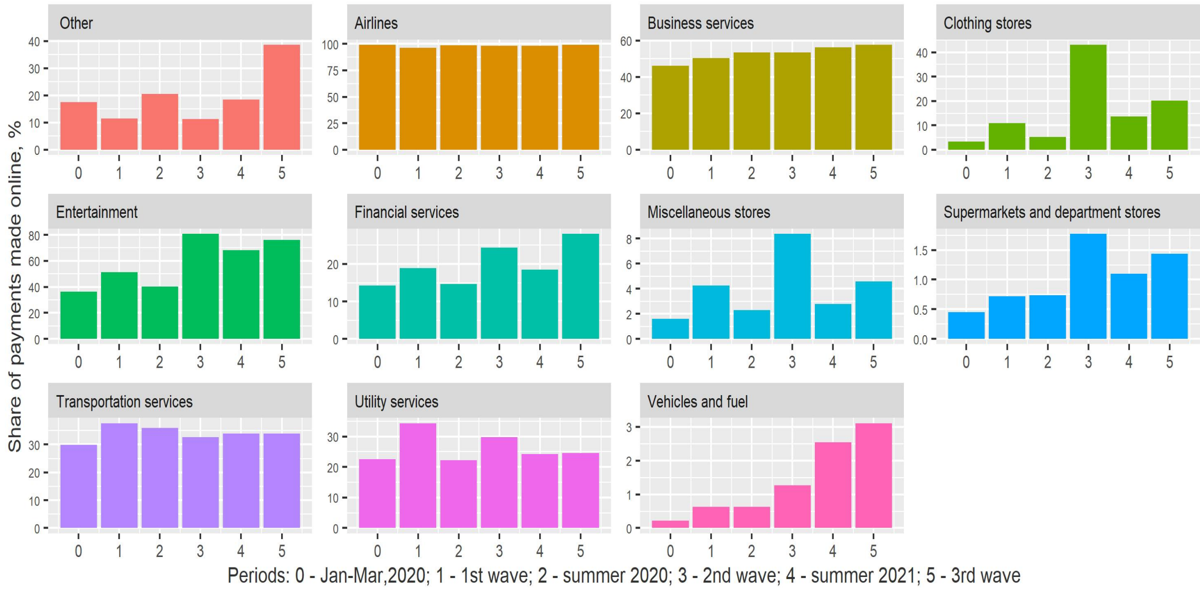

Figure 5: Share of online payments by broad MCC categories and time periods (%)

Notes: Only MCC groups with the largest volume of online payments are depicted. Six periods correspond to: 0 – the prepandemic period (between 01-01-2020 and 12-03-2020), 1 – the first wave (between 13-03-2020 and 09-06-2020), 2 – the first recovery period (between 10-06-2020 and 09-11-2020), 3 – the second wave (between 10-11-2020 - 06-04-2021), 4 – the second recovery (between 07-04-2021 and 10-10-2021), 5 – the third wave (from 11-10-2021 to the end of the observation period).

transactions accounting for up to 75% of all card spending (as compared to maximum of 25% during the first wave and 4% in the prepandemic period). Another three noteworthy groups, which saw a sharp increase in the online spending activity during the second wave of the Covid-19 pandemic, are Miscellaneous stores (on average from 4% to 8%) and Supermarkets and department stores (from 0.75% to 2.0%).

In the recovery phase between the second and the third waves, the total amount of online payments declined slightly, but did not return to the prepandemic level, nor, in fact, to the level observed in the summer 2020. Such dynamics could partially be explained by the gradual recovery of Airlines services, and partially by structural changes in transaction behaviour. Category-level data reveal that during the second recovery phase in mid-2021, the share of online transactions in most of the MCC groups was on average above the levels seen in the first recovery period (summer 2020) (see Figure 5).

During the lockdown phase of the third wave (between 21 October and 16 November, when all non-essential shops had to be closed and curfew was imposed from 8pm until 5am), the share of online transactions once again increased to 10% (see Figure A1). However, once most of the CMs were eased for the vaccinated individuals, the online payment share in total card payments returned to the level seen during the second recovery period.

At merchant category level, the increase in online transaction share during the lockdown phase of the third wave was rather similar to that of the second wave (see Figure A2). The only exception is Miscellaneous stores where online transaction share was somewhat lower in the third wave. After 15 November 2021 (when CMs were eased for the vaccinated individuals), the online transaction share declined for most of the merchant categories.

Figure A3 provides details on dynamics in total amount of in-store and online payments in Clothing stores, Supermarkets as well as in Eating places/restaurants. It is important to note that the increase in the online transaction activity was not always forced by the CMs (which was the case for the Clothing stores and Restaurants, where online transactions, at least partly, acted as a substitute for the in-store spending). In some cases, for example, the Supermarkets, the switch to higher online transaction activity seems to have occurred voluntarily, since these stores largely remained open throughout all waves of the Covid-19 pandemic.

4.3 Estimating the Impact of Online Transactions on Total Transaction Activity

Did higher online transaction activity offset lower offline transaction volumes? To answer this question, we exploit the cross-category heterogeneity and investigate whether the drop in total card spending during the second and third waves of the pandemic was related to the online transaction share in the prepandemic period and the first wave of the pandemic. Respectively, we want to see (a) whether merchants with higher capacity to service online trade (approximated by the share of online transactions in the prepandemic period) fared differently over three consecutive waves of the pandemic; and (b) whether those merchants which invested into online platforms in the first wave of the pandemic (proxied by growth in share of online payments relative to the prepandemic period) coped differently in the following waves.

Simple linear regressions with broad MCC group fixed-effects are employed to address these questions:

$$\Delta Y_i^{1st-prepandemic} = \beta_0 + \beta_1 X_i^{prepandemic} + \kappa_i + \epsilon_i \tag{1}$$

$$\Delta Y_i^{2nd-1st} = \beta_0 + \beta_1 X_i^{prepandemic} + \beta_2 \Delta X_i^{1st-prepandemic} + \kappa_i + \epsilon_i \tag{2}$$

$$\Delta Y_i^{2nd-1st} = \beta_0 + \beta_1 X_i^{prepandemic} + \beta_3 \Delta X_i^{Summer20-prepandemic} + \kappa_i + \epsilon_i, \tag{3}$$

where i is a narrow MCC group, ΔY is a percentage change in total card transaction volume (online and in-store), ΔX is a percentage point change in share of online transactions in total transactions, $X^{prepandemic}$ is a share of online transactions before the Covid-19 pandemic (January–March 2020), and κ is a fixed-effect for broad MCC groups which accounts for sector specific CMs. To account for two slightly different versions of a period during which a change in the share of online transactions is observed, we use (a) a percentage point change in the share of online transactions between the first wave of the pandemic and the prepandemic period, and (b) a percentage point change in the share of online transactions between the first recovery phase in the summer 2020 and the prepandemic period.[5]

Table 2: Regression results for different waves of the Covid-19 crisis

Model (1) *Dependent variable:*	*Change in total payments between the 1st wave and the prepandemic months, %*		
Share of online trade during the prepandemic months, %	0.178 (0.193)		
Number of observations	247		
Adjusted R^2	0.092		
Model (2),(3),(4) *Dependent variable:*	*Change in total payments between the 2nd and 1st waves, %*		
Share of online trade during the prepandemic months, %	0.799*** (0.228)	0.861*** (0.222)	0.862*** (0.229)
Change in the share of online trade between the 1st wave and the prepandemic months, pp		2.187*** (0.568)	
Change in the share of online trade between summer 2020 and the prepandemic months, pp			1.470** (0.709)
Number of observations	246	246	245
Adjusted R^2	0.050	0.105	0.061
Model (5),(6),(7) *Dependent variable:*	*Change in total payments between the 3rd and 2nd waves, %*		
Share of online trade during the prepandemic months, %	0.888*** (0.247)	0.948*** (0.250)	0.980*** (0.253)
Change in the share of online trade between the 2nd and 1st waves, pp		-0.396 (0.496)	
Change in the share of online trade between summer 2021 and summer 2020, pp			0.338 (0.558)
Number of observations	246	244	245
Adjusted R^2	0.171	0.175	0.174

Notes: Regressions include dummies for broad MCC groups. The third wave used in regressions is defined as period from 21 October 2021 to 15 November 2021. The extension of the third period to the end of the first week of 2022 does not significantly change the coefficients.

*p<0.1; **p<0.05; ***p<0.01; standard errors in parentheses.

[5]Both are likely to indicate adaptation of merchants and consumers to new methods of commerce. The former should capture the adaptation in times of crisis, whereas the latter would be the part applicable also in "normal times".

Results of regressions are presented in Table 2. The immediate response of transaction volumes during the first wave of the pandemic (see Model(1) in Table 2) shows that volumes declined irrespective of the share of online transactions in the prepandemic period. However, as the pandemic crisis evolved, merchants with higher share of online transactions in the prepandemic period fared better than others (see Model(2)–(4) in Table 2). Coefficient estimates suggest that a 1 percentage point increase in the initial online transaction share leads to a 0.8 percentage point milder drop (or larger increase) in the total transaction volumes during the second wave of the Covid-19 pandemic if compared to the first one. Similarly, we also find evidence that merchants which saw an increase in the share of online transactions in the first wave of the pandemic (or, in fact, in the recovery phase during the summer 2020), coped better in the second wave. Hence, investment in online platforms during the initial phases of the pandemic seems to have resulted in better resilience in the future waves[6].

Next, we conduct a similar exercise to investigate whether further change in the share of online transactions during the second wave of the pandemic (compared to the first one) had any impact on the change in total transaction activity during the period of the most stringent restrictions in the third wave. The last part of Table 2 (see Model(5)–(6)) shows little evidence that the change in the online transaction share between the second and the first waves of the Covid-19 pandemic had any effect on the way merchants fared in the third wave. Nevertheless, we confirm that merchants with a higher share of online transactions in the prepandemic period also fared better than others during the third wave of the pandemic.

5 Nowcasting Retail Activity

In this section we investigate whether our data on the card transaction volume (CTV) can be used to nowcast retail trade turnover (RTT) dynamics. Specifically, we will focus on nowcasting *total retail trade without automotive fuel* (G47_X_G473). The RTT data is released by the Central Statistical Bureau of Latvia and spans the period from January 2000 until December 2021. The RTT data is neither seasonally nor calendar adjusted. The targeted time series is shown in Figure 6. The shaded area indicates the period for which the card transaction data is available.

In our nowcasting exercise, we capitalise on the fact that the card transaction data for the

[6]The findings remain mostly unchanged if the Airlines, Lodging and Car rental MCC categories are excluded from the sample (see Table A1).

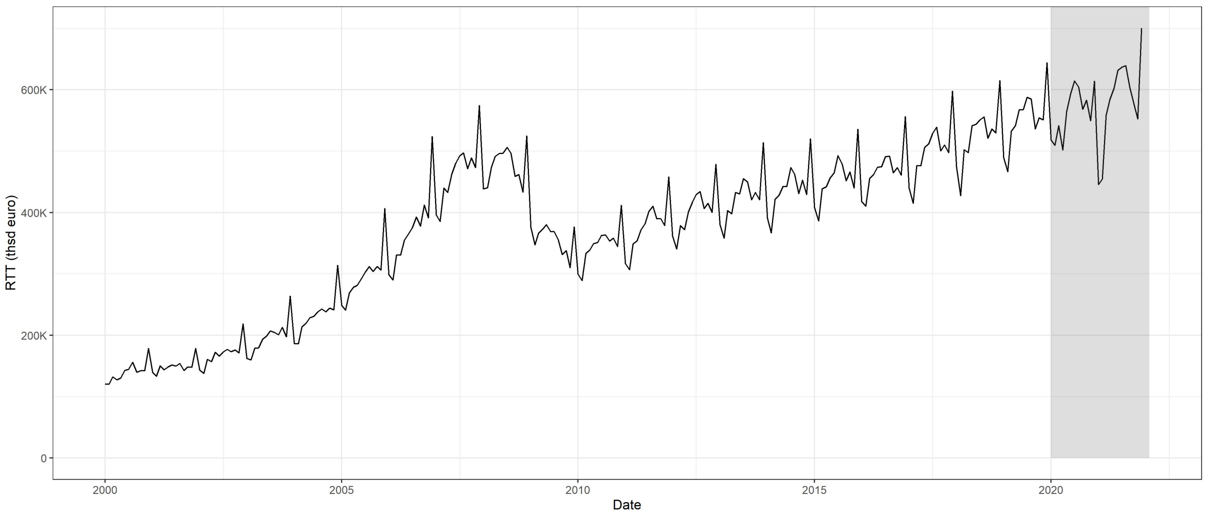

Figure 6: Total retail trade without automotive fuel (G47_X_G473)

Note: The shaded area indicates the period for which the card transaction data is available.

previous months becomes available for the analysis 13 days after the end of this month at the latest.[7] Observe that the Central Statistical Bureau of Latvia releases RTT data with a four-week delay. This means that the information about CTV can be used in order to gauge the dynamics of retail trade at least two weeks ahead of official data releases.

To do so, we perform the following procedures to make our card transaction data operational from the nowcasting point of view. First, we resort to MCC-NACE bridge tables in order to filter card transactions that are related to the retail trade in the G47_X_G473 category. Second, since the RTT variable is available at monthly frequency, we also aggregate our daily card transaction data to the monthly frequency.

In Figures 7 and 8 we present the levels and the corresponding month-on-month growth rates of both time series for the common sample, respectively. As seen, both time series exhibit very similar dynamics in both figures.

The observation of the very close comovement between these two time series is very encouraging and suggests that the card transaction data whose availability precedes the release of official retail trade statistics may indeed be informative about dynamics of the latter time series. In sequel, we will verify this hypothesis empirically.

Our choice of the nowcasting model is based on the following considerations. We treat both time series as integrated of order one variables, I(1), that are cointegrated. Hence, the cointegration theory suggests that the dynamic relationship between these two I(1) variables

[7] Banks deliver the daily card transaction data for the previous week on the following Friday. The data is uploaded to our SQL data bank on Sunday such that on the following Monday the data is available for the analysis. Such data delivery and storing schedule implies that the card transaction data that fully covers all days of the reference month is operational for the analysis as soon as on the 8th–14th days after the end of this month.

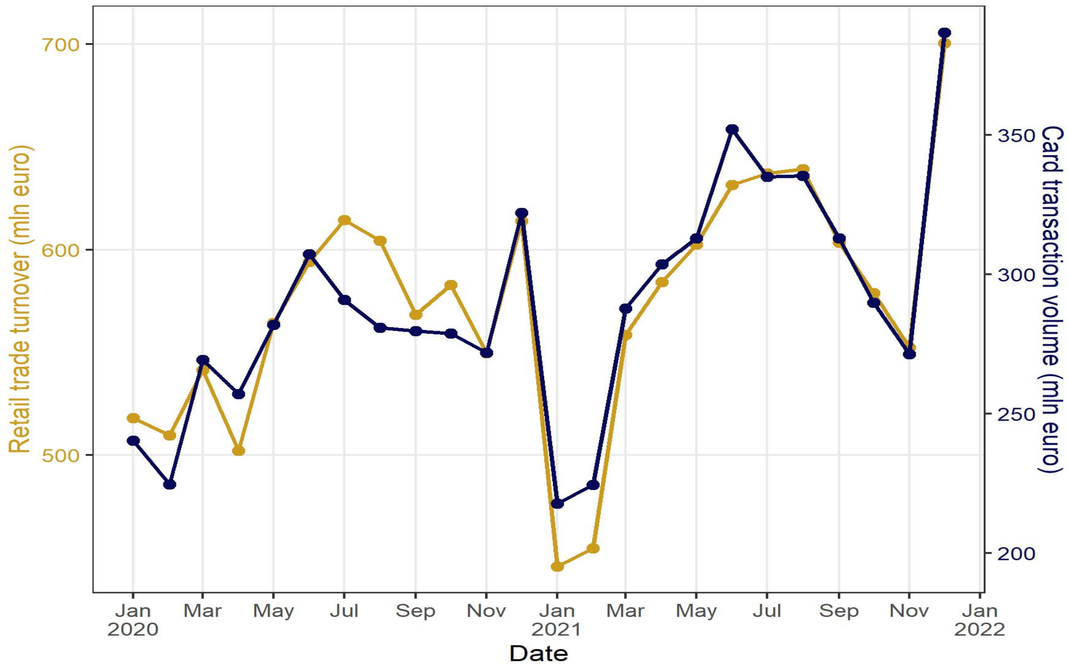

Figure 7: Card transaction volume and retail trade turnover in levels (mln EUR)

Notes: CTV covers about 50% of the recorded retail trade turnover in the category "total retail trade, except of automotive fuel". As seen, the levels of both time series exhibit quite close comovement both in the state of emergency periods and outside of those.

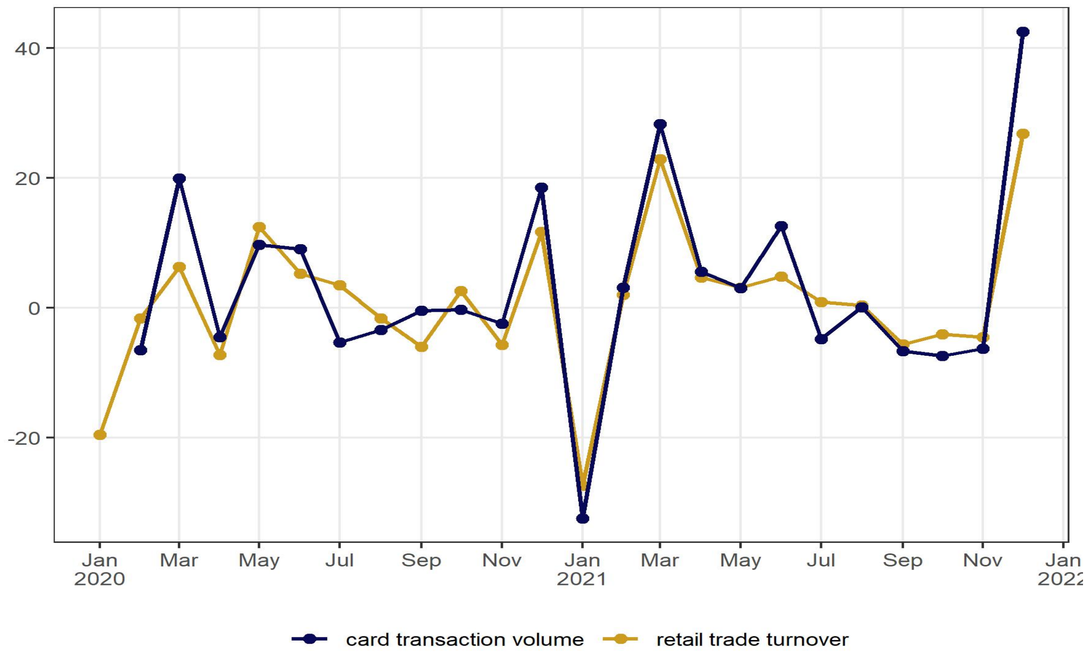

Figure 8: Data in month-on-month growth rates (%)

can be modelled by means of an error-correction model.

The error-correction model can be derived from the AutoRegressive Distributed Lag (ARDL) model allowing maximum one lag of each variable, ARDL(1,1). When making this choice, we acknowledged a rather short sample period that is available for estimation of this model. In fact, the longest estimation sample is from 2020M02 to 2021M12, reflecting the availability of the card transaction data.[8]

The initial ARDL(1,1) model can be written as follows

$$\log(rtt)_t = \beta_0 + \beta_1 \log(ctv)_t + \beta_2 \log(ctv)_{t-1} + \beta_3 \log(rtt)_{t-1} + u_t$$

Observe that we condition on the contemporaneous value of the CTV variable, $\log(ctv)_t$, reflecting its release timeliness. The ARDL(1,1) model can be further transformed into an unrestricted error-correction model

$$\Delta log(rtt)_t = \beta_0 + \beta_1 \Delta \log(ctv)_t + \alpha \log(ctv)_{t-1} + \gamma \log(rtt)_{t-1} + u_t \tag{4}$$

where $\alpha = \beta_1 + \beta_2$ and $\gamma = \beta_3 - 1$.

And then further to the restricted error-correction model, collecting the long-run cointegrating relationship into the error-correction term, ECT_{t-1}

$$\Delta \log(rtt)_t = \beta_0 + \beta_1 \Delta \log(ctv)_t + \gamma \left[\log(rtt)_{t-1} + \kappa \log(ctv)_{t-1}\right] + u_t$$

where $\kappa = \frac{\beta_1+\beta_2}{\gamma} = -\frac{\beta_1+\beta_2}{1-\beta_3}$

$$\Delta \log(rtt)_t = \beta_0 + \beta_1 \Delta \log(ctv)_t + \gamma ECT_{t-1} + u_t. \tag{5}$$

The estimation results of the model in Equation (5) for the longest available sample 2020M02 – 2021M12 are presented in Table 3. The goodness-of-fit measures $R^2 = 0.924$ are quite high and both terms appear to be statistically significant, even though some reservations regarding the sample size need to be kept in mind.

Table 3: Restricted error-correction model, estimation sample 2020M02 – 2021M12

Term	Estimate	Std. error	Statistic	P-value
$\Delta \log(ctv)_t$	0.71	0.05	15.75	0.00
ECT_{t-1}	-0.53	0.18	-2.90	0.01

Notes: Constant is not shown. $R^2 = 0.924$.

In order to shed more light on the stability of relationship between the RTT and CTV data, we report the recursively estimated coefficients of the unrestricted error correction model given

[8]The card transaction data starts in January 2020. One observation is lost due to taking one-month difference of this time series to compute monthly growth rates.

in Equation (4), see Figure 9.[9] Despite the fact that the first estimates are obtained using only 11 observations (from 2020M02 to 2020M12), the coefficient estimates are remarkably stable.

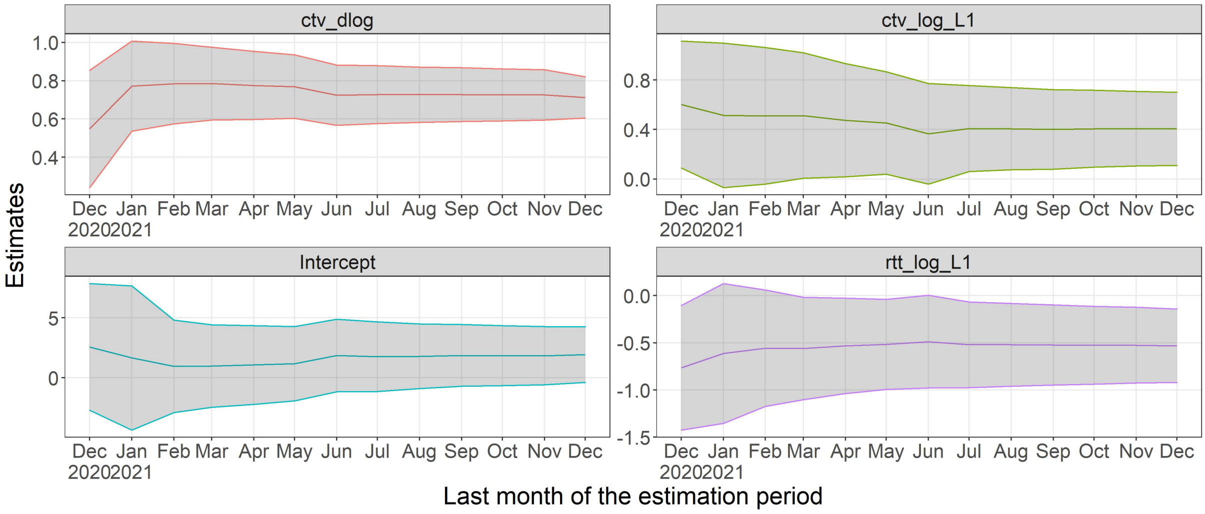

Figure 9: UECM recursively estimated coefficients, Equation (4).

Notes: Various coefficient estimates are plotted against the last month in the recursively defined estimation sample. The first estimation sample is 2020M02–2020M12, and the last estimation sample is 2020M02–2021M12.

The timing of our nowcasting exercise is as follows. Given the rather short period for which card transaction data are available, we make forecasts for the sample starting from January 2021 and ending in December 2021. This means that the first sample used for model estimation is from February 2020 until December 2020, consisting of 11 observations. Nevertheless, we use these coefficient estimates for making the first out-of-sample prediction for January 2021. The next out-of-sample prediction is made for February 2021 after extending the estimation sample by one observation (2020M02–2021M01). We produce the subsequent forecasts in a similar fashion until the last forecast is made for December 2021.

The forecasts generated by the model augmented with the CTV data are compared with a number of the following benchmark models. The first two benchmark models are univariate and the last one is augmented by the confidence composite indicator in retail trade for Latvia that is released by the European Commission.

It is important to note that the estimation of all benchmark models is not limited by the availability of the card transaction data and therefore when estimating these models we use the longer sample period. More specifically, we use data starting from January 2010 to eliminate the effect of the structural break during the Great Financial Crisis, see Figure 6.

[9]The OLS standard errors are reported for an illustrative purpose.

The first univariate benchmark model is a seasonal random walk model (SRWM) as such:

$$\log(rtt)_t = \mu + \log(rtt)_{t-12} + \epsilon_t.$$

The second univariate model is a seasonal ARIMA model

$$ARIMA(p, d, q) \times (P, D, Q)S$$

where p is non-seasonal AR order, P – seasonal AR order, d – non-seasonal differencing, D – seasonal differencing, q – non-seasonal MA order, Q – seasonal MA order and S – time span of repeating seasonal pattern (=12). In selecting the best specification we rely on the **auto.arima** function of the **forecast** R-package (Hyndman and Khandakar 2008).

The third benchmark model is an ARDL model augmented with the composite retail trade confidence indicator (RETA):

$$\Delta^{12}\log(rtt)_t = const + \alpha\Delta^{12}\log(rtt)_{t-1} + \beta_0 reta_t + \beta_1 reta_{t-1} + \epsilon_t.$$

For each competing model we produce forecasts of levels, annual, and monthly growth rates of the RTT. We evaluate forecast accuracy of level forecasts using the Mean Absolute Percentage Error

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|,$$

whereas for evaluation of growth rate forecasts we use the Root Mean Squared Forecast Error

$$RMSFE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2},$$

where A_t is the actual value and F_t is the forecast value.

The summary of forecasting accuracy of the models in question is presented in Table 4. We find that the model with card transaction data (ARDL) outperforms all benchmark models. This model yields about 50% reduction in MAPE/RMSFE forecast accuracy measures if we compare with forecasts generated by the benchmark Seasonal Random Walk model. It is also interesting to observe that the model ranking is uniform across different evaluation metrics and the second-best model is the model augmented with the retail confidence indicator. This second-best model yields a substantially less reduction in MAPE/MSFE with respect to the Seasonal Random Walk model of only about 20%.

Table 4: Forecast evaluation metrics

	levels		m-o-m growth		y-o-y growth	
Models	MAPE	rMAPE	RMSFE	rRMSFE	RMSFE	rRMSFE
SRWM	6.25	1.00	8.27	1.00	8.48	1.00
ARIMA	5.87	0.94	6.77	0.82	6.74	0.79
RETA	5.04	0.81	6.41	0.77	6.45	0.76
ARDL	2.73	0.44	3.87	0.47	4.35	0.51

Notes: MAPE is measured in percentage points. rMAPE and rRMSFE denote ratios of MAPE/RMSFE of each model with respect to those of the SRWM model. The forecast period is from January 2021 to December 2021.

6 Conclusions

The speed at which the Covid-19 pandemic wreaked havoc on the global economy was unprecedented therefore standard economic indicators were ill-suited for a timely assessment of the size and the scope of economic damage. This study takes advantage of a novel high frequency card transaction data from Latvijas Banka to investigate the consumption response to the Covid-19 pandemic in Latvia. Information on card transactions is available with a lag of only a few days compared to weeks and months in the case of more traditional economic indicators. Furthermore, the card transaction data is available at daily and weekly frequencies opposed to monthly or even quarterly frequencies of key economic statistics.

We use this novel data set to uncover the magnitude of consumption response to the Covid-19 pandemic in Latvia, covering three separate outbreaks of the virus and the related waves of the CMs. We find that card transaction activity fell to similar extent in all three waves of the pandemic, however, there is some indicative evidence showing that reasons for the drop in spending activity were not always the same. In the first wave of the pandemic, card transaction volumes fell sharply after the state of emergency was declared, although restrictions on retail activity were still relatively mild. This contrasts to the situation in the second and the third wave of the pandemic, when card spending did not react noticeably to the worsening epidemiological situation and the introduction of a state of emergency, and fell only after stringent CMs were imposed.

Exploiting the detailed information on 262 merchant categories present in our data set, we also study how the consumption response varied across merchants. Similarly to previous studies we find that the consumption response to the Covid-19 pandemic varied greatly across different sectors, with merchants in the Airlines and Entertainment sectors faring the worst. However, the situation was not homogeneous in all three waves of the pandemic, given the changing composition of the CMs.

We also find that merchants with higher share of online transactions in the prepandemic period fared better than others during the second and the third waves of the pandemic. Similarly, our results also provides some evidence that investment in online platforms during the initial phases of the pandemic seems to have resulted in better resilience to future shocks.

Finally, we explore whether card transaction data can be useful for nowcasting retail trade turnover in Latvia. We compare the accuracy of card-based forecasts with those generated using univariate benchmark models as well as a model augmented with the retail composite indicator released by the European Commission. We demonstrate that the nowcasting model augmented with card transaction data provides more accurate out-of-sample forecasts of retail trade turnover than those generated from all benchmark models. This conclusion holds both when we focus on forecasting levels as well as monthly or yearly growth rates of retail trade turnover.

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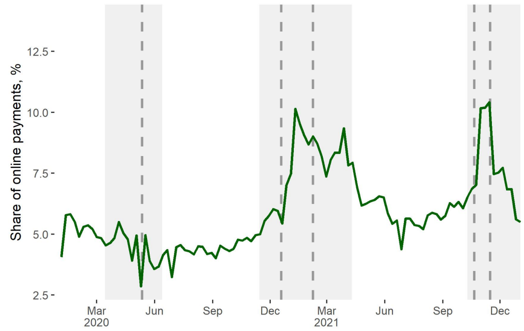
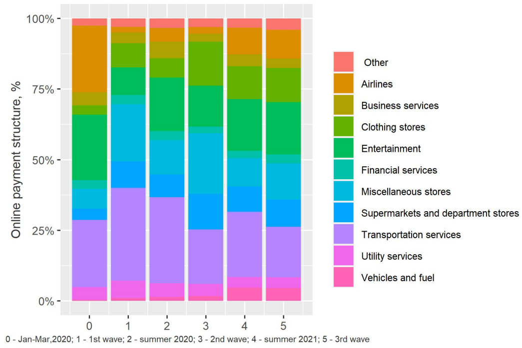
Appendix



(a) Share of online payments in total card payments



(b) Distribution of online payments by broad MCC categories

Figure A1: Share and distribution of online payments, %

Notes: Gray areas represent the periods when the state of emergency was in place. Vertical dashed lines indicate important dates in which CMs were significantly altered within the state of emergency period. Six periods correspond to: 0 – the prepandemic period (between 01-01-2020 and 12-03-2020), 1 – the first wave (between 13-03-2020 and 09-06-2020), 2 – the first recovery period (between 10-06-2020 and 09-11-2020), 3 – the second wave (between 10-11-2020 - 06-04-2021), 4 – the second recovery (between 07-04-2021 and 10-10-2021), 5 – the third wave (from 11-10-2021 until the end of the observation period).

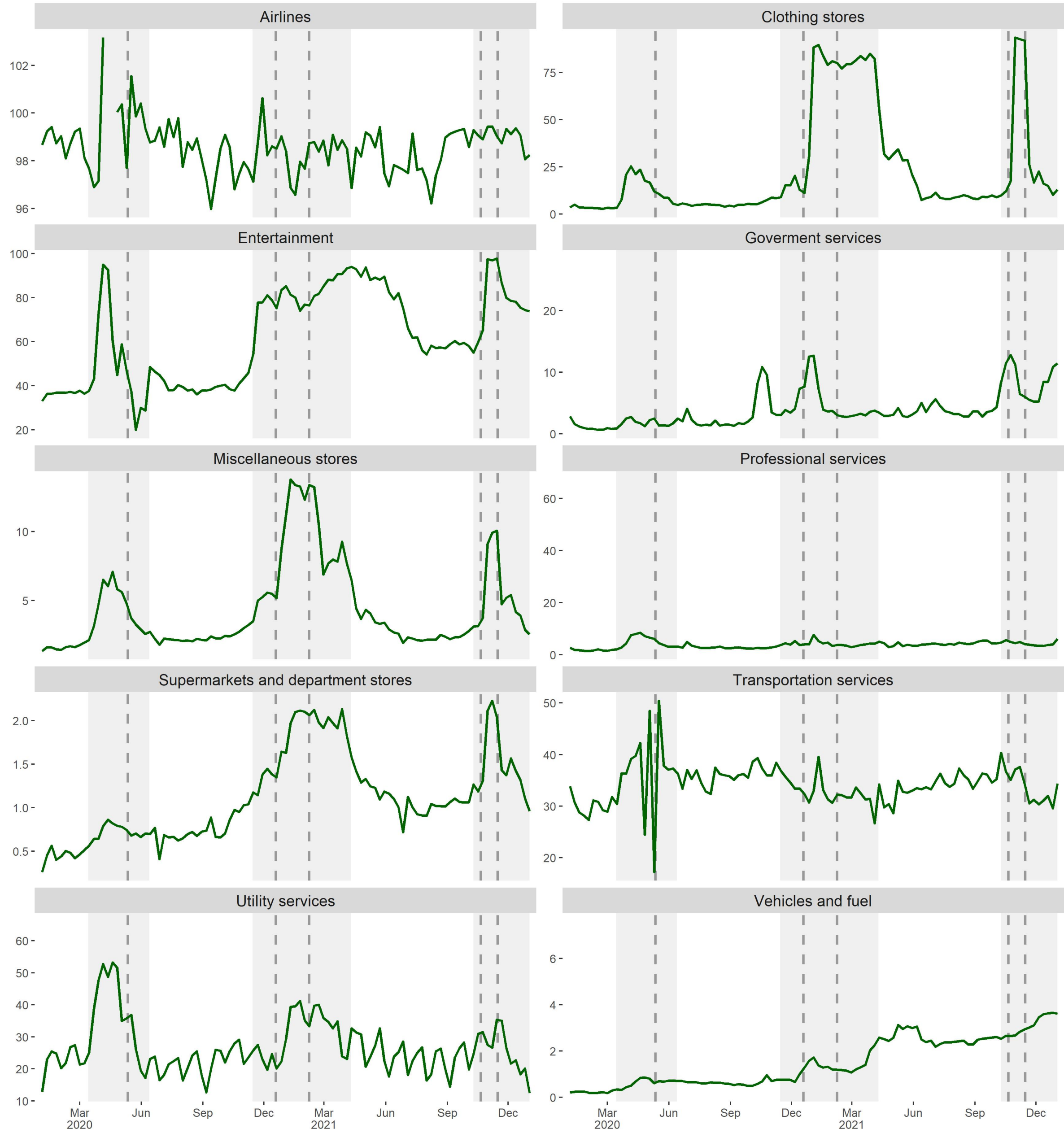
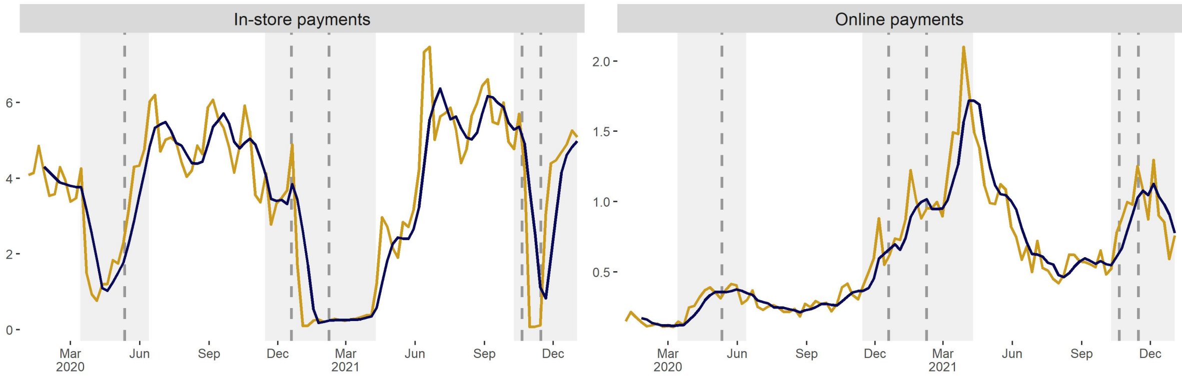
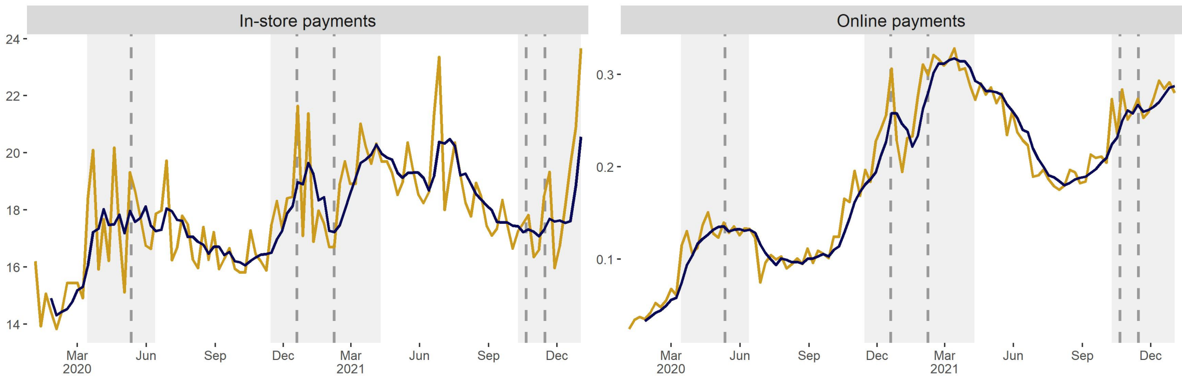


Figure A2: Share of online payments in selected merchant categories (%)

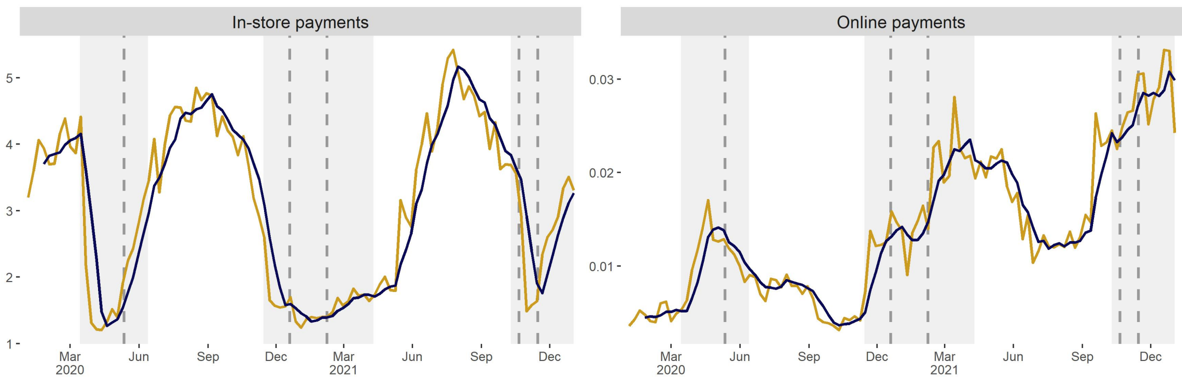
Notes: Only 10 MCC groups with maximum weekly online payment volumes are depicted. Gray areas represent the periods when the state of emergency was in place. Vertical dashed lines indicate important dates in which CMs were significantly altered within the state of emergency period (left to right): 12 May 2020 (the state of emergency was prolonged until 9 June, but restrictions were eased); 19 December 2020 (only essential stores could operate in-person; curfew was imposed on weekends and holidays); 7 February 2021 (the state of emergency was prolonged until 6 April, but curfew was lifted and restrictions were eased); 21 October 2021 (all non-essential shops had to be closed; curfew was imposed from 8pm until 5am.); 16 November 2021 (most of the CMs were eased for the vaccinated individuals).



(a) Clothing stores (MCC groups 5600-5699)



(b) Supermarkets (MCC group 5411)



(c) Eating places and restaurants (MCC group 5812)

Figure A3: Online and in-store weekly payment card transactions in 3 types of stores, mil EUR

Notes: The yellow line represents weekly payment card transactions and the dark line shows 4-week moving average. Gray areas represent the periods when the state of emergency was in place. Vertical dashed lines indicate important dates in which CMs were significantly altered within the state of emergency period.

Table A1: Regression results for different waves of the Covid-19 crisis (excluding Airlines, Car rentals and Lodging MCC categories)

Model (1) *Dependent variable:*	*Change in total payments between the 1st wave and prepandemic months, %*		
Share of online trade during the prepandemic months, %	0.178 (0.193)		
Number of observations	244		
Adjusted R^2	0.099		
Model (2),(3),(4) *Dependent variable:*	*Change in total payments between the 2nd and 1st waves, %*		
Share of online trade during the prepandemic months, %	0.799*** (0.228)	0.861*** (0.222)	0.862*** (0.229)
Change in the share of online trade between the 1st wave and the prepandemic months, pp		2.187*** (0.568)	
Change in the share of online trade between summer 2020 and the prepandemic months, pp			1.470** (0.709)
Number of observations	243	243	242
Adjusted R^2	0.061	0.115	0.072
Model (5),(6),(7) *Dependent variable:*	*Change in total payments between the 3rd and 2nd waves, %*		
Share of online trade during the prepandemic months, %	0.888*** (0.247)	0.948*** (0.250)	0.980*** (0.253)
Change in the share of online trade between the 2nd and 1st waves, pp		-0.396 (0.496)	
Change in the share of online trade between summer 2021 and summer 2020, pp			0.338 (0.558)
Number of observations	243	241	242
Adjusted R^2	0.069	0.074	0.073

Notes: Regressions include dummies for broad MCC groups. The third wave used in regressions is defined as period from 21 October 2021 to 15 November 2021. The extension of the third period to the end of the first week of 2022 does not significantly change the coefficients.

*p<0.1; **p<0.05; ***p<0.01; standard errors in parentheses.