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Card spending dynamics in Turkey during the COVID-19 pandemic

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ABSTRACT

This paper provides an extensive analysis of card spending during the COVID-19 pandemic in Turkey by using weekly aggregated and sectoral credit and debit card spending data from March 2014 to December 2020. At an aggregated level, we show that aggregate demand decreases significantly at the early stages of COVID-19 and seems to reinstate its pre-COVID trend. However, when we include the pre-existing conditions of Turkey, the 2018 currency crisis, we observe that the recovery in demand is not that strong. To highlight the underlying reasons for structural change in aggregate demand, we estimate the model with *stringency index* and *unemployment-related search index*. The estimated model indicates that containment measures and restrictions and fear of job/income loss mainly explain the overall impact of COVID-19 on aggregate demand. We also examined sectoral data to understand aggregate demand dynamics better. Only stable and delayable sector groups have reached a trend above their pre-pandemic trajectories. However, the social and work-related sectors are far from their respective pre-pandemic trend.

1. Introduction

Turkey already had had a fragile economy before it was hit by the COVID-19 shock. In addition to the high rates of unemployment and inflation, Turkey experienced a substantial depreciation of the Turkish Lira in 2018, which resulted in a negative wealth effect for the individuals. Therefore, the economic ramifications of COVID-19 have been severe for the Turkish economy. During the COVID-19, unemployment reached higher levels, and the income of many households plummeted with increasing economic uncertainty. These unfavorable developments lead to a change in the behavior of consumers, hence aggregate demand. Moreover, while some sectors were positively affected by this unprecedented event, some sectors came to a standstill. The pace and shape of the recovery phases differ among industries.

In this paper, we provide an extensive analysis of the card spending in Turkey during the COVID-19 crisis to make inferences about aggregate demand in Turkey. We use weekly debit and credit card data, which the Central Bank of the Republic of Turkey collects from the banks operating in Turkey. Our data from banks or other financial institutions has been shown to be one of the most fruitful sources of research of this kind, and have been studied by, among others, Bounie et al. (2020) (for France) Andersen et al. (2020) (for Denmark), Baker et al. (2020) (for the US), Carvalho et al. (2020) (for Spain), and Chen et al. (2020) (for China). Unlike the data sets used in the literature, the data provided by the Central Bank of Turkey includes information gathered from all the banks in Turkey. The series we use provides quite enough information for the macroeconomic analysis we are interested in. On the other hand, these studies use credit and debit card expenditure data provided by a specific bank. One exception is Bank of England's “UK spending on credit and debit cards” experimental data series, which uses 100 major United Kingdom retail corporates. To the extent of our knowledge, this is the first paper with an extensive analysis of the aggregate demand in Turkey during COVID-19 using debit and credit card spending data. The weekly nature of the data helps us study card expenditures at a high frequency, entertaining the fast-paced nature of the pandemic. Our approach also takes into account the pre-existing economic conditions in Turkey before the pandemic, which we believe is crucial to decipher the recovery process.

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We use interrupted time series analysis—a segmented-regression design —that relies on *trends* before and after the introduction of a discrete interruption to assess its impact. The main *interruption* of interest in this study is the COVID-19 pandemic shock. COVID-19 shock is not only a health-related shock but also an economic shock stemming from the uncertainties led by the pandemic. Therefore, it is crucial to understand the economic environment of the country and introduce it into the analysis. We include currency and debt crisis to distinguish the impact of the pandemic shock.

Our analysis proceeds in three steps. First, we estimate how the nature of aggregate card spending changed at the early stages of the COVID-19 pandemic. To highlight the peculiarity of the COVID-19 crisis, we compare responses of card spending to COVID-19 shock with the Lira crisis in 2018. Second, we delve into possible explanations of the impact of COVID-19 on aggregate demand. Using the stringency index, we examine whether the mobility/containment measures explain the change in aggregate demand. We also analyze the impact of fear of income or job loss using Google Trends data. Finally, we study the heterogeneity in spending across categories of expenditure using sectoral data.

Our findings show that there is a significant decline in card spending at the early stages of the pandemic, and the total demand *seems* to be back on track for a recovery path. However, when we carry out the same analysis by considering the Turkish Lira crisis as another *interruption*, the recovery during COVID-19 disappears. Both COVID-19 and currency shocks result in a decline in income and wealth of individuals, hence demand; however, the shape and the pace of recovery from these detrimental events are not similar. During the Turkish Lira crisis, the recovery was sluggish. On the other hand, the recovery from COVID-19 seems to follow a steeper upward trend. This result suggests that the impact of COVID-19 will not be long-lasting as opposed to the currency and debt crisis. We are aware that some of the increase in card spending may also be due to change in the payment methods, not the spending behavior. It should be taken into account when interpreting the results. Hence the observed recovery might have been even weaker during the analyzed period.

We also delve deeper into the matter by focusing on the disaggregated sectoral data. We observe that the staple —essentials —sectors did not experience severe contraction, unlike the others. On the contrary, behavioral transformation in consumption and substitutability of physical shopping with online shopping results in a notable increase in demand in these sectors compared to the pre-pandemic trend. The demand in some delayable sectors decreased on average, but the recovery phase is stronger than the social and work-related sectors in the subsequent periods of the pandemic. The social and work-related groups experienced massive declines, and they are far from attaining the pre-pandemic levels.

Our paper is organized as follows. Section 2 describes the data and the methodology. In Section 3, we discuss the results of the analysis. Section 4 provides an extensive discussion of the findings. Section 5 concludes.

2. Data and methodology

2.1. Card spending data

This study uses the weekly credit card and debit card total expenditure data from March 2014 to December 2020.[1] The data is compiled by the Central Bank of the Republic of Turkey (CBRT) taken from POS devices—virtual POS are also included—of all banks operating in Turkey comprising domestic banks and foreign-owned banks. Data excludes cash withdrawals and cash advances by means of credit and debit cards.[2] Data is also available at a disaggregated level by sector categories consisting of car rental; car sales, services, and parts; petrol stations; airlines; travel agencies; accommodation; casino; jewelry; health, health products, cosmetics; food; clothing and accessory; markets and shopping centers; furnishing and decoration; electric and electronic goods, computers; telecommunication; service; insurance; building supplies, hardware, hard goods; direct marketing; various food; club, association, social services; education, stationary; contractor services; government tax payments; private pension; others.[3]

The coverage of card transactions data is exceptional, allowing us to capture a significant proportion of all consumer expenditure in Turkey. Unfortunately, it is not possible to extract expenditures of businesses and foreigners from the data, but we believe that these are relatively small; therefore, card data is an indicator of consumption.[4] Over the sample period, the volume of the card spending accounts for —on average—23% of Turkish GDP, 39% percent of total personal consumption expenditures, and 51% percent of total personal consumption expenditures excluding rents. Fig. 1 demonstrates yearly evolution of these figures. Excluding rents from household consumption expenditure is particularly relevant as these are typically paid by cash and direct debit transfers. The dynamics in card spending are important indicators for aggregate demand, thus overall economic activity in Turkey. The weekly nature of the data helps us study card expenditures at a high frequency, entertaining the fast-paced nature of the pandemic. Since consumer spending might exhibit patterns due to New Year sales, seasonal clearance sales, moving holidays, etc., we seasonally and holiday adjust data using month dummies and dummies for religious holidays to filter out card spending patterns. We also adjust the data for inflation by normalizing it with the headline consumer price index of the corresponding month.

2.2. Interrupted time series analysis

Interrupted Time Series Analysis (ITSA) is a widely used technique based on trends of a time series before and after the realization of an event, intervention, or interruption to evaluate its impact.[5,6] ITSA builds upon the idea that the outcome variable would not be altered if there were no interruptions. By design, an ITSA has no comparable reference group; instead, the pre-

[1] The beginning of our sample is determined by the time coverage of the data.

[2] Data is provided as a combination of debit card and credit card spending. It should be noted that the data may represent quite different consumption expenditures or even different types of consumers with different levels of credit constraints. We cannot detect these dynamics in our analysis as the data is not given at this level.

[3] Sectors are classified according to the sector specifications in Merchant Category Codes that are determined by ISO 18245 —the ISO standard concerning the assignment of Merchant Category Codes in retail financial services —and shared with banks by the Interbank Card Center of Turkey. Detailed information can be found at https://evds2.tcmb.gov.tr/help/videos/Metaveri_Creditcards.pdf.

[4] The Interbank Card Center (ICC) gathers similar data on a monthly frequency. Using their data, we calculate the share of households' expenditure —only in—credit card spending is 78% on average in the analyzed period. ICC also publishes a household card payment index and a general card payment index. As shown in Fig. 4, the dynamics of these indices are quite similar, and the correlation is 95%. However, we do not use them in analysis because ICC's data is only published monthly.

[5] See Campbell and Stanley (1963), Glass and Gottman. (1975), Anderson-Cook (2005), Linden (2015) and Linden (2017) for details of the methodology.

[6] ITSA has especially been used in assessing the impact of deliberate interventions such as the treatment effects in health technology (Ramsay et al., 2003), public policy (Andersson et al., 2006), and community interventions (Muller, 2004), among others.

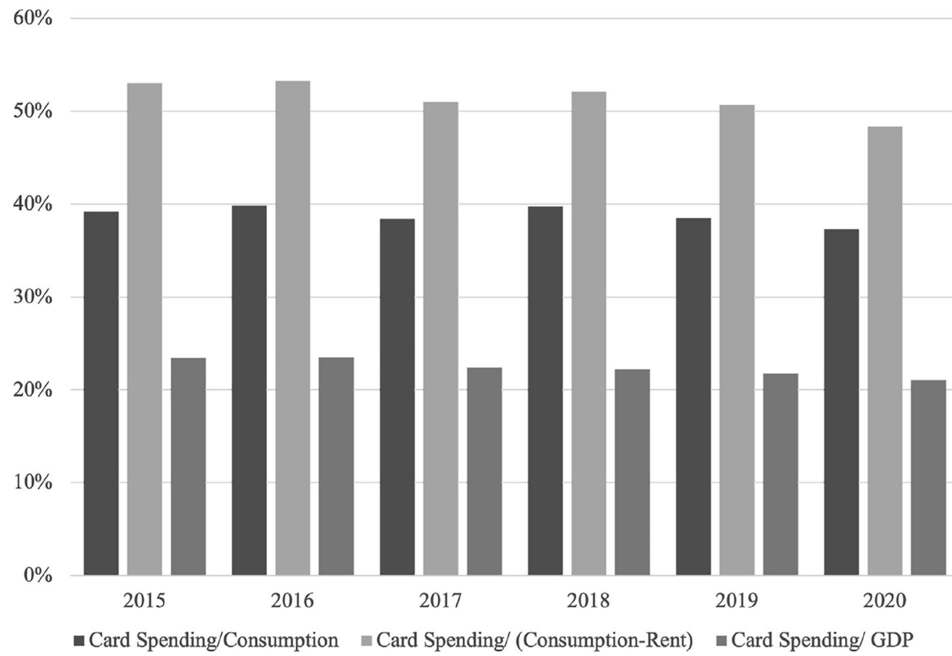


Fig. 1. Total Card Spending as Percentages of Consumption, Consumption Excluding Rent and GDP.
Sources. CBRT, Turkish Statistical Institute and Authors' Own Calculations.
Notes. Consumption excluding rent is calculated by using the ratio of housing from the Household Budget Survey provided by CBRT.

interruption trend projected into the interruption period serves as the *counterfactual*. The methodology relies on segmented-regression to analyze the impact of the interruption. ITSA requires two segments: the one before the interruption and the one after the interruption. A separate slope and intercept are estimated for each segment and compared to derive the impact of the interruption.

The general model for an ITSA is as follows:

$$Y_t = \beta_0 + \beta_1 Time_t + \beta_2 Interruption_t + \beta_3 Time_t \times Interruption_t + \epsilon_t$$
$$\epsilon_t = \rho\epsilon_{t-q} + \nu_t \tag{1}$$

where *Time* is a variable which equals one at the first time point and is incremented by one for each subsequent time point; *Interruption* is an indicator variable which takes one at the time following the interruption of interest and for every time point thereafter; *Time* $\times$ *Interruption* is an interaction term. Accordingly, β_0 is the starting level of outcome *Y*; β_1 is the slope until the occurrence of the intervention (pre-period trajectory of *Y*); β_2 is the change in level of the outcome at time of interruption; β_3 is the difference between pre-intervention and the post-intervention trends. In Equation (1), β_2 and β_3 represent the immediate and prolonged effects of the interruption, respectively. This is a strength of the design, since it allows to differentiate short term effects from the impacts over time. To account for autocorrelation, the error term ν_t is represented by Newey-West standard error with lag *q*. A limitation of ITSA is that the resulting estimates of the intervention may be biased if the underlying trends are not adequately accounted for. Control variables could be a solution to this problem. However, the control variables should share the same confounders, e.g., a common trend, as the intervention series and be unaffected by the intervention. When no control variable is available, or where the quality of the controls is in doubt, as in our case, the segmented-regression model may provide a useful tool to detect the trend (Bottomley et al., 2019). Since COVID-19 has an impact on all economic variables, finding a confounding variable related to the question of interest is not possible for this analysis.

3. Model specification and results

3.1. Total card spending

The main interruption of interest in this study is the COVID-19 pandemic crisis. Since Turkey has not declared a national emergency in response to coronavirus outbreak but rather put several restrictions in place spreading through a long time, to establish the timing of the interruption, we use the peak of Google search queries related to *koronavirüs* —coronavirus in Turkish.[7] Google trends data —information search on a particular term/topic—are proven to be useful projections of one's level of attention (Wohlfarth, 2018; Yılmazkuday, forthcoming). The peak date of Google search queries corresponded to the 16th of March when schools were closed, and governmental offices switched to home offices —in accordance with the general description of social-distancing measures in the previously published typology (Hale et al., 2021).[8]

To account for the impact of the pandemic on card spending, we estimate the following segmented-regression specification:

$$Spending_t = \beta_0 + \beta_1 Time_t + \beta_2 Pandemic_t + \beta_3 Time_t \times Pandemic_t + \beta_4 Dec2020 + \epsilon_t$$
$$\epsilon_t = \rho\epsilon_{t-q} + \nu_t \tag{2}$$

where the dependent variable is seasonally-and-holiday-adjusted total credit and debit card expenditure amounts. *Pandemic* is a dummy variable equals one at the beginning of the pandemic and after, yielding an interaction term, *Time* $\times$ *Pandemic*, a variable that takes zero for pre-pandemic times, and incremented by one for every subsequent week. There is a methodological change in the

[7] The data is publicly available and can be retrieved by the following link: https://trends.google.com/trends/explore?geo=TR&q=koronavirüs.

[8] As in the spirit of Morris and Shin (2000)'s global games, when agents observe noisy idiosyncratic signals on the underlying state of the world, public announcements provide strong coordinating signals, which are represented by the Google search data.

Table 1
Total card spending.

	(1)	(2)	(3)	(4)
Time	20.73[a]	35.16[a]	35.16[a]	37.05[a]
	(2.43)	(2.63)	(2.63)	(7.45)
Crisis		−3567.66[a]	−3567.66[a]	−2823.89[a]
		(716.44)	(717.47)	(808.12)
Time × Crisis		−6.43	−6.43	−13.88
		(13.64)	(13.66)	(14.79)
Pandemic	−9615.40[a]	−8795.81[a]	6336.40	5241.61
	(2219.34)	(2194.21)	(4632.31)	(3875.98)
Time × Pandemic	381.58[a]	373.57[a]	341.09[a]	269.44[a]
	(84.18)	(86.96)	(52.49)	(54.08)
Stringency Index			−227.24[a]	−179.62[a]
			(64.24)	(58.72)
Unemployment Search				−72.21[b]
				(28.44)
Dec 2020	−8408.98[a]	−8408.98[a]	−7777.13[a]	−7055.22[a]
	(1515.52)	(1519.86)	(1319.63)	(1134.97)
Constant	38743.04[a]	37507.81[a]	37507.81[a]	42146.61[a]
	(412.37)	(378.93)	(379.47)	(870.73)
Observations	355	355	355	259
Adjusted R^2	0.33	0.39	0.44	0.34
Post-Crisis Trend				
		28.74[b]	28.74[b]	23.16[b]
		(13.35)	(13.37)	(12.77)
Post-Pandemic Trend				
	402.31[a]	402.31[a]	369.83[a]	292.61[a]
	(84.10)	(84.34)	(49.25)	(53.55)

Notes. Interrupted time series analysis on the credit and debit card spending. Parenthesis contains Newey-West-corrected standard errors.
[a] indicates significance at the 1% level.
[b] indicates significance at the 5% level.
[c] indicates significance at the 10% level.

COVID-19-related data sharing policy in Turkey. On the 30th of September, the Ministry of Health announced that they were sharing only the number of hospitalized cases instead of the total number of confirmed cases —which is the standard measure for the rest of the world —since the 29th of July. However, for the first time since July, the daily number of confirmed coronavirus cases was announced on the 26th of November.[9] This might add to the existing uncertainty about the pandemic in Turkey. Hence, variable *Dec*2020 is a dummy taking one for all the weeks of December 2020, which captures this incidence.[10] The value for the lag-length of the error term is determined using the Cumby-Huizinga general test for autocorrelation.[11]

The results of the specification (2) are summarized in the column (1) of Table 1. We document that the initial level of card spending is 38743.04 Thousand TRY per week using debit and credit cards. We also find a significant pre-pandemic trend equal to 20.73 Thousand TRY per week. After controlling for this trend, we find strong evidence of a reduction in the level of spending following the pandemic by 9615.40 Thousand TRY between the pre- and post-interruption periods. The last row of Table 1 shows that the post-pandemic trend is equal to 402.31, which significantly differs from the pre-pandemic trend.

Our aim is to detect the trend in card spending pre- and post-COVID accurately. Disregarding the pre-existing economic conditions in Turkey could mislead the detection of the trend of card spending. A natural candidate for a recent economic shock is the 2018 currency and debt crisis. Although the two crises have fundamentally different characteristics —the former being financial in origin and the latter being related to uncertainty and restriction of movement —both are relevant factors in determining consumption patterns. We treat the currency crisis and the pandemic as separate interruption periods to account for the recent economic shocks. To further point out the interruption period due to the Lira crisis in 2018, we pick the 10th of August since the Turkish Lira had undergone a dramatic depreciation of nearly 10 percent in a day, hitting the mark of 6 TRY per US Dollar.[12]

We estimate the following *multiple* segmented-regression:

$$\begin{aligned} Spending_t = {} & \beta_0 + \beta_1 Time_t + \beta_2 Crisis_t + \beta_3 Time_t \times Crisis_t \\ & + \beta_4 Pandemic_t + \beta_5 Time_t \times Pandemic_t + \beta_6 Dec2020 \\ & + \epsilon_t \\ \epsilon_t = {} & \rho\epsilon_{t-q} + \nu_t \end{aligned} \tag{3}$$

where *Crisis* is a dummy variable taking one on the week of August 10, 2018 and after, *Time* × *Crisis* is a variable that takes zero until the end of 2018 and incremented by one for every subsequent week. Additional variables do not alter the value for optimal lag-length for the Newey-West standard error, ν_t, chosen using the Cumby-Huizinga general test for autocorrelation.

The column (2) of Table 1 shows the estimation results of Equation (3). When we account for the Lira plunge, we estimate a trend equal to 35.16 for pre-interruption periods. As we have conjectured, consumers' initial response to the crisis manifests as a drop in the intercept by 3567.66 Thousand TRY; however, post-crisis periods do not yield a statistically significant change in the spending trend. The impact of the pandemic remains similar. However, estimation results exhibit a larger trend in card spending in pre-crises periods, suggesting that the crisis is driving the pre-pandemic trend down.

Results of the estimated impact of the pandemic are demonstrated in Fig. 2. We create a counterfactual scenario that serves as the baseline point to attribute the modified trajectory to the presence of the pandemic. Comparing the counterfactual to the predicted trend yields information about the speed of the recovery and whether the recovery has been achieved yet. Fig. 2A demonstrates the counterfactual analysis only with the COVID-19 shock and exhibits that the pre-pandemic trend has already been achieved. Fig. 2B illustrates the counterfactual scenario considering the 2018 currency and debt crisis as an additional shock. In Fig. 2B, the pre-Lira crisis trend is steeper since, in Fig. 2A, the trend was suppressed by the currency and debt crisis. The pandemic causes a significant change in the trend of card spending after a large drop in the level, suggesting a path for recovery. However, when we account for the Turkish Lira plunge, recovery to the pre-crises trend has not been attained yet.[13]

3.1.1. *Dissecting the impact of the pandemic*

COVID-19 pandemic has been directly associated with the fall in card spending. However, the underlying factors leading to the fall in

[9] See Fig. 5 for the jump in the weekly number of confirmed cases.

[10] As a robustness check, we also conduct the analysis by excluding the post-November period. The results are presented in the Appendix.

[11] We conduct the test for $q = 12$ and use the lag with the smallest p-value, which yields an optimal lag-length as $q = 4$.

[12] Note that including the currency crisis as an additional interruption is practically having dummy variables that allow changes in the intercept and the slope.

[13] As robustness for our analysis, we also extend the data set until April 2021. One downside of extending the sample is that 2021 is a relatively new phase due to the proliferation of vaccination studies globally and the vaccination of healthcare workers in Turkey. Hence, we also present the results with vaccination policy measured by Hale et al. (2021). The results are robust to extending the data; however, the vaccination policy does not appear significantly. One should note that data on vaccination policy captures only government policies on the availability of vaccinations and does not track the number of people who have been vaccinated.

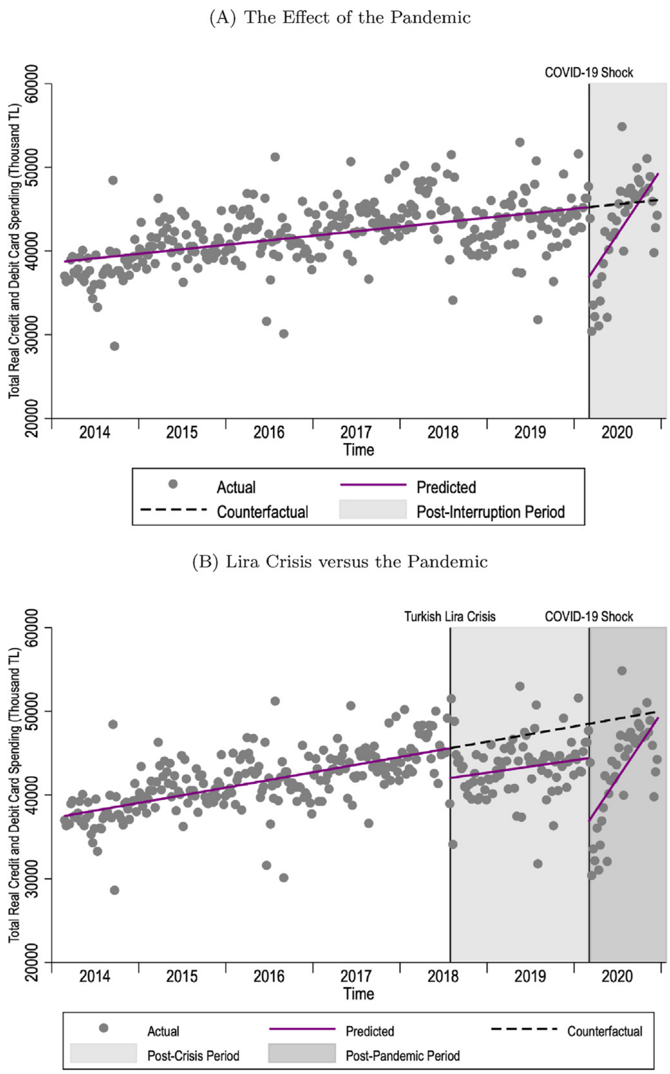


Fig. 2. Interrupted Time Series Analysis on Total Card Spending.
Notes. Scatter plots and predictions are derived from segmented-regression models of weekly credit and debit card spending. The vertical lines indicate the dates of interruption. Counterfactual shows trends in the absence of the interruption.

demand remain unclear. To address this point, we estimate specification (3) with control variables: *the stringency index* and *unemployment search index*. It is worth emphasizing that by this analysis, we deviate from the common norm of reporting the results of ITSA because the additional control variables will replace the information carried by the pandemic-related dummies.

3.1.1.1. Stringency index. To account for the effect of the intensity of government restrictions, we employ the stringency index -provided by Hale et al. (2021)- which represents a measure of the intensity of non-medical government interventions during the pandemic, including containment measures and public information campaigns. The index aggregates the following response indicators: school closing, workplace closing, cancellation of public events, restrictions on gatherings size, public transport closed, stay at home requirements, restrictions on internal movement, and international travel restrictions. It is re-scaled to create an ordinal score between 0 and 100 (100 = strictest). We use the weekly averages of the index data published at a daily frequency. The results of the analysis are provided in column (3) of Table 1. When we include the stringency index, the coefficient of *Pandemic* becomes insignificant, and a change in trend is mitigated. Therefore, the immediate impact of the pandemic is caused by government measures, which are reflected by the stringency index. The rest of the results remain statistically and economically significant and of similar magnitude. Including the stringency index improves the performance of the analysis by providing a time-varying indicator for the lockdown-related change in total card spending.

3.1.1.2. Unemployment search index. We further employ Google Trends data on search trends related to *işsizlik* —unemployment in Turkish.[14] Top questions in this category are related to the unemployment benefits, short-term employment allowance, unemployment insurance fund, etc.[15] We believe that the data reveal information about individuals' perceptions of job security.

Column (4) of Table 1 reports that part of the information carried by the trend is now shared among the stringency and unemployment search indices. We show that fear of job loss is negatively correlated with consumer spending. The negative coefficient suggests that when consumers are stressed about job security or income flow, they cut back from spending. The results indicate that lockdown measures causing disruptions in supply chains and income loss explain part of the decline in card spending during COVID-19.

3.2. Sectoral card spending

To understand the nature of the response of card spending to the COVID-19 crisis, we classify sectors as staple, delayable, social, and work-related groups by using disaggregated data. Fig. 3 lists the sectors under each category.[16]

The staple group consists of the sectors that include necessities such as bakery, dairy stores, cigarette shops and buffets, grocery stores and supermarkets, etc. Building supplies sector includes construction materials, hardware, hard goods, etc., which are non-delayable investment spending of the construction sector. Table 4 presents the results of the interrupted time series analysis of the staple category. We document that consumers spend, on average, a larger portion of their budget on the staple group as indicated by the constant terms in the regression results. The demand for the goods produced by these sectors did not experience any fall due to the pandemic. Specifically, there is a significant increase in the intercept for electric & electronic goods, computers, and markets & shopping centers. Table 4 shows that there is a significant change in the trend after the pandemic except for the markets and shopping centers sector. Overall, the impact of pandemic worked contrariwise compared to the aggregate data for this category. Fig. 7 compares the predicted trend after the crises and the counterfactual trend in the absence of the interruptions. The counterfactual analysis demonstrates that the staple sectors have a trend above the pre-pandemic trajectory. Especially for electric & electronic goods, computers, and telecommunication, the historical downward movement seems to be reversed by the pandemic.

The delayable group includes the spending items that are not essential. The results in Table 5 show that clothing & accessories, service, club, association, social services, jewelry, and health exhibits a significant drop in the level of spending early stages of the

[14] The data can be reached by the following link: https://trends.google.com/trends/explore?geo=TR&q=İşsizlik.

[15] A complete list of search keywords related to the fear of job loss is presented in Table 2 in Appendix.

[16] Considering that it is not common to use credit/debit card for *government tax payments* and *private pension*, we exclude these sectors from category specifications. We also leave out *others* as the items listed here would fall into multiple categories.

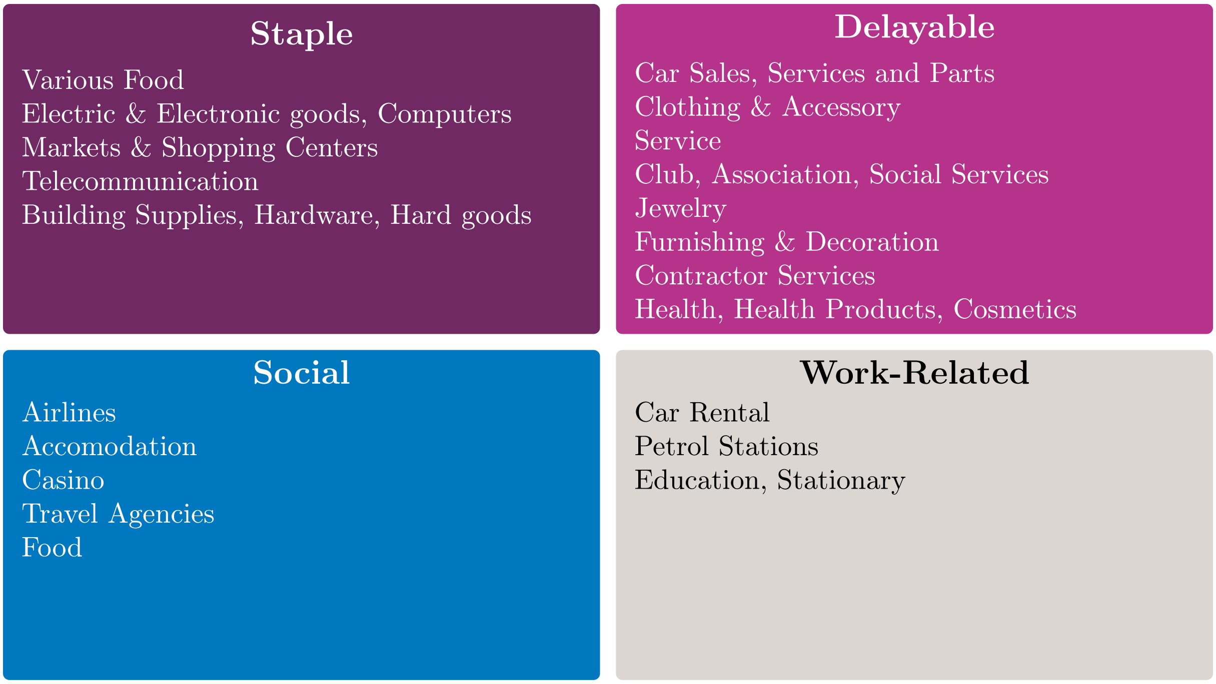


Fig. 3. Classification of groups in credit and debit card spending.

pandemic. Although they can potentially be postponed by classification, expenditure on furnishing & decoration, contractor services, and car sales, services & parts did not show a fall from the pandemic. The finding that the early effects of the pandemic are relatively weak in these sectors —except for car sales, services & parts—may be because people have paid more attention to their habitat due to stay-at-home-restrictions. Car sales, services & parts sector stands out from others in this category mainly due to the strong demand despite supply disruptions.[17] Furthermore, the whole category shows a significant, positive post-pandemic trend. In terms of the shape of the recovery, as demonstrated in Fig. 8, all sectors show a reversal to the pre-crises pattern, but those that did not initially decline seem to have overtaken the pre-crisis path, while those that fell sharply at the start of the pandemic seem to have caught this path. In addition, since non-COVID-19-related health concerns had been postponed —either compulsory or voluntary—the recovery in spending on the health sector is quite strong.

Tables 6 and 7 presents the estimation results of the multiple segmented-regression of the social and work-related categories, respectively.[18] All sectors in these categories exhibit dramatic declines as an initial response. The counterfactual comparison, presented in Figs. 9 and 10, indicates a sluggish recovery. Accordingly, these categories are far from their respective pre-pandemic trajectories in the analyzed period. We leave further discussion and policy implications of our results to the next section.

4. Discussion

While the economic damage of COVID-19 varies around the world, the heterogeneity of contractionary experiences is mainly driven by pre-existing conditions, timing, and persistence of the slowdowns. Turkey has already been in an unfavorable position before the COVID-19 shock. Just a year ago, Turkey experienced a substantial plunge in the value of its currency, combined with increasing inflation and high borrowing costs, and loan default, which resulted in financial vulnerabilities in the economy. We believe that the results of the paper will provide guidance for policymakers for quick and minimum harm recovery during the COVID-19 phase. Our results can be grouped in a three-pronged discussion.

At the early stage of the COVID-19 shock, we observe a considerable decline in the total card spending level. In later stages, the counterfactual analysis demonstrates that the pre-pandemic trend has already been achieved. However, when we enhance our analysis by including the 2018 currency and debt crisis, we observe that the recovery shown by the previous analysis disappears. During the 2018 crisis, the aggregated debit and credit card spending data show a decline only in the level, not in the trend, implying a negative wealth effect on demand. When we isolate the impact of the 2018 crisis, we observe from the counterfactual analysis that the card spending has not reached the pre-crises trend during the COVID-19 period thanks to the taken policy actions which prevented the pandemic recession from becoming the pandemic depression. Hence, the positive outlook for the recovery partially depends on the pre-existing contraction in the Turkish economy.

We also attempt to discuss the underlying reasons that explain the impact of the pandemic on aggregate demand. To do so, we test the explanatory power of the stringency index and the fear of job/income loss on consumers' behavior using Google Trends data. We choose labor market conditions since it has been a risk that the people face during both crises. Both of the factors improve the findings of our analysis, and the results suggest that the decline in card spending can be partially attributed to the expected negative income effect.

Finally, we delve deeper into the matter by focusing on the disaggregated data, and we observe the recovery for the aggregated data disappears for some sectors. It could be explained by the lack of sector-specific financial support, supply disruptions, or the

[17] Buyers, who had difficulty in finding new cars due to supply disruptions, turned to the second-hand market, which increased expenditure on second-hand vehicles in Turkey.

[18] Since data for sector-specific containment measures is not available, we cannot dissect the underlying reasons of the pandemic.

behavioral changes in consumption patterns of individuals. We already discussed that the staple sectors group did not experience severe contraction, unlike the others. On the contrary, behavioral transformation in consumption and substitutability of physical shopping with online shopping results in a notable increase in demand compared to the pre-pandemic trend. Fig. 11 shows that the card spending on online shopping has a substantial increase during the pandemic, without experiencing any fall. The demand in some sectors of the delayable group decreased on average, but the recovery phase is stronger than the social and work-related groups in the subsequent periods of the pandemic. The social and work-related groups experienced massive declines, and they are far from attaining the pre-pandemic levels. The reasons for the slow recovery in these sectors are supply disruptions imposed by the government and changes in consumer behavior due to stay-home restrictions. For example, spending more time at home substitutes clothing and accessory shopping with electric & electronic goods, computers purchases. When we focus on this issue from an income perspective, the evidence on disaggregated data shows divergence within groups, resulting in the distribution of income. Besides short-run recovery plans and actions, policymakers should also account for the expected redistribution of income of COVID-19 shock when designing their policies.

One should be careful in interpreting the findings of the analysis. Consumers have changed their means of payment due to infectious disease-related precautionary motives.[19] Some of the increase in card spending may also be due to a change in payment methods, not spending behavior. Therefore, consumers switching from cash transactions to touchless payments may be one reason for the relatively quick recovery in card spending (Wisniewski et al., 2021; Jonker et al., 2020). This behavioral change strengthens our results, indicating that the observed recovery might have been weaker in the analyzed period.

5. Conclusions

Using weekly credit and debit card spending data from March 2014 to December 2020, we show that card spending in Turkey has been significantly affected by the COVID-19 pandemic. We further provide evidence that excluding the Turkish Lira crisis yields biased results about the *normal* or *long-term* trend in card spending. A comparison of responses of card spending to COVID-19 shock with the Lira crisis in 2018 documents that the shape and the pace of recovery from these detrimental events are substantially different. During the Turkish Lira crisis, the signs of recovery were sluggish. Although the recovery phase of COVID-19 shows a steeper upward trend, thanks to economic relief packages and behavioral changes in consumption patterns, recovery to pre-crises has not been achieved yet. The analysis also shows that the overall impact of the pandemic is due to changes in safety measures affecting the mobility of consumers and the production process and fear of losing their jobs/income.

We also exploit the granularity of credit and debit card expenditure data and dissect the results by sectoral analysis. We find that the COVID-19 shock had heterogeneous effects on aggregate demand across different industries. One key finding of our study is that the recovery is unevenly distributed across sectors. Our counterfactual analysis demonstrates that only stable and delayable sector groups have reached a trend above their pre-pandemic trajectories. However, the social and work-related sectors are far from their respective pre-pandemic trajectories. In terms of policymaking, the main implications to consider are that the evidence for disaggregated data varies across sectors, leading to inter-industry distributional effects. Besides short-run recovery plans and actions, policymakers should account for the expected redistribution of income of COVID-19 shock when designing their policies.

Appendix

Interbank card center data on card spending

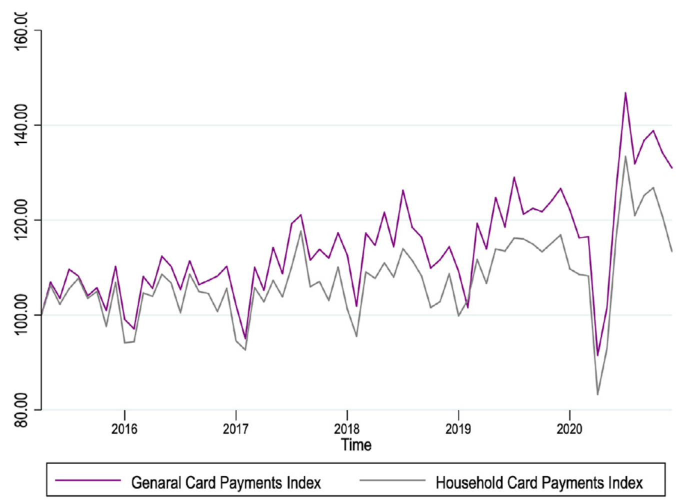


Fig. 4. Interbank Card Center Indices on Card Spending.
Notes: Base month is April 2015. General Card Payments Index is calculated using all payment transactions, whereas Household Card Payments Index is calculated based on card payment transactions with domestic cards excluding Private Pensions payments and Government/Tax payments.

Number of confirmed cases

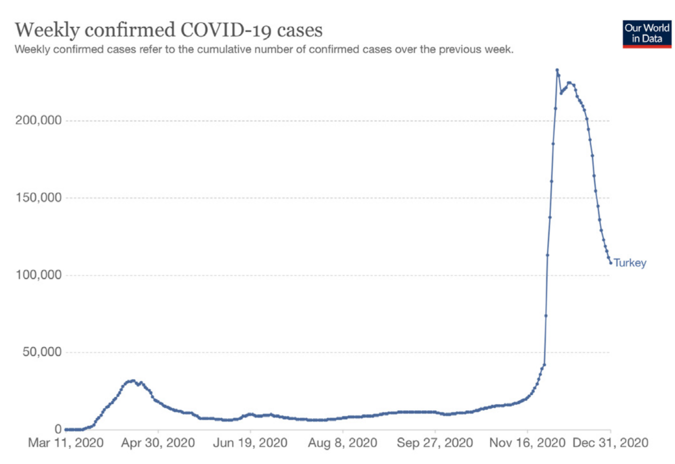


Fig. 5. Number of Confirmed Cases.
Source: COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.

[19] We thank the anonymous referee for pointing out this dimension.

More on google trends data

Table 2
Search Keywords Related to “işsizlik”

	Top	Rising
1	işsizlik	işsizlik maaşı 2019
2	işsizlik maaşı	işsizlik maaşı 2018
3	işsizlik hesaplama	2020 işsizlik maaşı
4	işsizlik maaşı şartları	2019 işsizlik maaşı ne kadar
5	işsizlik maaşı hesaplama	kısa çalışma ödeneği
6	işkur	işsizlik maaşı hesaplama 2018
7	işkur işsizlik	işsizlik maaşı hesaplama 2019
8	işsizlik ödeneği	işsizlik maaşı şartları 2017
9	işsizlik maaşı ne kadar	2021 işsizlik maaşı
10	işsizlik nasıl alınır	işsizlik maaşı ne kadar 2020
11	işsizlik maaşı nasıl alınır	işsizlik maaşı ne kadar 2018
12	e devlet işsizlik	işsizlik maaşı hesaplama 2020
13	işkur işsizlik maaşı	işsizlik maaşı hesaplama 2017
14	işsizlik başvuru	işsizlik maaşı şartları 2020
15	işsizlik maaşı e devlet	işsizlik ödeneği ne zaman yatacak
16	işsizlik maaşı başvuru	işsizlik maaşı ne kadar 2017
17	işsizlik başvurusu	işsizlik maaşı şartları 2018
18	işsizlik maaşı 2019	pandemi işsizlik maaşı
19	işsizlik maaşı alma şartları	işsizlik oranı 2019
20	işsizlik maaşı sorgulama	işsizlik maaşı nasıl alınır 2018
21	işsizlik maaşı 2018	işsizlik maaşı ne kadar
22	işsizlik maaşı başvurusu	işsizlik maaşı alma şartları 2019
23	işsizlik oranı	işsizlik maaşı nasıl alınır 2019
24	2020 işsizlik maaşı	işsizlik maaşı alma şartları 2017
25	işsizlik sigortası	işsizlik maaşı şartları neler 2020

Robustness checks

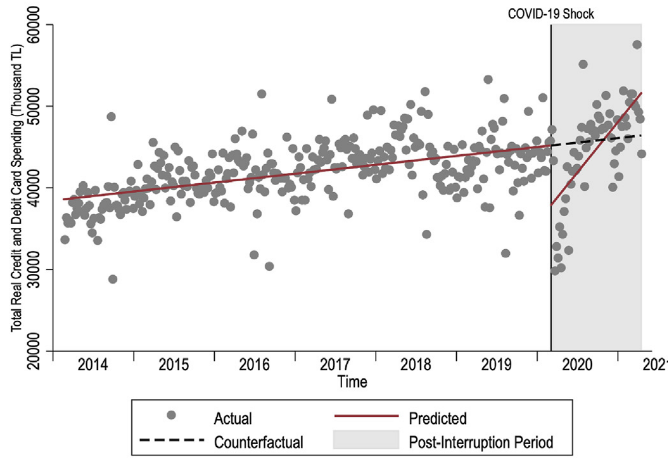
In this subsection, we presents the results of the interrupted time series analysis on total card spending with extended data set.

Table 3
Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mar14-Nov20	Mar14-Nov20	Mar14-Nov20	Mar2014-Apr21	Mar2014-Apr21	Mar2014-Apr21	Mar2014-Apr21
Time	20.97[a]	35.46[a]	35.46[a]	20.97[a]	35.46[a]	35.46[a]	35.46[a]
	(2.38)	(2.53)	(2.54)	(2.38)	(2.53)	(2.54)	(2.54)
Crisis		−3454.74[a]	−3454.74[a]		−3454.74[a]	−3454.74[a]	−3454.74[a]
		(728.39)	(729.44)		(728.03)	(730.02)	(731.02)
Time × Crisis		−9.67	−9.67		−9.67	−9.67	−9.67
		(13.05)	(13.07)		(13.04)	(13.08)	(13.09)
Pandemic	−9931.09[a]	−8973.68[a]	6501.45	−7301.64[a]	−6344.23[a]	5257.59	5936.66
	(2258.51)	(2239.25)	(4491.68)	(2105.73)	(2118.49)	(4246.92)	(4507.62)
Pandemic × Crisis	403.99[a]	399.17[a]	365.95[a]	215.44[a]	210.63[a]	386.98[a]	376.51[a]
	(85.76)	(87.86)	(51.64)	(51.56)	(53.57)	(47.75)	(51.66)
Stringency Index			−232.39[a]			−219.02[a]	−226.61[a]
			(63.83)			(60.15)	(63.31)
Dec 2020						−6047.01[a]	−6106.59[a]
						(1666.97)	(1596.74)
Vaccination Policy							55.62
							(97.36)
Constant	38605.87[a]	37356.31[a]	37356.31[a]	38605.87[a]	37356.31[a]	37356.31[a]	37356.31[a]
	(402.48)	(363.12)	(363.64)	(402.35)	(362.94)	(363.93)	(364.43)
Observations	352	352	352	373	373	373	373
Adjusted R^2	0.35	0.41	0.45	0.37	0.42	0.50	0.50
Post-Crisis Trend							
		25.79	25.79[b]		25.79[b]	25.79[b]	25.79[b]
		(12.76)	(12.78)		(12.75)	(12.79)	(12.80)
Post-Pandemic Trend							
	424.96[a]	424.95[a]	391.74[a]	236.41[a]	236.41[a]	412.72[a]	402.30[a]
	(85.74)	(85.98)	(49.16)	(51.51)	(51.65)	(45.16)	(49.12)

Notes. Interrupted time series analysis on the credit and debit card spending for the work-related category. Vaccination Policy tracks government policies on the availability of vaccinations. Parenthesis contains Newey-West-corrected standard errors.
[a] indicates significance at the 1% level.
[b] indicates significance at the 5% level.
[c] indicates significance at the 10% level.

(A) The Effect of the Pandemic



(B) Lira Crisis versus the Pandemic

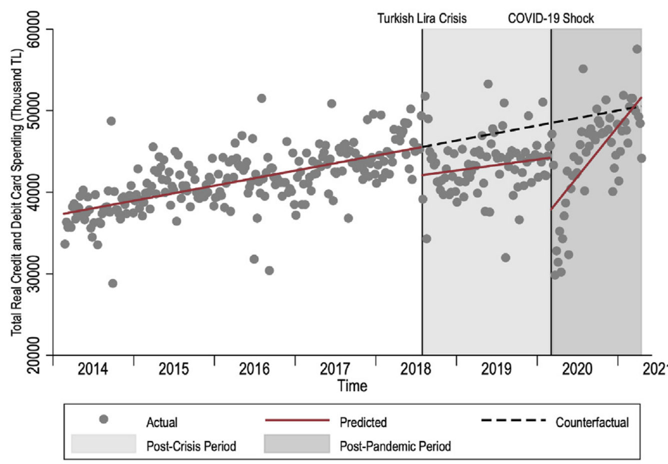


Fig. 6. Interrupted Time Series Analysis on Total Card Spending.
Notes. Scatter plots and predictions are derived from segmented-regression models of weekly credit and debit card spending during Mar14-Apr21. The vertical lines indicate the dates of interruption. Counterfactual shows trends in the absence of the interruption.

Results on sectoral data

In this subsection, we present the results of the interrupted time series analysis on sectoral card spending.

Table 4
Interrupted Time Series Analysis on Sectoral Card Spending-Staple Group

	(1) Various Food	(2) Electric-Electronic	(3) Markets	(4) Telecommunication	(5) Building Supplies
Time	2.38[a]	−1.41[a]	4.75[a]	−1.92[a]	0.50[b]
	(0.19)	(0.37)	(0.62)	(0.10)	(0.20)
Crisis	−122.03[a]	−373.26[a]	−590.08[a]	−101.08[a]	−132.58[a]
	(38.87)	(89.07)	(125.65)	(16.50)	(46.05)
Time × Crisis	1.33[c]	7.71[a]	−3.06	1.17[a]	0.55
	(0.73)	(2.07)	(3.22)	(0.29)	(0.87)
Pandemic	7.52	551.68[b]	1898.01[a]	−58.25	−71.69
	(74.62)	(233.27)	(282.99)	(40.38)	(126.37)
Time × Pandemic	5.33[c]	21.70[b]	5.39	11.79[a]	15.60[a]
	(3.16)	(9.16)	(10.22)	(1.59)	(5.20)
Constant	2204.93[a]	2628.40[a]	6802.13[a]	1355.70[a]	1537.33[a]
	(27.84)	(53.96)	(93.57)	(16.25)	(28.01)
Observations	355	355	355	355	355
Adjusted R^2	0.70	0.63	0.67	0.77	0.34
Post-Crisis Trend					
	3.71[a]	6.30[a]	1.69	−0.75[a]	1.06
	(0.70)	(2.04)	(3.17)	(0.28)	(0.85)
Post-Pandemic Trend					
	9.04[a]	28[a]	7.09	11.04[a]	16.66[a]
	(2.97)	(9.02)	(9.02)	(1.57)	(5.08)

Notes. Interrupted time series analysis on the credit and debit card spending for the staple category. Parenthesis contains Newey-West-corrected standard errors.
[a] indicates significance at the 1% level.
[b] indicates significance at the 5% level.
[c] indicates significance at the 10% level.

Table 5
Interrupted Time Series Analysis on Sectoral Card Spending-Delayable Group

	(1) Car Service	(2) Clothing	(3) Service	(4) Clubs	(5) Jewelry	(6) Furnishing	(7) Contractor Services	(8) Health
Time	1.70[a]	2.19[a]	3.88[a]	−0.01	−0.61[a]	0.28	0.86[a]	1.72[a]
	(0.15)	(0.42)	(0.47)	(0.04)	(0.13)	(0.17)	(0.07)	(0.15)
Crisis	−212.16[a]	−272.56[a]	13.35	−24.06[c]	−139.96[a]	−163.99[a]	−33.93[c]	−145.80[a]
	(31.96)	(93.37)	(70.83)	(14.14)	(24.46)	(39.41)	(20.05)	(31.54)
Time × Crisis	0.06	4.62[a]	0.14	0.34	3.82[a]	−0.51	−0.30	1.73[a]
	(0.70)	(1.67)	(1.10)	(0.25)	(0.47)	(0.78)	(0.38)	(0.58)
Pandemic	−97.62	−1744.58[a]	−231.47[c]	−42.65[b]	−427.66[a]	−146.95	7.55	−379.11[b]
	(131.50)	(447.58)	(120.36)	(18.75)	(86.76)	(159.14)	(37.15)	(165.45)
Time × Pandemic	10.82[b]	37.73[b]	4.76	0.71	2.96	14.33[b]	3.35[b]	13.35[b]
	(5.27)	(17.57)	(5.00)	(0.64)	(2.88)	(6.00)	(1.46)	(6.48)
Constant	1155.13[a]	2928.37[a]	1738.09[a]	200.50[a]	779.66[a]	1474.64[a]	205.64[a]	1152.75[a]
	(21.99)	(53.09)	(43.92)	(5.21)	(18.57)	(22.48)	(9.85)	(19.96)
Observations	355	355	304	355	355	355	355	355
Adjusted R^2	0.37	0.29	0.67	0.03	0.48	0.18	0.72	0.49
Post-Crisis Trend								
	1.77[b]	6.80[a]	4.02[a]	0.34	3.22[a]	−0.23	0.55	3.45[a]
	(0.68)	(1.63)	(1)	(0.25)	(0.45)	(0.76)	(0.37)	(0.55)
Post-Pandemic Trend								
	12.59[b]	44.54[b]	8.78[c]	1.05[c]	6.18[b]	14.1[b]	3.91[a]	16.8[a]
	(5.18)	(17.58)	(4.83)	(0.58)	(2.89)	(5.92)	(1.41)	(6.35)

Notes. Interrupted time series analysis on the credit and debit card spending for the delayable category. Parenthesis contains Newey-West-corrected standard errors.
[a] indicates significance at the 1% level.
[b] indicates significance at the 5% level.
[c] indicates significance at the 10% level.

Table 6
Interrupted Time Series Analysis on Sectoral Card Spending-Social Group

	(1)	(2)	(3)	(4)	(5)
	Airlines	Accommodation	Casino	Travel Agencies	Food
Time	1.96[a]	0.63[a]	0.05[a]	2.45[a]	3.37[a]
	(0.29)	(0.15)	(0.02)	(0.29)	(0.29)
Crisis	116.06[c]	−27.98	21.26[c]	−3.92	−101.08[c]
	(67.35)	(29.67)	(11.44)	(85.50)	(51.94)
Time × Crisis	1.55	−0.47	0.14	−2.76	1.63[b]
	(0.95)	(0.46)	(0.23)	(1.89)	(0.71)
Pandemic	−1179.42[a]	−516.86[a]	−61.38[a]	−966.39[a]	−1107.26[a]
	(134.70)	(81.57)	(16.51)	(163.83)	(311.20)
Time × Pandemic	12.08[a]	9.82[a]	0.21	12.95[a]	17.50
	(4.08)	(2.98)	(0.56)	(3.73)	(14.28)
Constant	61.11[a]	558.31[a]	36.65[a]	809.05[a]	1057.99[a]
	(30.09)	(20.03)	(1.78)	(29.37)	(36.92)
Observations	355	355	355	355	355
Adjusted R^2	0.80	0.56	0.47	0.63	0.61
Post-Crisis Trend					
	3.5[a]	0.16	0.19	−0.3	5[a]
	(0.9)	(0.44)	(0.23)	(1.87)	(0.66)
Post-Pandemic Trend					
	15.58[a]	9.98[a]	0.4	12.64[a]	22.49
	(4.19)	(2.99)	(0.52)	(3.69)	(14.25)

Notes. Interrupted time series analysis on the credit and debit card spending for the social category. Parenthesis contains Newey-West-corrected standard errors.
[a] indicates significance at the 1% level.
[b] indicates significance at the 5% level.
[c] indicates significance at the 10% level.

Table 7
Interrupted Time Series Analysis on Sectoral Card Spending- Work-Related Group

	(1)	(2)	(3)
	Car Rental	Petrol Stations	Education
Time	0.33[a]	0.65	2.20[a]
	(0.03)	(0.50)	(0.32)
Crisis	−25.25[a]	−2.40	−81.78
	(4.55)	(104.11)	(99.49)
Time × Crisis	−0.47[a]	−12.01[a]	−2.75
	(0.07)	(1.80)	(2.05)
Pandemic	−32.23[a]	−753.91[a]	−326.10[a]
	(11.96)	(232.84)	(123.60)
Time × Pandemic	1.51[a]	35.41[a]	6.71
	(0.49)	(8.43)	(4.19)
Constant	61.11[a]	3560.80[a]	918.33[a]
	(3.08)	(65.63)	(46.63)
Observations	355	355	355
Adjusted R^2	0.49	0.71	0.16
Post-Crisis Trend			
	−0.14[b]	−11.37[a]	−0.55
	(0.06)	(1.73)	(1.99)
Post-Pandemic Trend			
	1.38[a]	24.05[a]	6.16[c]
	(0.49)	(8.09)	(3.68)

Notes. Interrupted time series analysis on the credit and debit card spending for the work-related category. Parenthesis contains Newey-West-corrected standard errors.
[a] indicates significance at the 1% level.
[b] indicates significance at the 5% level.
[c] indicates significance at the 10% level.

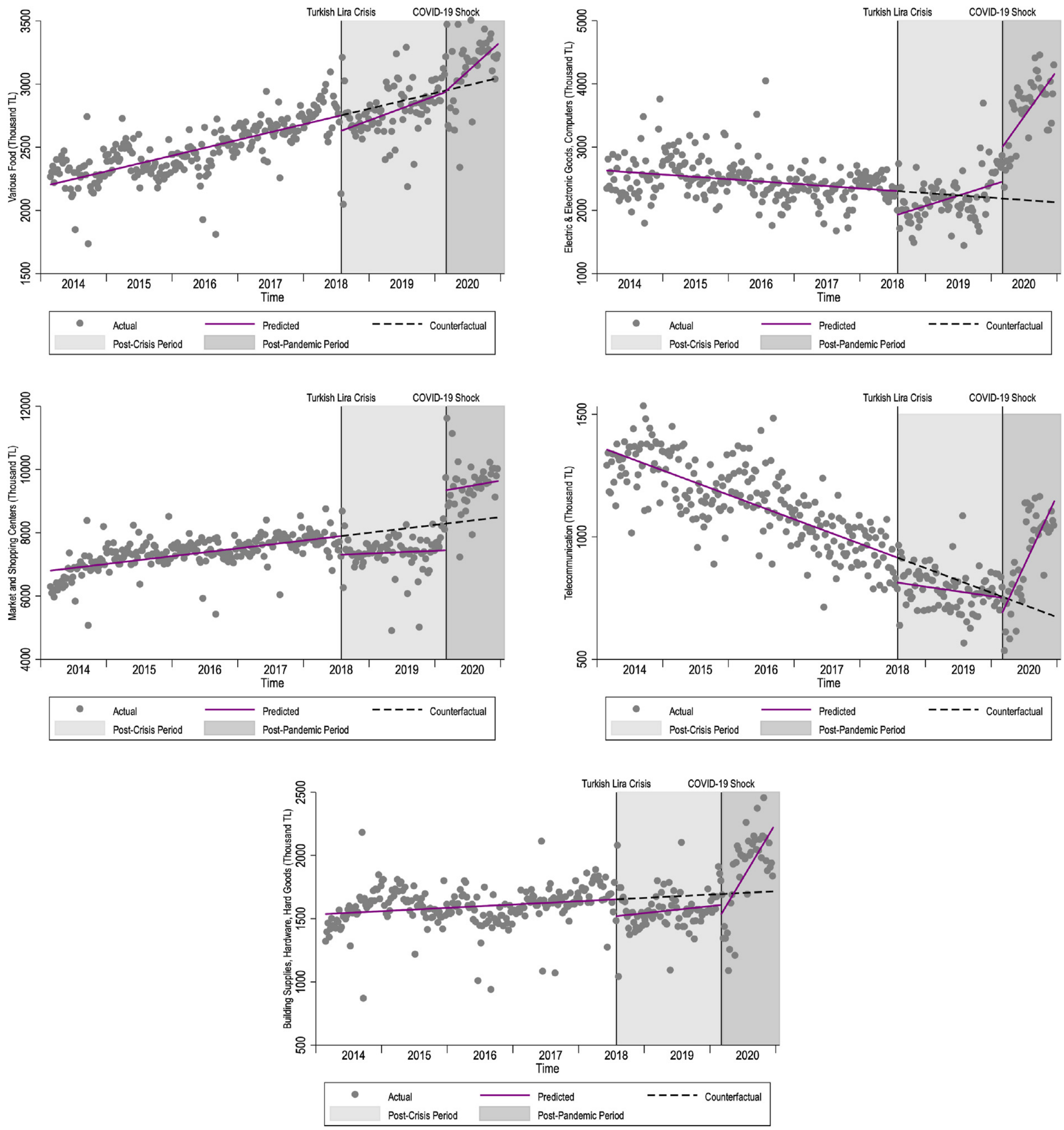


Fig. 7. Counterfactual analysis on staple group.
Notes. Scatter plots and predictions are derived from segmented-regression models of weekly credit and debit card spending. The vertical lines indicate the dates of interruption. Counterfactual shows trends in the absence of the interruption.

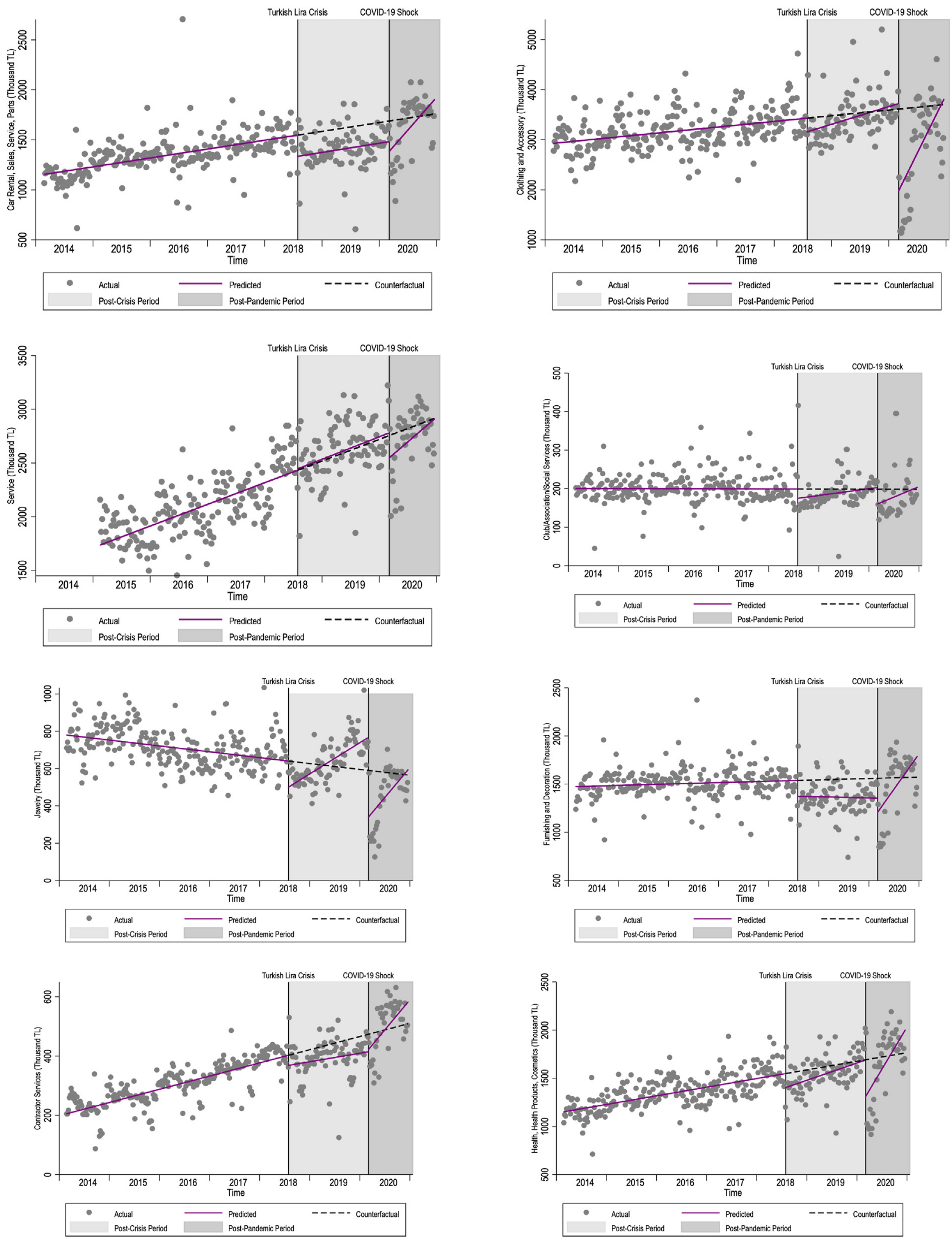


Fig. 8. Counterfactual analysis on delayable group.
Notes. Scatter plots and predictions are derived from segmented-regression models of weekly credit and debit card spending. The vertical lines indicate the dates of interruption. Counterfactual shows trends in the absence of the interruption.

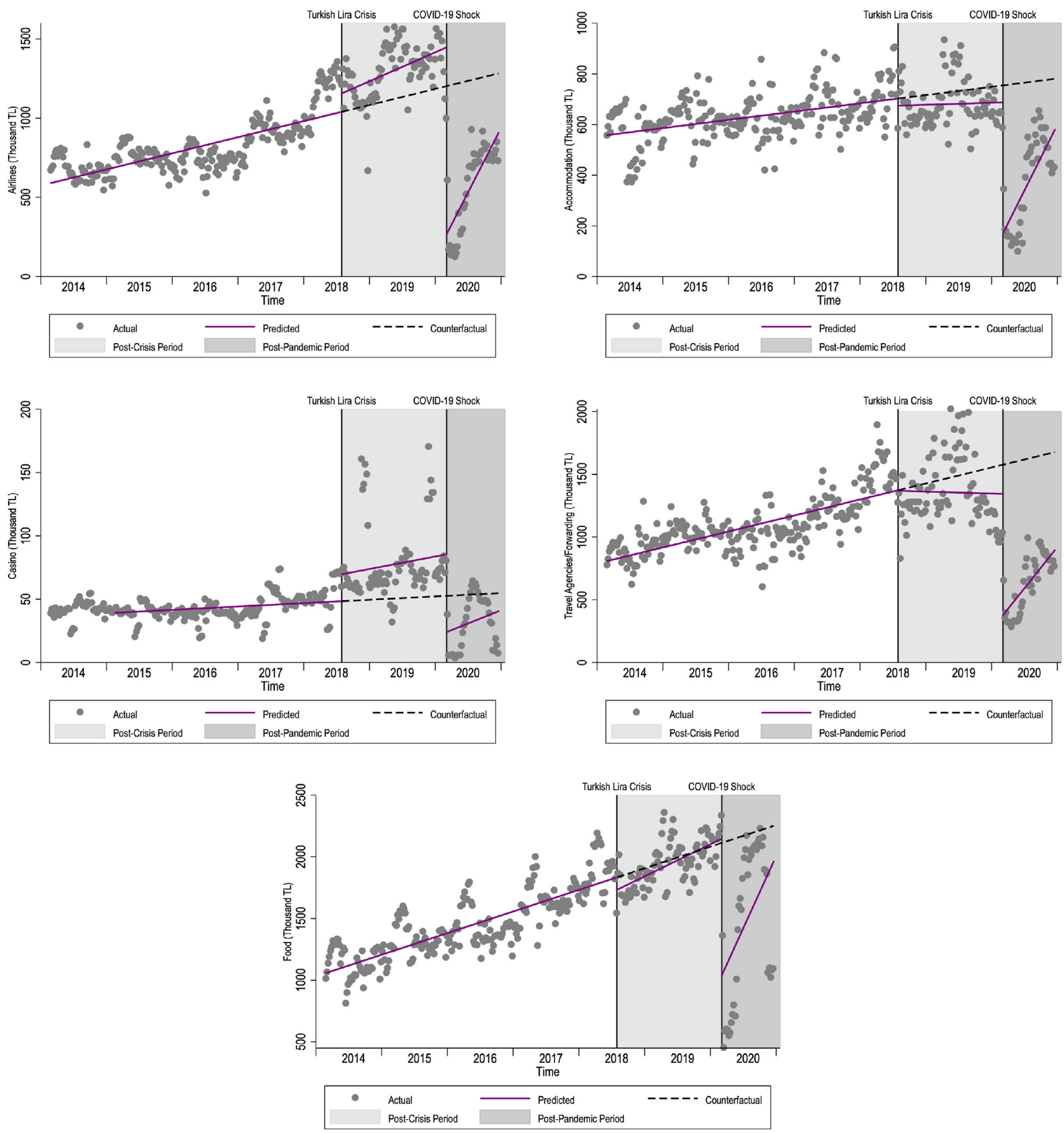


Fig. 9. Counterfactual analysis on social group.

Notes. Scatter plots and predictions are derived from segmented-regression models of weekly credit and debit card spending. The vertical lines indicate the dates of interruption. Counterfactual shows trends in the absence of the interruption.

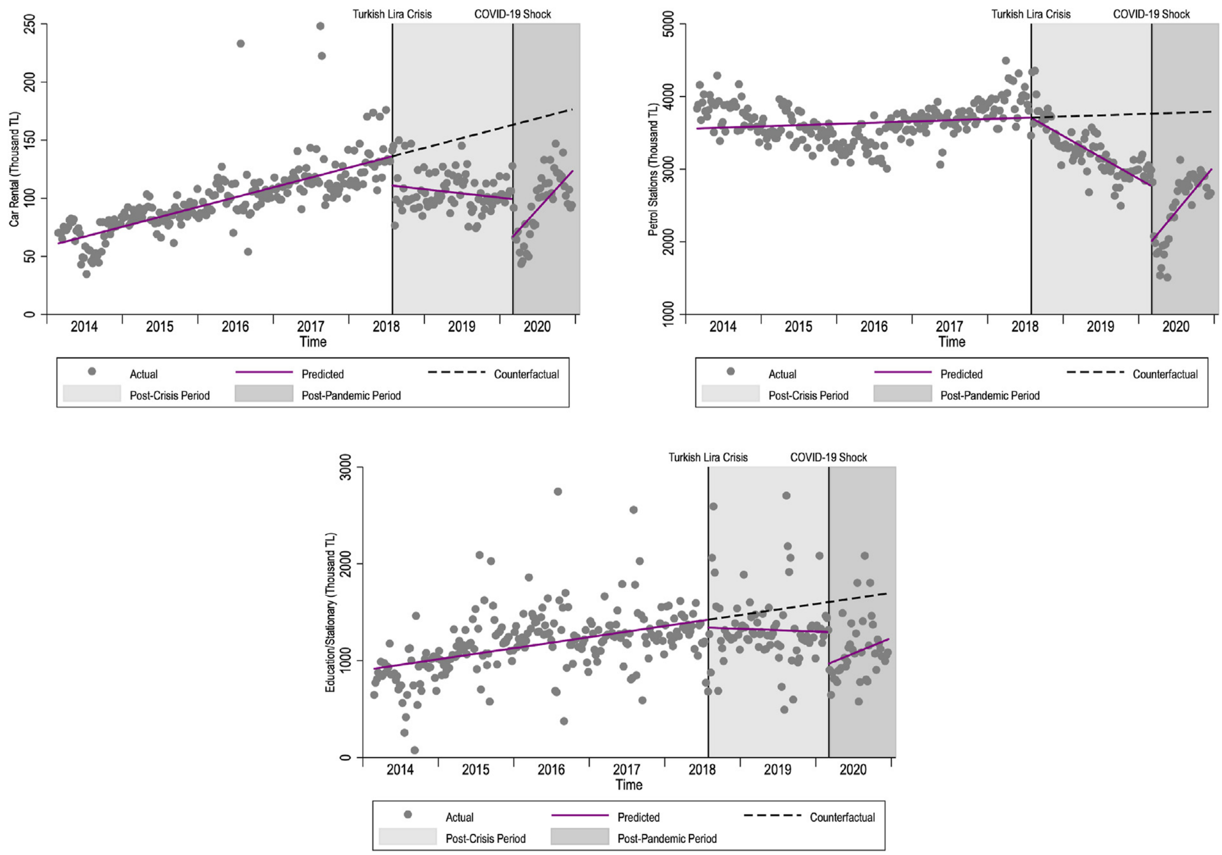


Fig. 10. Counterfactual analysis on work-related group.
Notes. Scatter plots and predictions are derived from segmented-regression models of weekly credit and debit card spending. The vertical lines indicate the dates of interruption. Counterfactual shows trends in the absence of the interruption.

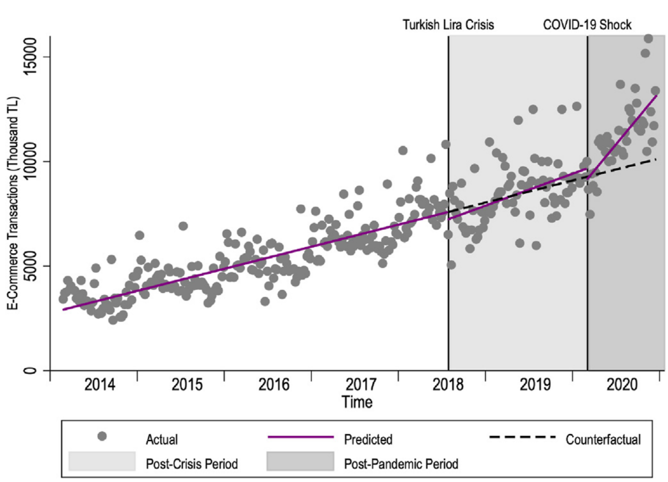


Fig. 11. Online Shopping.
Notes. Scatter plots and predictions are derived from segmented-regression models of weekly credit and debit card spending. The vertical lines indicate the dates of interruption. Counterfactual shows trends in the absence of the interruption.

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