Consumer Reponses to the COVID-19 Crisis: Evidence from Bank Account Transaction Data *

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Abstract

This paper uses transaction-level customer data from the largest bank in Denmark to estimate consumer responses to the COVID-19 pandemic and the partial shutdown of the economy. We find that aggregate card spending has dropped sharply by around 25% following the shutdown. The drop is mostly concentrated on goods and services whose supply is directly restricted by the shutdown, suggesting a limited role for spillovers to non-restricted sectors through demand in the short term. The spending drop is somewhat larger for individuals more exposed to the economic risks and health risks introduced by the COVID-19 crisis; however, pre-crisis spending shares in the restricted sectors is a much stronger correlate of spending responses.

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1 Introduction

The COVID-19 pandemic represents a grave risk to public health and most governments have attempted to contain the virus by shutting down parts of the economy (e.g. Kraemer et al., 2020). Beyond the direct health consequences, the economic costs have been staggering: millions of workers have lost their jobs and trillions of dollars of stock market wealth has been destroyed.

A key concern for firms and policymakers is the size and the nature of the consumer response. While some highlight that the shutdown is, in essence, a supply shock with possible spill-overs to the demand side (Guerrieri et al, 2020), others stress that the pandemic may also affect demand directly because the health risk of going to public spaces like shops, restaurants and hairdressers deters consumption (Eichenbaum et al, 2020). In either case, the dynamics on the demand side may lead to a recession that persists long after the epidemic has ended and restrictions on economic activity have been lifted (Gourinchas, 2020). If consumers respond to mass lay-offs, falling asset prices (Gormsen and Koijen, 2020) and an uncertain financial outlook (Baker et al., 2020a) by slashing private consumption, the epidemic may mark the beginning of a demand-driven economic meltdown. In the face of this risk, governments have initiated massive programs, including fiscal, monetary and regulatory measures, to support businesses and households.

In this paper, we use transaction data for card spending in Denmark to study consumer responses to the COVID-19 crisis. The crisis has unfolded in Denmark as in many other developed countries in Europe and North America: the first case of COVID-19 was confirmed on 28 February 2020 and the government announced a partial shutdown of the economy on 11 March to get the virus under control and a series of interventions to sustain the economy in the following days. At the time of writing, the cumulative mortality is comparable to Germany and the United States (John Hopkins, 2020) whereas fiscal stimulus is somewhat larger than in the United Kingdom but lower than in the United States (Bruegel, 2020).[1]

Our analysis proceeds in three steps. First, we estimate the change in aggregate consumer spending since the onset of the crisis. Consumer spending is the largest component of private demand and therefore of immediate interest to governments designing policy responses in the form of fiscal and monetary stimulus. Second, we study heterogeneity in spending responses across categories of expenditure. As entire sectors of the economy are effectively shut down,

[1] As of 7 April 2020, the cumulative mortality in Denmark stood at 3.5 per 100.000 inhabitants compared to 2.4 in Germany and 3.9 in the United States (John Hopkins, 2020). The immediate fiscal stimulus in Denmark is estimated at 2.1% of GDP compared to 1.4% in the United Kingdom and 5.5% in the United States (Bruegel, 2020).

consumer spending on the goods and services produced in those sectors is bound to decline. Guided by recent theory (Guerrieri et al, 2020), we conduct a simple test of spill-overs to the demand-side by estimating the change in consumer spending on categories that are not constrained on the supply-side. Third, we study heterogeneity in spending responses across individuals with different characteristics. We investigate the mechanisms underlying the drop in consumer spending by estimating how the spending drop varies with measures of income risk, wealth losses, health risk and *ex ante* spending on supply-constrained goods and services.

Our analysis uses transaction data for about 760,000 individuals who hold their main current account at Danske Bank, the largest retail bank in Denmark with a customer base that is roughly representative of the Danish population. For each individual, we observe every purchase made by cards through accounts at the bank from 1 January 2018 through the shutdown of large parts of the Danish economy on 11 March to the end of our sample period on 5 April 2020. This allows us to construct a customer-level measure of total spending at the daily frequency and, exploiting a standardized classification of merchants, a breakdown of total spending by expenditure category. The dataset also contains basic demographic information such as age and gender and allows us to construct a measure of income based on the bank's algorithm for categorizing account inflows.

Our aim is to estimate the drop in consumer spending relative to a counterfactual without the pandemic and without the shutdown. The main empirical challenge is the strong cyclicality of spending over the week, the month and the year. We address the cyclicality by comparing consumer spending on each day in 2020 to consumer spending on a reference day 364 days earlier, which is always the same day of the week and almost exactly the same place in the monthly and annual spending cycle. We first compute *excess spending* as the difference between spending on a given day in 2020 and spending on the reference day in 2019. We then compute the consumer response as the difference between excess spending in the post-shutdown period (11 March - 5 April) and excess spending in the pre-shutdown period (1 January - 15 February).[2] The identifying assumption is that the year-over-year growth in consumer spending observed in the pre-shutdown period would have continued in the post-shutdown period absent the COVID-19 crisis.

Our main finding is that aggregate card spending dropped by around 25% relative to the counterfactual trajectory. This estimate reflects that excess spending averaged 2% over the pre-shutdown period and -23% over the post-shutdown period. The dynamics supports a causal

[2]We do not include the days immediately before the shutdown (15 February - 10 March) to avoid that anticipation effects affect the counterfactual.

interpretation: aggregate spending remained remarkably similar to the reference period until the shutdown and then fell sharply. The magnitude of the estimated response is enormous compared to consumer responses to other types of shocks. For instance, two recent studies using similar data find that job losses are associated with spending drops of around 5-10% (Ganong and Noel, 2019; Andersen et al., 2020).

The responses vary widely across sectors and correlate strongly with the severity of the restrictions imposed by the government. On the one hand, spending increased modestly in grocery stores and pharmacies, which remained open throughout the shutdown. On the other hand, spending dropped dramatically on items where restrictions were particularly severe such as travel, restaurants and personal services. In aggregate, we find that spending increased by around 10% in sectors where supply was totally unconstrained by government interventions (around half of the economy) while it dropped by almost 70% in sectors where supply was most constrained (around one quarter of the economy). Our results suggest that the partial shutdown had negative spill-overs on certain open sectors through the demand side (Guerrieri et al, 2020). For instance, spending on fuel and commuting plummeted although gas stations remained open, presumably because shopping centers and work places shut down. More generally, however, our results suggest a limited role for negative spillovers of supply shocks through the demand side, at least within the relatively short time frame covered by our analysis.

To investigate the causal mechanisms, we provide estimates for subsamples that are heterogeneous in one dimension (e.g. age) while re-weighting observations to make the subsamples homogeneous in other dimensions (e.g. income). Consistent with an important role for *supply constraints*, a high spending share on items such as travel and restaurants before the shutdown is associated with a differential spending decrease of around 12 percentage points. It seems that *economic risks* play a smaller role as the differential spending cut for individuals working in closed sectors (exposure to job loss) and for individuals holding stocks (exposure to bleeding stock markets) is modest. The evidence that the direct *health risks* associated with shopping deter spending is mixed: individuals above 65 years (exposure due to age) reduce spending more than others whereas spending in pharmacies before the shutdown (exposure due to pre-existing condition) is almost uncorrelated with the spending response.

In summary, our results document that the closed sector of the economy is at the heart of the drop in consumer spending. There are two possible interpretations. Either, the drop in spending is caused directly by the shutdown, e.g. consumers do not go to restaurants because they are closed. Or, the drop in spending is caused by the health risks that motivated the shutdown, e.g. consumers would not go to restaurants if they were open because it would expose them to the virus. Our results provide some support for both of these interpretations. Within the relatively short time frame of our analysis, economic risks such as income and wealth losses play a limited role, but this may change over longer horizons.

Our analysis contributes to a growing empirical literature on the economic consequences of the COVID-19 crisis. Two papers make predictions about the likely macro-economic effect of the pandemic using forward-looking indicators: uncertainty measures based on stock market data, newspaper articles and business expectation surveys (Baker et al., 2020a) and price information for dividend futures (Gormsen and Koijen, 2020). Other papers draws lessons for health and economic outcomes by comparing to epidemics in the past (e.g. Barro et al., 2020; Correia et al., 2020). The most closely related paper is Baker et al. (2020b) who describe spending dynamics in the U.S. in the early weeks of the COVID-19 epidemic based on a sample of 5,000 users of a financial app.

Our paper also contributes to the broader literature on consumption dynamics. Many papers have studied how household consumption responds to macro-economic events such as *financial crisis* (e.g. Mian et al., 2013; Andersen et al., 2016; Jensen and Johannesen, 2017), *economic policies* (e.g. Shapiro and Slemrod, 2003; Johnson et al., 2006; Parker et al., 2013; Di Maggio et al., 2017) and idiosyncratic changes in *income* (e.g. Baker, 2018; Kueng, 2018; Ganong and Noel, 2019), *wealth* (e.g. Di Maggio et al., 2018; Aladangady, 2017), *health* (e.g. Mohanan, 2013) and *uncertainty* (e.g. Carroll, 1994). We relate to this literature by, first, quantifying the aggregate spending response to an immense shock encompassing income losses, wealth destruction, health risks and financial uncertainty and, next, assessing the importance of each of these elements by comparing samples with different exposure to the different shocks. While most papers rely on consumption data from household surveys (e.g. Shapiro and Slemrod, 2003) or imputed consumption from administrative data on income and wealth (Browning and Leth-Petersen, 2003), we follow a recent wave of papers using transaction data (e.g. Gelman et al., 2014; Baker, 2018).

The paper proceeds in the following way. Section 2 briefly accounts for the Danish context. Section 3 describes the data sources and provides summary statistics. Section 4 develops the empirical framework. Section 5 reports the results. Section 6 concludes.

2 Background

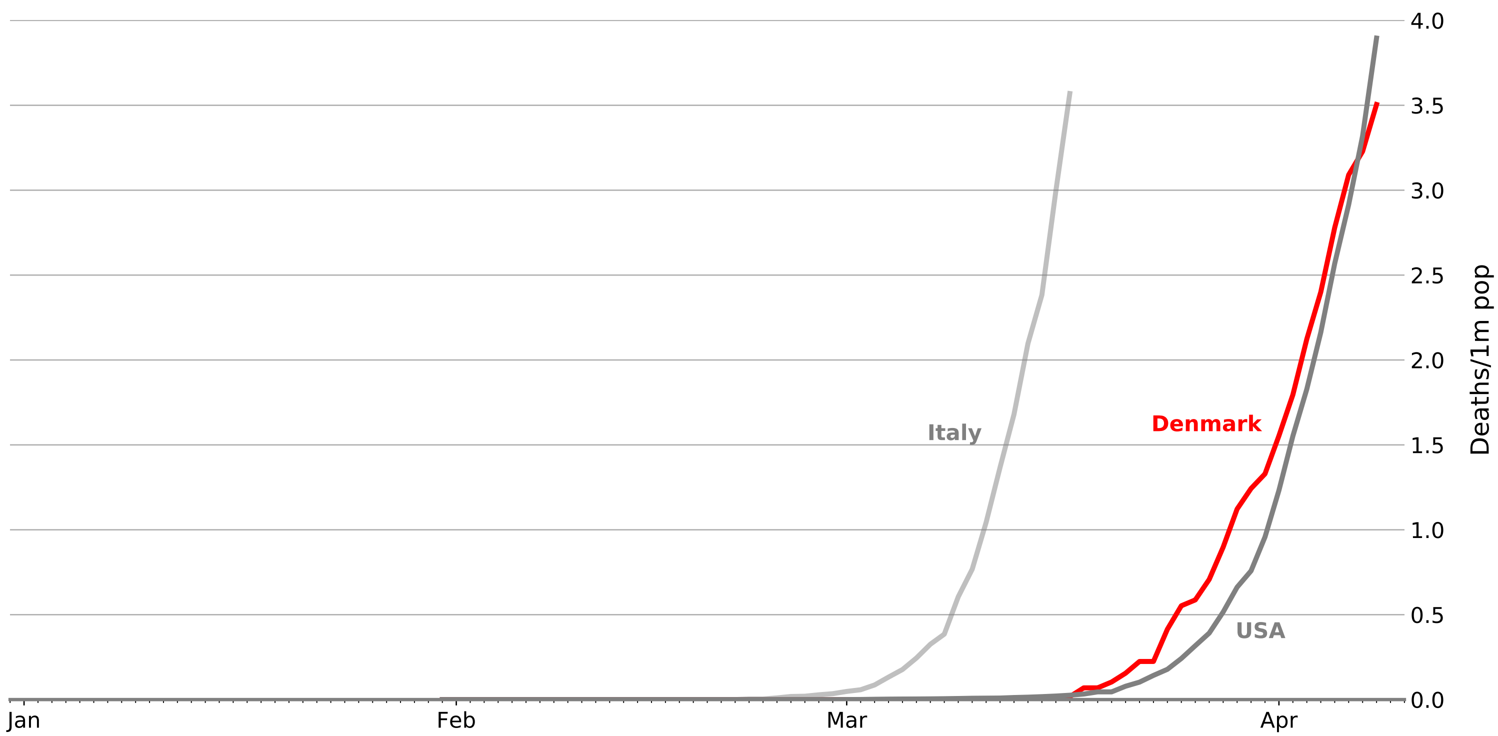
The first case of COVID-19 in Denmark was confirmed on 28 February 2020 and more cases quickly followed. Initially, all cases were related to travelling in the most affected areas of Europe, but the virus soon started spreading within the country. So far, the dynamics has resembled the experience of the United States, as illustrated in Figure 1, and that of many developed countries. As of 7 April 2020, cumulative mortality per 100.000 inhabitants due to COVID-19 stood at 3.5 in Denmark and 3.9 in the United States compared to 28 in Italy, which has the highest recorded per capita mortality in the world together with Spain (European Centre for Disease Prevention and Control, 2020).

The Danish authorities initially attempted to contain the virus by placing COVID-19 patients as well as individuals with recent contact to the patients in home quarantine and by discouraging travel to the most affected areas in the world. However, on 11 March, the Prime Minister announced a national lockdown in a televised speech: all non-essential parts of the public sector were shut down (including schools, libraries and universities); private sector employees were urged to work from home; borders were closed for foreign nationals and air traffic therefore virtually closed; the population was generally encouraged to avoid social contact. On 18 March, the government announced further restrictions banning congregations of more than 10 individuals, shutting down shopping centers, hairdressers and nightclubs and restricting restaurants to take-away service. The timing and severity of the measures were generally comparable to most of Northern Europe (such as Germany, Netherlands and Norway), but less restrictive than in Southern Europe where the virus spread more rapidly (such as Italy, France and Spain).

The Danish shutdown was accompanied by massive government programs to mitigate the financial damage to businesses and households. First, to help firms overcome temporary liquidity problems, deadlines for making tax payments were postponed and regulatory constraints on bank credit were loosened. Second, to prevent mass lay-offs, the government committed to pay 75% of the salary of private sector employees who were temporarily sent home as long as the employer committed to keep them on the payroll at full salary. Third, to mitigate business failures, separate policies offered partial compensation to all firms for fixed costs and to self-employed for lost revenue. These programs were all proposed by the government within the first week after the shutdown and received unanimous support in the Danish Parliament. The programs were similar in scale and scope to those launched by many other governments in Europe (Bruegel, 2020).[3]

[3]For instance, the immediate fiscal stimulus in Denmark is estimated at 2.1% of GDP compared to 1.2% in

Figure 1: COVID-19 mortality. The figure shows cumulative mortality due to COVID-19 for Denmark, Italy and the United States over the period 1 January 2020 - 8 April 2020. Numbers for Italy are only shown until 17 March 2020. Source: European Centre for Disease Prevention and Control (2020).



3 Data

We measure consumer spending with transaction data from Danske Bank, the largest retail bank in Denmark. We have information about every purchase made with payment cards (credit cards and debit cards): the date and the amount as well as the branch code and location of the shop. Moreover, we extract information on income using the bank's own algorithm for classifying money flows coming into accounts. Finally, we obtain basic demographic information such as age and gender from the bank's customer records.

We use two criteria to define a sample of adult individuals who consistently use Danske Bank as their main bank and for whom we measure their income relatively well. First, we require that customers have held their main current account at Danske Bank between 1 January 2018 and the end of the sample period.[4] Second, we require that customers made at least one card payment in each month between 1 January 2018 and 31 December 2019. We do not impose a spending requirement in 2020 as we want to allow that card spending falls to zero in response to the crisis.[5] With these restrictions, our sample consists of around 760,000 individuals.

We create a measure of *aggregate spending* by summing the card payments by all individuals in the sample on a given day.[6] Further, we create measures of specific *spending categories*, such as groceries, travel and restaurants, based on a standardized coding of the type of goods and services each shop provides.[7] Finally, we create three composite spending categories that aggregate individual spending categories based on the extent to which the supply was constrained by government restrictions. At one extreme, we consider travel, restaurants, personal services (e.g. dentists, hairdressers and beauty salons) and entertainment (e.g. cinemas, theatres and bars) as *closed sectors*. These sectors were, in principle, shut down although there were exceptions. For instance, restaurants were not allowed to seat guests, but could sell take-away food; dentists

France, 1.4% in the United Kingdom, 4.4% in Germany and 5.5% in the United States.

[4] In Denmark, all citizens need to register a bank account for monetary transactions with the public sector, e.g. tax refunds, child subsidies, pensions, student loans, unemployment benefits, housing support and social welfare payments. We assume that this "EasyAccount" is also the main current account.

[5] We make two additional sample restrictions, both very minor. First, we require that individuals have active joint accounts with at most one other individual. We define couples as individuals who share a joint account and live on the same address, however, this definition is ambiguous for individuals sharing accounts with multiple others. Second, we require that the ratio of total spending to disposable income is below two. When individuals seemingly spend many times their disposable income, the most likely explanation is that we do not measure their income well. The two restrictions jointly reduce the sample size by 2%.

[6] Card payments account for around 75% of total spending in our sample while other payment methods (e.g. bills, wire transfers, cash) account for the remaining 25%.

[7] Following the emerging literature that uses transaction-data from banks and financial apps to study consumer spending (Ganong and Noel, 2019), we categorize spending by four-digit Merchant Category Code, which is an international standard for classifying merchants by the type of goods and services they provide.

were closed, but could take emergency patients; international travel was virtually impossible as borders were closed, but domestic tourism was possible. At the other extreme, we consider online retail (except airlines etc), groceries and pharmacies to be *open sectors*. These sectors faced only very mild constraints. For instance, the government instructed consumers to limit the number of shopping trips and to keep distance in the stores. As an intermediate case, we consider retail (except online), fuel and commuting to be *constrained sectors*. Within the retail sector, malls were shut down but high-street shops were generally allowed to remain open. In the public transport sector, trains and buses continued to operate but at much reduced frequencies. We provide more detail on the coding of supply constraints in Table A1 in the Appendix.

Finally, we divide the full sample into various subsamples in order to compare spending responses across individuals who are exposed to the epidemic in different ways. Here, it becomes important to account for household structure. Since economic resources are usually pooled within households, it is generally not meaningful to assign spouses to different income groups based on their individual incomes. Similarly, since one spouse often buys items for other members of the household when shopping, it is not meaningful to divide spending across spouses based on their individual purchases. We address this issue by assigning individuals to households based on the information available in the bank's records: when two individuals live on the same address and have a joint bank account, we assume that they are cohabiting partners and divide each income flow and each purchase equally between them.[8] Averaging income and spending across cohabiting partners has no bearing on the main analysis in the full sample.

We split the sample along a number of dimensions. First, to capture differences in the distortions created by *supply constraints*, we split the sample by the ratio of supply constrained spending to total spending measured in 2019 before the supply constraints kicked in. Second, to capture differences in *health risk*, we split the sample by age (above and below 65 years) and by pharmacy spending in 2019 reflecting that COVID-19 is much more dangerous for the elderly and for individuals with pre-existing medical conditions. Third, to capture the differences in *wealth losses*, we create subsamples of stockholders and non-stockholders in 2019 reflecting that stock markets both in Denmark and elsewhere plunged around the shutdown (Gormsen and Koijen, 2020). Finally, to capture differences in the exposure to *job losses*, we split the sample by the income level in 2019 reflecting that low-income jobs constitute a large share of total employment in the closed sectors.[9] We also study exposure to job losses in an alternative way

[8]For instance, when one spouse spends DKK 200 at the pharmacy, we consider that each spouse has spent DKK 100 and when the other spouse receives a DKK 20,000 pay check, we consider that each spouse has received income of DKK 10,000.

[9]In the United Kingdom, employees in the shut-down sectors constituted 35% of all individuals in the bottom

Table 1: Summary statistics. This table presents summary statistics for our analysis sample of Danske Bank customers (Column (1)) and the approximate population of Denmark from which they are drawn (Column (2)). Statistics in Column (1) are calculated on an annual basis as of December 2019. Population figures are sourced from the Danish Statistics Agency's (DST) online Statistics Bank for the most comparable population available: 18+ year olds in 2018. Some differences between variable construction are explained below.
* Individual-level measure constructed for the 14+ years population in 2018.
** Individual-level measure for the 14+ years population in November 2018, without any tenure requirement.
Details on the construction of the income, industry and spending measures for the analysis sample (Column (1)) can be found in the Appendix.

		Sample	**Population**
		(1)	(2)
Female		51.6%	50.6%
Age:			
	18-29 years	21.5%	19.9%
	30-44 years	22.1%	22.5%
	45-64 years	33.0%	32.9%
	65+ years	23.4%	24.7%
Disposable income (USD)		37,554.6	34,615.4*
Stockholder		27.8%	25.2%*
Industry:			
	At-risk, Private	4.2%	6.8%**
	Other, Private	33.4%	36.7%**
	Public	19.5%	18.2%**
Total card spending (USD)		16,900.60	-
Spending by category, %Total:			
	Groceries	30.3%	-
	Pharmacies	1.7%	-
	Retail	20.3%	-
	Entertainment	3.8%	-
	Fuel & commuting	8.1%	-
	Prof. & pers. svcs	5.5%	-
	Food away from home	8.6%	-
	Travel	6.2%	-
Online spending, %Total:			
	All online	26.7%	-
	Groceries	1.3%	-
	Retail	8.7%	-
	Food away from home	0.9%	-
	Travel	5.0%	-
Spending by shutdown effect, %Total:			
	Closed	26.1%	-
	Constrained	26.6%	-
	Open	47.2%	-
N		760,571	4,670,227

by splitting the sample by employer industry: public sector where employees should not expect to be laid off, private sector firms directly affected by the shutdown (e.g. restaurants, hotels, personal care) and other private sector firms. We provide more detail on the coding of industries in Table A2 in the Appendix.

Table 1 reports summary statistics for our estimating sample (Column 1) and compare to socio-economic information for the full adult population obtained from government registers (Column 2). Our sample of 760,000 individuals is largely representative of the adult population of 4,670,000 individuals in terms of gender, age, income and stock market participation. This reflects that Danske Bank is a broad retail bank present in all parts of the country and catering to all types of customers. Our sample seemingly includes a smaller fraction of individuals working in at-risk sectors than the full population. This may reflect that we impose a 3-month tenure requirement when assigning individuals to industries combined with the fact that at-risk sectors generally have a higher turnover. By comparison, the industry distribution in population-wide statistics is a snapshot with no tenure requirement.

4 Empirical strategy

The main aim of the empirical analysis is to measure the change in consumer spending induced by the corona crisis: the COVID-19 epidemic, the shutdown of the economy and the various stimulus policies.

To capture the sharp change in behavior around the shutdown, we use spending information at the daily level. The high frequency creates empirical challenges as spending exhibits strong cyclicality over the week, the month and the year. We address the cyclicality by comparing consumer spending on each day in 2020 to consumer spending on a reference day 364 days earlier. The reference day is always the same day of the week and almost exactly the same place in the monthly and annual spending cycle. For example, we compare 8 February 2020 (a Saturday) to the reference day 9 February 2019 (also a Saturday). While the method does not account for the fact that spikes in spending due to pay days (Gelman et al., 2014; Olafsson and Pagel, 2018) may fall on different weekdays in different years, this will not affect our key estimates as explained below.[10]

For each day of our window of analysis, 1 January 2020 – 5 April 2020, we thus compute the

decile of the income distribution compared to 5% of the individuals in the top decile (Joyce and Xu, 2020). We expect that a similar relationships exists in Denmark.

[10]We refer to the notion of pay days in a loose way. While there is no uniform pay day in Denmark, most salary payouts in a given month typically fall on a few days around the end of the month.

difference between aggregate spending on the day itself and aggregate spending on the reference day the year before. Scaling with average daily spending over a long period before the window of analysis, we obtain a measure of excess spending on a given day expressed as a fraction of the normal level of spending:

$$excess\ spending_t = \frac{spending_t - spending_{t-364}}{average\ spending}$$

where $spending_t$ is spending on day t and *average spending* is average daily spending taken over all days in 2019.

Equipped with this machinery, we measure the effect of the crisis as the difference between average excess spending in the post-shutdown period, 11 March – 5 April, and average excess spending in the early pre-shutdown period, 1 January – 15 February:

$$\Delta spending = \underbrace{E[excess\ spending_t | t \in post]}_{\substack{\text{average excess spending} \\ \text{post-shutdown}}} - \underbrace{E[excess\ spending_t | t \in pre]}_{\substack{\text{average excess spending} \\ \text{pre-shutdown}}}$$

We effectively use excess spending in the pre-shutdown period as a counterfactual for excess spending in the post-shutdown period. In plain words, we assume that year-over-year spending growth between 2019 and 2020 would have been the same after 11 March as before absent the epidemic and the shutdown. However, we exclude 16 February - 11 March from the pre-shutdown period as early restrictions (e.g. on air travel to Asia) and anticipation of the broader crisis may have affected spending prior to the shutdown. While pay day spending creates spikes in excess spending on individual days - positive when we compare a pay day to a normal day and negative when we do the opposite - they do not affect $\Delta spending$ because both its terms average over the same number of positive and negative pay day spikes.

While $\Delta spending$ remains our summary measure of the spending response, we also show plots that compare spending on each day in the window of analysis to spending on the reference day the year before. The plot allows us to visually assess whether consumer spending behaved similarly in the pre-shutdown period as on the same days the year before (except for a level shift). This is key to assessing the credibility of our identifying assumption that consumer spending would have behaved similarly in the post-shutdown period as on the same days the year before (except for the same level shift) absent the epidemic and the shutdown.

To assess the importance of the various mechanisms that may be driving the aggregate change in spending, we study heterogeneity in spending responses across groups that were exposed differentially in a particular dimension. For instance, we compare the spending response of young and old to assess the importance of health risk. Correlations across different dimensions of exposure is an important caveat. For instance, the old are more likely to hold stocks and therefore also more exposed to stock market losses than the young. We address that concern by reweighting observations so that the subsamples we compare are balanced in other dimensions of heterogeneity. For instance, if stockholders are underrepresented in the young sample, we put more weight on individuals with this characteristic when we estimate the spending response for the young.

Formally, let individuals differ in N observable dimensions (age, income, and so on) and let $m_n = 1, ..., M_n$ denote the possible characteristics within dimension n (e.g., young and old in the age dimension). Suppose we want to compare spending responses for individuals who differ in dimension N. We then define a type as a combination of characteristics in the $N-1$ other dimensions, summarized by the vector $\mathbf{m} = (m_1, ...m_{N-1})$. Let $\lambda(\mathbf{m})$ denote the share of individuals with characteristics $\mathbf{m}$ in the full sample and let $\beta(\mathbf{m}, \widetilde{m}_N)$ denote the spending response for individuals of this type with characteristic $\widetilde{m}_N$ in the dimension of interest (e.g. the young). We define the re-weighted spending response for individuals with this characteristic as:

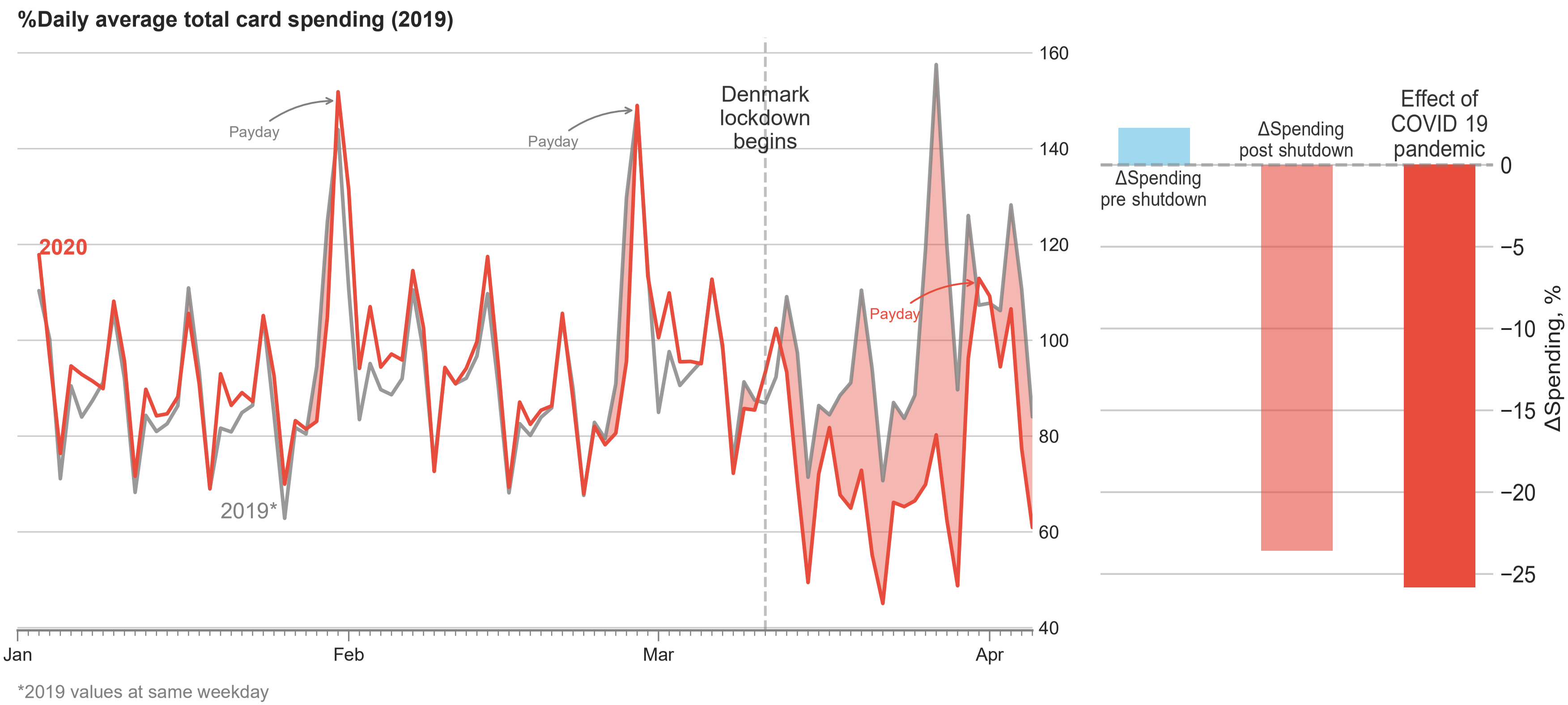
$$(\Delta spending | m_N = \widetilde{m}_N) = \sum_{\mathbf{m}} \lambda(\mathbf{m}) \cdot \beta(\mathbf{m}, \widetilde{m}_N)$$

This is effectively a weighted average of the type-specific responses $\beta(\mathbf{m}; \widetilde{m}_N)$ where the weights ensure that characteristics in other dimensions than N match those of the full sample. To implement the formula, we replace the sample shares $\lambda(\mathbf{m})$ with their empirical analogues and replace the spending responses $\beta(\mathbf{m}; \widetilde{m}_N)$ with estimates obtained by applying equation (4) to the sample of individuals of type m with characteristic $\widetilde{m}_N$.

5 Results

Figure 2 illustrates our findings concerning the drop in aggregate card spending. The left side of the figure plots spending on each day of the window of analysis (red line) and spending on the reference day one year earlier (gray line), both scaled by average daily spending in 2019. Both series exhibit a pronounced weekly cycle with spikes around weekends as well as a pay day cycle with spikes around the end of the month. Until the shutdown on 11 March 2020, both the level and the dynamics of spending are strikingly similar to the reference period. After 11 March 2020, spending is generally below the level in the reference period as indicated by the

Figure 2: Aggregate card spending. The figure shows the drop in household spending on credit and debit cards associated with the COVID-19 crisis. The left panel shows the evolution of daily average card spending in 2020 (red line) and on equivalent days in 2019 (gray line), where each series is shown as a percentage of average daily card spending throughout 2019. Labelled "paydays" are the final bank day of the month, when the majority of individuals in Denmark receive their salary and/or government transfers. The right bar chart summarises our approach to estimate the impact of the crisis and provides our headline estimate of the drop in card spending.



shaded differences.

Our headline estimate is that spending dropped by around 25% in response to the pandemic and the shutdown. The right side of the figure illustrates the mechanics underlying this estimate. The blue bar indicates average excess spending over the pre-shutdown period 1 January – 15 February 2020: consumers spent around 2% more over these days than over the reference days in 2019. The black bar indicates average excess spending over the post-shutdown period 11 March – 5 April 2020: consumers spent around 23% less over these days than over the reference days in 2019. Under the identifying assumption that the year-over-year growth between 2019 and 2020 would have continued to be 2% absent the epidemic and the shutdown, we estimate the spending response at -25%.

Figure 3 shows similar estimates for selected expenditure groups. The left side plots scaled daily spending in the window of analysis (red lines) and the reference days (gray line) whereas the right side shows the estimated spending response. In all categories, spending in 2019 and 2020 followed similar patterns until the shutdown. Spending responses to the shutdown, however, varied widely across categories: spending in grocery shops and pharmacies increased modestly relative to the counterfactual (blue bars and blue shading) whereas spending on restaurant meals, travel, retail , personal services, fuel and entertainment exhibited pronounced decreases (red bars and red shading).

Spending responses are closely linked to the restrictions on mobility and activity imposed by the government to prevent the spreading of the virus. Grocery shops and pharmacies where spending increased are both in the open sector whereas travel, restaurants and personal services were spending plummeted are all in the closed one. Figure 4 makes this point more formally by showing estimates of the spending response by sector. In all three sectors, spending in the pre-shutdown period tracked spending in the reference period closely. After the shutdown, the three sectors fared very differently: our estimates of the spending responses are around 10% for the open sector (roughly half of the economy), around -40% for the constrained sector (roughly one quarter of the economy) and almost -70% for the closed sector (roughly one quarter of the economy).

The pandemic and the partial shutdown of many economies have been presented as a golden opportunity for online retail: with high-street retail shops being partly shut down and associated with health risks to the extent that they remained open, the conditions for online substitutes should be ideal. While total online spending decreased considerably less than traditional offline spending (15% verus 30 %), as shown in Figure 5, these overall responses do not provide support

Figure 3: Spending categories. The figure shows the impact of the COVID-19 crisis on spending at different categories of merchant, identified using Merchant Category Codes associated with card payments. The graphs follow the same format as Figure 2: the left panel shows the evolution of spending in each category in 2020, relative to the reference period in 2019, and the right panel summarises our estimate of the effect on spending in each category. Blue shading and bars identify categories of spending that increase; red shading and bars identify categories of spending that decrease.

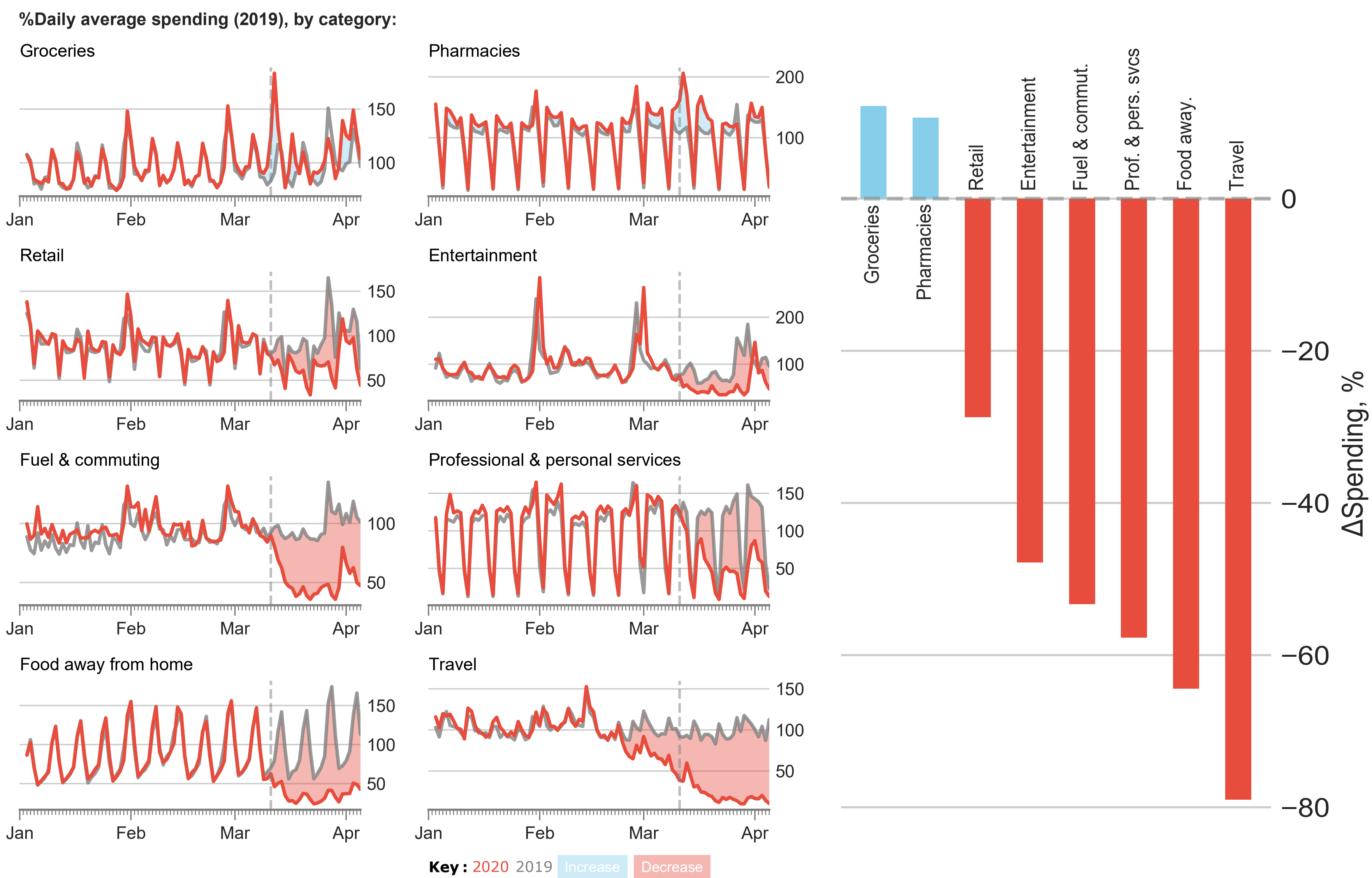


Figure 4: Supply constraints. The figure shows the impact of the COVID-19 crisis on consumer spending in the Open, Constrained and Closed sectors of the economy under the government controls. Appendix Table A1 contains the crosswalk of spending categories into each group of supply constraints.

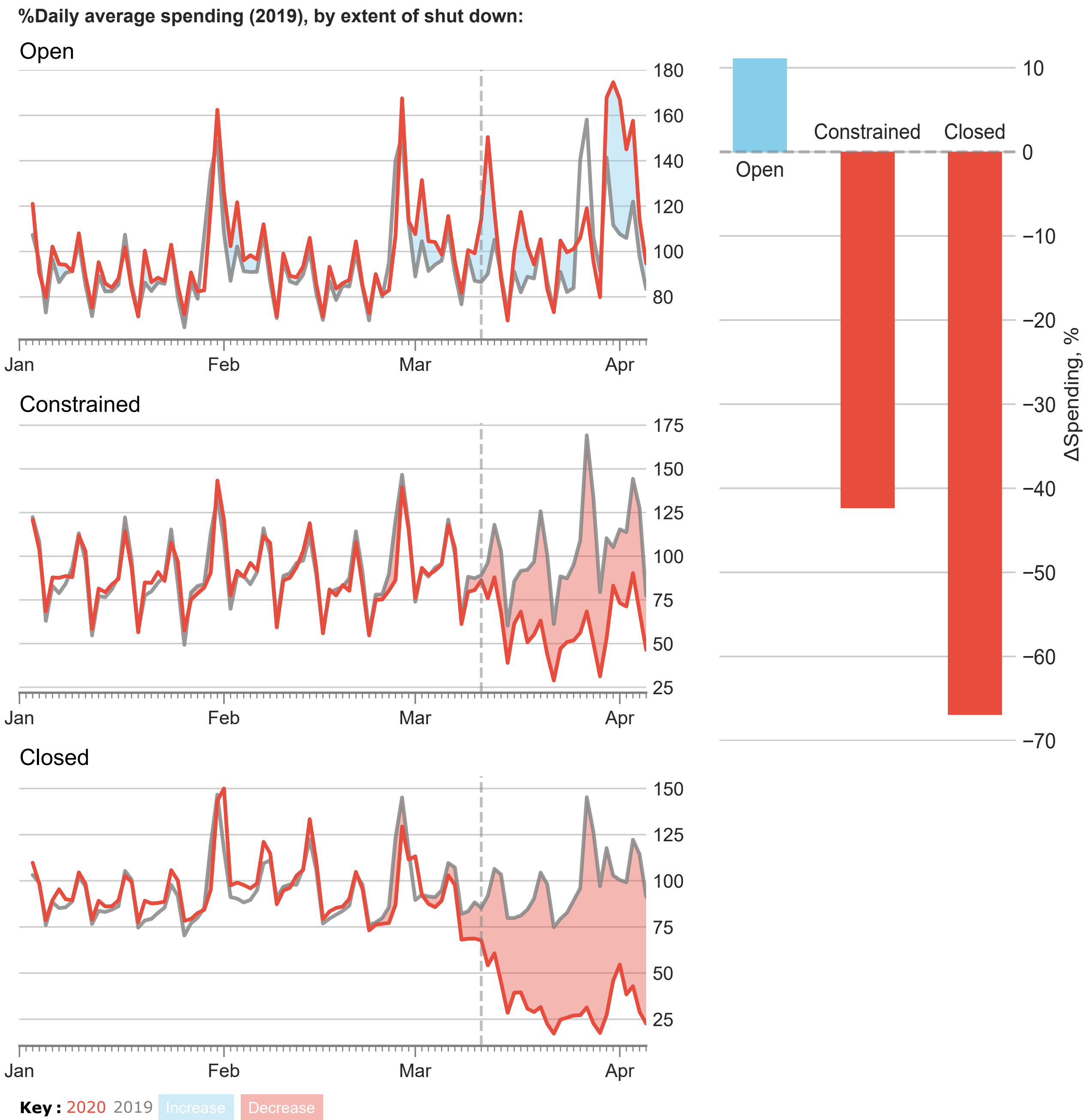
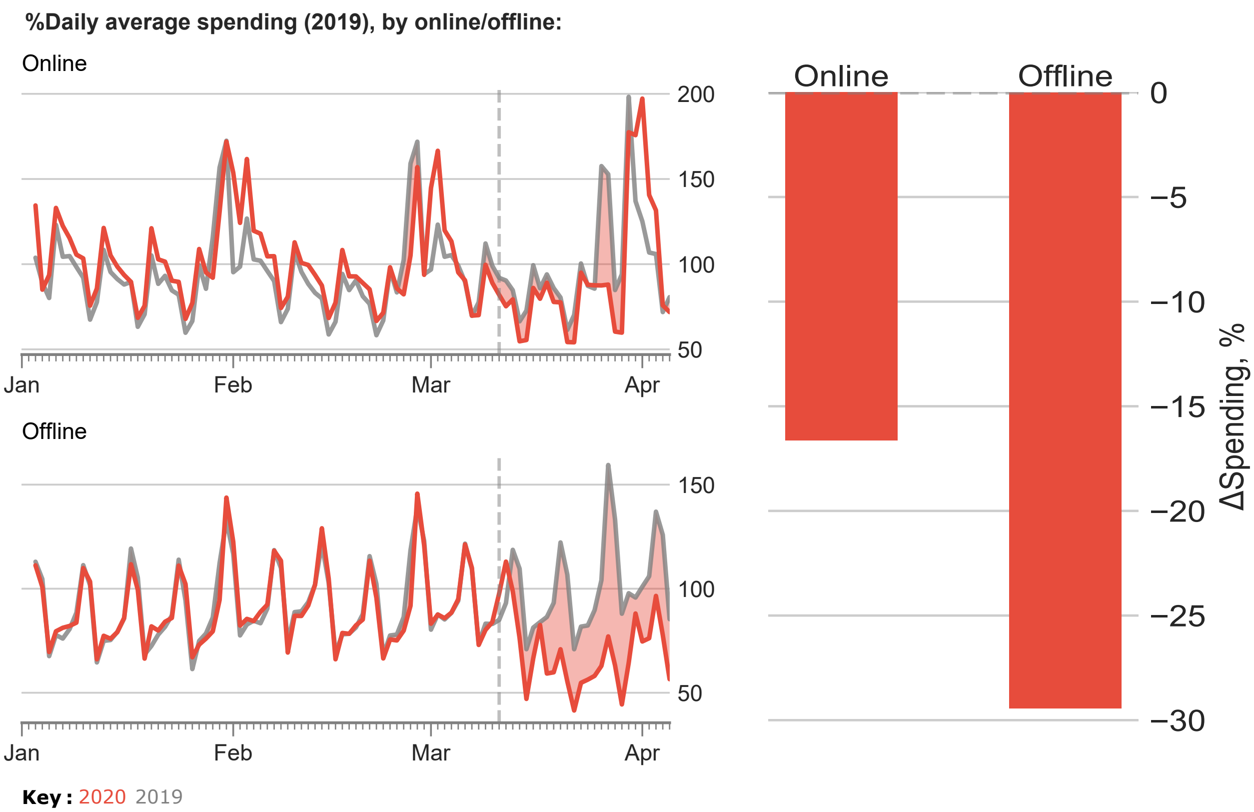


Figure 5: Online vs offline spending. The figure shows the impact of the COVID-19 crisis on online and offline consumer spending. We identify whether a payment takes place online or offline based on payment metadata associated with each transaction.



for a massive substitution into online retailing. However, Figure 6 shows that the modest decrease in overall online spending conceals enormous heterogeneity: online spending on travel almost disappeared whereas online spending on groceries almost doubled.

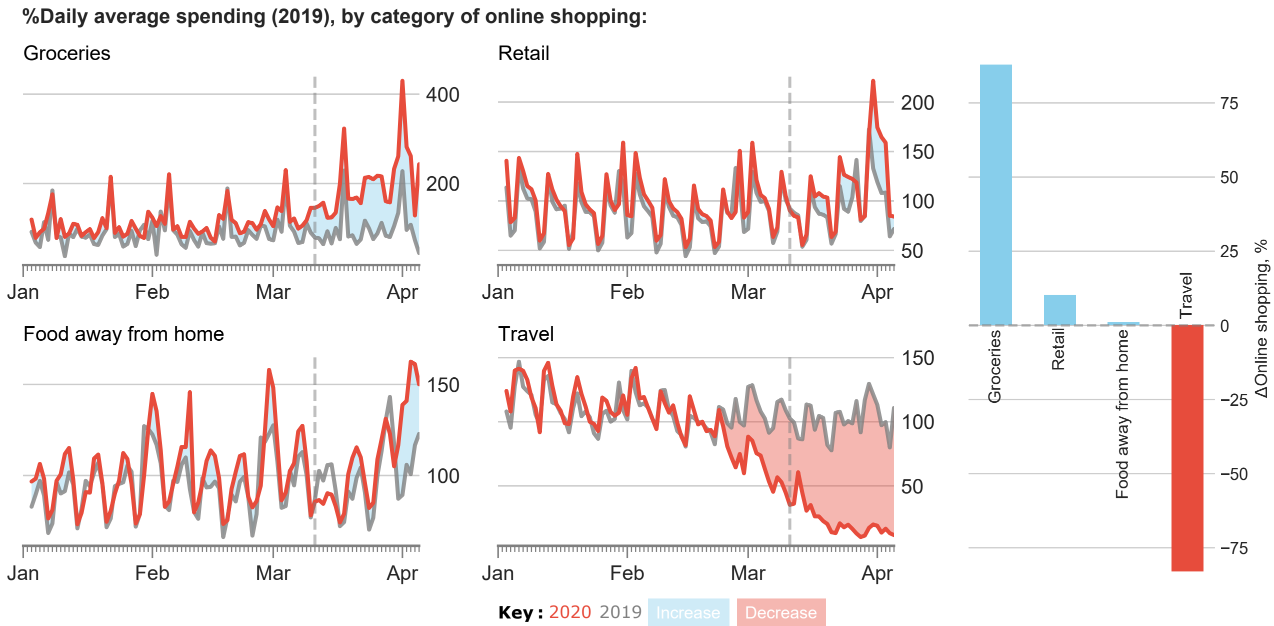
Finally, we study heterogeneity in spending responses across groups that were exposed differentially to the pandemic and the shutdown of the economy. Figure 7 illustrates the estimated drop in card spending for various subsamples. Observations are weighted so that the bars can be interpreted as the spending response for a subsample that has the same characteristics as the full sample in all other observable dimensions *except* in the highlighted dimension.[11].

We first compare individuals facing different income risk as a result of the crisis: those working in private businesses in the closed sector where lay-offs were frequent and those working in the public sector where jobs remained secured.[12] The results indicate that the spending

[11] Specifically, types are defined as combinations of the following characteristics: Age (indicators for ages 18-35, 35-64, 64+), Gender (binary indicator), Spending in closed sector in 2019 (binary indicator for being above or below median), Pharmacy spending in 2019 (binary indicator for being above or below median), Public sector employee (binary indicator), Stockholder (binary indicator), Income level in 2019 (indicators for income quartile

[12] The sample of private sector employees at risk of unemployment covers passenger transportation (air and sea), hotels, restaurants, cafes, bars, travel agents, entertainment, personal care services and retail.

Figure 6: Categories of online spending. The figure shows the impact of the COVID-19 crisis on online and offline consumer spending in a number of key categories: Groceries, a sector that remains open throughout; Retail, including all purchases of consumer goods such as clothes, electronics, etc., Food away from home, which includes online and app based purchases of takeaway/prepared food; and Travel, including all purchases of flights, hotels, and rental cars.



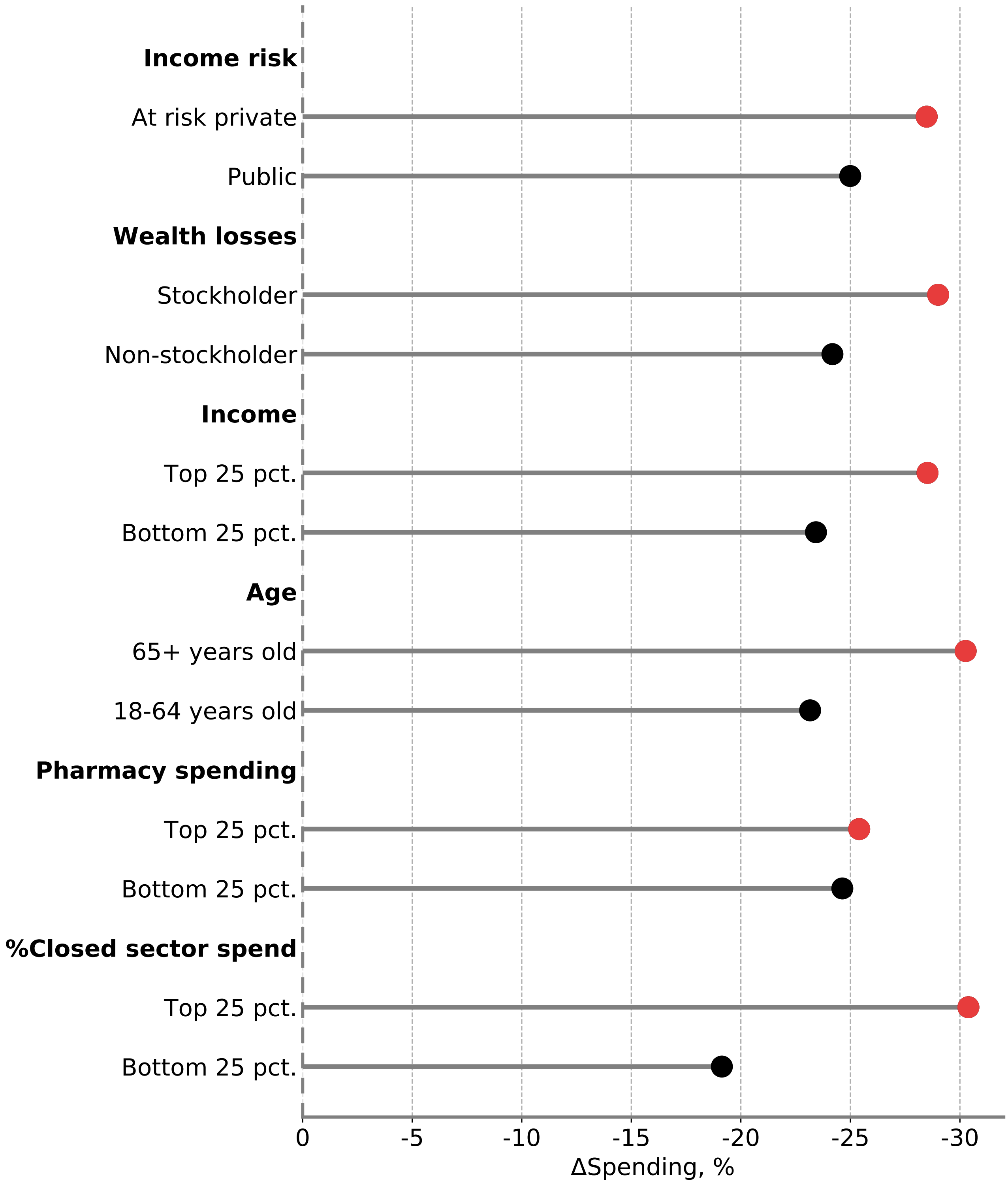
response is slightly larger (+3 percentage points) for individuals with higher income risk.

We then compare individuals with different exposure to wealth losses: stockholders who were exposed to the global stock market bust and non-stockholders who were not. The results suggest a somewhat larger spending response (+5 percentage points) for individuals with exposure to stock markets.

We provide separate results for individuals at different positions in the income distribution: those in the bottom quartile where the risk of job loss following the shut-down is relatively large and those in the top quartile where this risk is limited (Joyce and Xu, 2020). The results suggest a smaller spending response (-5 percentage points) for individuals with more exposure to job losses as proxied by their income level.

We proceed to split the sample by two measures of exposure to health risk. We first compare elderly individuals (above 65 years) who are the most likely to suffer serious health consequences if infected with the virus to the young and the middle-aged (below 65 years). The results indicate a larger spending response (+7 percentage points) for individuals with more exposure because of their age. We also compare individuals who generally spend a lot in pharmacies before the pandemic, an indication of a pre-existing condition that raises the health risks associated with the virus, to individuals who generally spend little in pharmacies. The results suggest a slightly

Figure 7: Individual heterogeneity. The figure quantifies heterogeneity in the impact of the COVID-19 crisis on consumer spending. We focus on comparing the impact across individuals who differ in exposure to different risks associated with the crisis and the shutdown.



larger spending response (+1 percentage points) for individuals with more exposure due to pre-existing health problems.

We finally compare individuals with different exposure to the shut-down of economic sectors such as restaurants and international travel: individuals who spent most in these sectors before the shutdown to those who spent the least. The results indicate a much larger spending response (+12 percentage points) for individuals with more exposure to the shut-down because of their inherent spending patterns.

The results provide some insights into the mechanisms underlying the massive drop in aggregate spending. Differential exposure to economic risks and health risks can account for some of the variation in spending responses but not nearly all of it. Pre-crisis spending shares on goods and services provided by the closed sector is clearly the strongest correlate of spending responses.

6 Conclusion

This paper uses transaction-level bank account data from the largest Danish bank to study consumer responses to the COVID-19 crisis. We present three key results. First, the drop in aggregate spending is around 25%. Second, the spending response varies widely across expenditure categories and correlate strongly with the severity of government restrictions. Third, the spending responses correlate moderately with exposure to economic risks and health risks while pre-crisis spending shares on supply-constrained goods and services is the strongest correlate of spending responses.

Our results consistently indicate that the closed sector of the economy is at the heart of the drop in consumer spending. This may reflect that the drop in spending is caused directly by the shutdown, e.g. consumers do not go to restaurants because they are closed, or that the drop in spending is caused by the health risks that motivated the shut-down, e.g. consumers do not go to restaurants because it exposes them to the virus. Economic risks such as income and wealth losses appear to play a limited role over the short horizon studied in this paper.

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ONLINE APPENDIX

Table A1: Aggregation of spending categories This appendix explains how spending categories obtained from MCCs are aggregated to measures of spending in open, constrained and closed sectors.

Sector	Description
Closed:	Travel: All expenditures on flights, hotels, travel, rental cars, etc.
	Food away from home: Any in-person expenditures at restaurants, cafes, bars, etc.
	Personal care: All expenditures on personal and professional services, including dentists, phyiotherapists, hairdressers, etc.
	Entertainment: All expenditures on entertainment, including cinema tickets, sporting events, etc.
	Department stores: Any in-person expenditures at department stores
	Auto: Any in-person expenditures on auto equipment or servicing in malls
	Home improvements: Any in-person expenditures on home improvements and furnishings in malls
	Retail: Any in-person expenditures on retail durables, non-durables and miscellaneous durables in malls
Constrained:	Fuel & commuting: Any expenditures on fuel or commuting, including payments at petrol stations, public transport passes, etc.
	Auto: Any non-mall, in-person expenditures on auto equipment or servicing
	Home improvements: Any non-mall, in-person expenditures on home improvements and furnishings
	Retail: Any non-mall, in-person expenditures on retail durables, non-durables and miscellaneous durables
Open:	Pharmacies: Any expenditure in pharmacies
	Groceries: Any expenditures at grocery stores
	Insurance: Any insurance purchases
	Television & communication: Any expenditures on television entertainment packages or phone and internet
	Utilities: Any utilities expenditures, including gas, electricity, etc.
	Department stores: Any online expenditures at department stores
	Auto: Any online expenditures on auto equipment or servicing in malls
	Home improvements: Any online expenditures on home improvements and furnishings in malls
	Retail: Any online expenditures on retail durables, non-durables and miscellaneous durables in malls

Table A2: Aggregation of industries This appendix explains how industries of employment are aggregated to at-risk private, other private and public sectors.

Industry	Classification by NACE industry codes/DB07 Danish section codes
At-risk, Private:	Passenger flight and sea transportation, including support services: 501000, 511010, 511020, 522300 Hotels: 551010, 552000, 553000, 559000 Restaurants, cafes, bars, etc: 561010, 561020, 562100, 562900, 563000 Travel and reservation agents: 791100, 791200, 799000 Entertainment, sports, recreation services, etc: 900110, 900120, 900200, 900300, 900400, 931100, 931200, 931900, 932100, 932910, 932990, 855100, 855200, 855300, 855900 Personal care services: 960210, 960220, 960400, 960900, 869020, 869030, 869040, 869090
Other, Private:	DB07 Sections A, B, C, D, E, F, G, H (excluding workers in passenger flight and sea transportation, above), J, K, L, M, T (excluding personal care services, above): Includes farming, manufacture, logistics, utilities, building and construction, retail, information and communication, financial services, real estate, professional and technical services
Public:	DB07 Sections N, O and P (excluding private sector activities grouped in recreation services, above), Q and 9101, 9102, 9103, 9104