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Consumer Responses 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 the change in consumer spending caused by the COVID-19 pandemic and the resulting shutdown of the Danish economy. We find that aggregate spending was on average 27% below the counterfactual level without the pandemic in the seven weeks following the shutdown. The spending drop was mostly concentrated on goods and services whose supply was directly restricted by the shutdown, suggesting a limited role for spillovers to non-restricted sectors through demand in the short term. The spending drop was larger for individuals with more *ex ante* exposure to the adverse consequences of the crisis in the form of job loss, wealth destruction, severe disease and disrupted consumption patterns and, most notably, for individuals with an *ex post* realization of crisis-related unemployment.

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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 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 bank account transaction data from Denmark to study the dynamics of consumer spending through the COVID-19 crisis. The crisis unfolded in Denmark roughly as in most of Northern Europe and North America: the first case of COVID-19 was confirmed on 27 February 2020 and the government announced a partial shutdown of the economy to contain the pandemic on 11 March and a series of interventions to sustain the economy in the following days. Shortly after the shutdown was reinforced on 18 March, the spreading of the virus slowed down markedly and the gradual lifting of the restrictions started on 20 April 2020. As of 3 May 2020, cumulative COVID-19 mortality in Denmark was similar to Germany and around half the level of the United States, whereas fiscal stimulus was somewhat below the level in both of these countries.

Our analysis proceeds in three steps. First, we estimate how aggregate consumer spending changed through the various stages of the COVID-19 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 were effectively shut down, 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 investigate the mechanisms underlying the drop in consumer spending by estimating how the drop varies across individuals with different *ex ante* exposure to the adverse consequences of the crisis in the form of job loss, wealth destruction, severe disease and disruption of consumption patterns, and across individuals with different *ex post* realizations of crisis-related unemployment.

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 all payments by card and mobile wallet through accounts at the bank as well as cash withdrawals. This allows us to construct a customer-level measure of total spending at the daily frequency. Exploiting a standardized classification of merchants, we measure card spending in three distinct sectors that vary by the severity of the supply constraints: the closed sector (e.g. hair dressers, were not allowed to operate), the constrained sector (e.g. commuting, as trains and buses continued to operate but at much reduced frequencies) and the open sector (e.g. online retail, which operated freely). Finally, our dataset contains basic demographic information such as age and gender as well as information on income (based on a categorization of incoming transfers) and balance sheet components (based on information from security accounts). The data is available in near real time and our sample period thus runs until 3 May 2020, which spans both the initial spreading of the virus, the partial shutdown of the economy and the first stages of the re-opening.

Our goal is to estimate the drop in consumer spending relative to a counterfactual without the COVID-19 pandemic. A key 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 crisis-induced change in spending as the difference between excess spending in the post-shutdown period (11 March - 3 May) and excess spending in the pre-shutdown period (2 January - 15 February).[1] 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

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

pandemic and the resulting shutdown of the economy.

Our first finding is that aggregate spending dropped by around 27% relative to the counterfactual trajectory. This reflects that excess spending was slightly positive in the pre-shutdown period and strongly negative in the post-shutdown period. The magnitude of the estimate is enormous compared to typical consumer responses to idiosyncratic shocks; for instance, it is around four times larger than recent estimates of the average spending response to job losses (Ganong and Noel, 2019; Andersen et al., 2020a). A closer analysis of the dynamics in Denmark shows that aggregate spending co-moved with the severity of the supply constraints: it barely changed in the weeks prior to the shutdown, it plunged when supply was first restricted, it dropped further when the restrictions were tightened and increased markedly when the first restrictions were lifted.

Our second finding is that changes in expenditure across categories correlates strongly with the extent of supply restrictions. For instance, spending increased modestly in grocery stores and pharmacies, which remained open throughout the shutdown, and dropped dramatically where restrictions were particularly severe such as travel, restaurants and personal services. In aggregate, we find that spending increased by more than 10% in the open sector (around half of the economy) and dropped by almost 70% in sectors where supply was most constrained (around one quarter of the economy). The results suggest that the partial shutdown had negative spillovers 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 mechanisms underlying the spending drop, we provide estimates for subsamples that are heterogeneous in one dimension of *ex ante* exposure to the adverse consequences of the crisis (e.g. unemployment) while re-weighing observations to make the subsamples homogeneous in other dimensions of exposure (e.g. serious health problems). Consistent with an important role for the disruption of consumption patterns, a high spending share in the closed sector before the shutdown is associated with a large differential drop in total spending (11 percentage points). We also find evidence that exposure to *health consequences* mattered for spending behavior as the elderly, who are much more likely to face hospitalized and death if contracting the virus, reduced spending differentially (8 percentage points). Exposure to wealth losses and unemployment appears to have played a smaller role as we find modest differential spending drops for individuals holding stocks (4 percentage points) and individuals working in the closed sector (1 percentage point). The latter result may reflect that government support programs induced many firms in the closed sector to keep employees on the payroll even as sales dropped dramatically. Indeed, we find much more pronounced effects of *ex post* realization of unemployment, with a massive differential spending drop (14 percentage points) in the last weeks of the sample period for individuals who lost their job after the shutdown. This illustrates the risks of negative dynamics on the demand side, with laid-off employees cutting back spending and thus reinforcing the contraction of the economy, and thus highlights the importance of policy interventions to sustain employment in the adversely affected sectors.

Our finding that the closed sector of the economy was at the heart of the drop in consumer spending lends itself to two distinct interpretations. Either, the drop in spending was caused directly by the shutdown, e.g. consumers did not go to restaurants because they were closed. Or, the drop in spending was caused by the disease risks that motivated the shut-down, e.g. consumers would not have gone to restaurants even if they had been open because it would expose them to the virus. While the heterogeneity analysis in the present paper provides suggestive evidence in favor of both of these interpretations, we are ultimately unable to disentangle them using variation from Denmark only. The empirical challenge is formidable because governments tend to shut down exactly the economic sectors that are associated with most disease risk exactly at the time when disease risk increases most rapidly. In another paper, we make progress on this issue by comparing spending dynamics in Denmark to Sweden where there was no shutdown despite a similar initial exposure to the pandemic (Andersen et al., 2020b).

Our analysis contributes to a growing empirical literature on the economic consequences of the COVID-19 crisis. Specifically, a number of papers emerging around the same time as ours use transaction data to study spending dynamics through the COVID-19 crisis in the United States (Baker et al., 2020), China (Chen et al., 2020), Spain (Carvalho et al., 2020), France (Bounie et al., 2020) and the United Kingdom (Hacioglu et al., 2020; Chronopoulos et al., 2020). Our dataset is unique in combining three important features. First, our sample is almost perfectly representative of the overall population in terms of age and income, which is crucial for making inference about aggregate spending if responses to the pandemic differ across socio-economic groups. Second, our spending measure includes both card payments and cash withdrawals, which may be important if spending categories where cards are the dominant mode of payment (e.g., travel) were affected differentially by the pandemic. Third, our dataset includes information about income, assets and demographics at the level of individual consumers, which allows us to shed light on the economic mechanisms underlying the spending drop.[2]

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 change in spending induced by 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 COVID-19 crisis in 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 27 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. In terms of cumulative mortality, the severity of the epidemic in Denmark (8.2 per 100.000 inhabitants on 3 May 2020) resembled the experience in Germany (8.0); it was less severe than in the U.S. (20.3) and Italy (47.5) but more severe than in Norway (3.8). We show trends in mortality from COVID-19 for this selected group of countries in Figure A1 in the Appendix.

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

[2]The other papers studying spending dynamics in the COVID-19 crisis use transaction data from financial apps (Baker et al., 2020; Hacioglu et al., 2020; Chronopoulos et al., 2020), where users are typically not representative of the overall population, or from credit card companies (Carvalho et al., 2020; Bounie et al., 2020; Chen et al., 2020), which typically do not have information on cash withdrawals and no background information on individual consumers.

discouraging travel to the most affected areas in the world. However, on *11 March*, the Prime Minister announced a national shutdown 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 stay at home and avoid social contact. On *18 March*, facing a still escalating epidemic, the government announced further restrictions banning congregations of more than 10 individuals, shutting down malls, hairdressers and nightclubs and restricting restaurants to take-away service. On *20 April*, some of the supply restrictions were lifted, specifically allowing providers of personal services (e.g. hair dressers and dentists) to resume business. Overall, the timing and severity of the measures were comparable to most of Northern Europe (such as Germany, Netherlands and Norway), but less restrictive than in Southern Europe where the outbreak was more extensive by the point at which measures were introduced.

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 roughly similar in scale and scope to those launched by many other governments in Europe (IMF, 2020).[3]

3 Data

We measure consumer spending with transaction-level data from Danske Bank, the largest retail bank in Denmark. For each customer, our dataset includes information about all payments with card and mobile wallet, all cash withdrawals and all incoming money flows. We also retrieve basic demographic information such as age and gender from the bank's customer records. We use two criteria to define a sample of individuals (above age 18) who consistently use Danske

[3]The fiscal stimulus is estimated at 2.7% of GDP in Denmark compared to 1.2% in Italy, 2.6% in Norway, 4.4% in Germany and 6.9% in the United States, as illustrated in Figure A2 in the Appendix.

Bank as their main bank. First, we require that customers held their main current account at Danske Bank between 1 January 2018 and the end of the sample period on 3 May 2020.[4] Second, we require that customers made at least one card payment in each month between January 2018 and December 2019. With these restrictions, our sample consists of around 760,000 individuals.

We create a daily measure of *aggregate spending* by summing the card payments, mobile wallet payments and cash withdrawals by all individuals in the sample on a given day. Further, we create measures of spending in specific *categories*, such as groceries, travel and restaurants, based on a standardized coding of the type of goods and services each shop provides.[5] Finally, we create three composite spending categories that aggregate individual spending categories based on the extent to which the supply was restricted. At one extreme, we consider travel, restaurants, personal services (e.g. dentists and hairdressers) and entertainment (e.g. cinemas, theatres and bars) as a *closed sector*. These businesses were, in principle, not allowed to operate although there were exceptions. For instance, restaurants were not allowed to seat guests, but could sell take-away food; dentists 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 an *open sector*. Such businesses faced only very mild constraints. For instance, the government instructed consumers to keep distance in the stores. As an intermediate case, we consider retail (except online), fuel and commuting to be a *constrained sector*. 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.[6]

To learn more about the causal mechanisms underlying the spending dynamics, we construct subsamples of individuals who had different *ex ante* exposure to the various negative consequences of the pandemic.[7] First, we use industry information about the firms making salary payments to define a subsample of individuals who worked in the private sector firms most affected by the shutdown (closed sector) and thus had high exposure to *job loss* and compare them to a subsample of public sector employees with low exposure.[8] Second, we use

[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] Following Ganong and Noel (2019), we categorize spending by four-digit Merchant Category Code, an international standard for classifying merchants, by the type of goods and services they provide.

[6] We provide more detail on the coding of supply constraints in Table A1 in the Appendix.

[7] Since resources are usually shared within households, we average spending, income and assets across cohabiting partners, defined as two individuals living on the same address and sharing a joint bank account, before creating the subsamples

[8] We provide more detail on the coding of industries in Table A2 in the Appendix.

information about security accounts at the end of 2019 to create a subsample of stockholders with high exposure to *wealth losses*, as stock markets both in Denmark and elsewhere plunged at the onset of the crisis (Gormsen and Koijen, 2020), and compare them to a subsample of non-stockholders with low exposure. Third, we use background information on customer age to create a subsample of elderly (age 65 and more) with high exposure to *severe health problems* and compare them to a subsample of non-elderly with low exposure. Fourth, we use spending data for 2019 to construct a subsample with high spending in the closed sector (relative to total spending) and thus with high exposure to *disruption of consumption patterns* and compare them to a subsample with low spending in the closed sector and low exposure.

Finally, we construct subsamples with different *ex post* realizations of crisis-related unemployment shocks using counterpart information on incoming transfers to distinguish labor earnings and government transfers. The analysis considers a sample of individuals with significant labor earnings (above $1,200) in each of the six months prior to the shutdown (October 2019 - March 2020). We consider individuals to suffer crisis-related unemployment if, in April 2020, they had virtually no labor earnings (below $150) or received significant government transfers (above $1,200).[9] We consider individuals to be in continued employment if, in April 2020, they had significant labor earnings (above $1,200).

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.[10] We also provide a detailed breakdown of spending by detailed category and by sector, for which there are no available equivalents in government registers.

4 Empirical strategy

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

[9] We use both criteria as laid off employees may receive significant severance payments from their former employer in the months after the lay-off and may only start receiving government transfers with a considerable delay.

[10] Our sample seemingly includes a smaller fraction of individuals working in the closed sector 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.

policies.

To capture the sharp change 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.[11]

For each day of our window of analysis, 2 January 2020 – 3 May 2020, we thus compute the 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 on aggregate spending as the difference between average excess spending in the post-shutdown period, 11 March – 3 May, and average excess spending in the early pre-shutdown period, 2 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 - 10 March from the pre-shutdown period as early restrictions (e.g. on air travel to Asia) and anticipation of the broader

[11] 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.

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 dynamics across groups with different *ex ante* exposure. Specifically, we consider four dimensions of heterogeneity: *industry* (exposure to job loss), *stock market participation* (exposure to wealth loss), *age* (exposure to severe health consequences) and *spending in the closed sector* (exposure to disruption of consumption patterns). We compare the spending drop across subsamples with different exposure in one particular dimension while reweighing the observations so that each of the subsamples has the same characteristics as the full sample in other dimensions. For instance, we estimate the spending drop separately for individuals with high and low exposure to job losses while reweighing the observations so that the prevalence of high exposure to wealth losses, high exposure to severe health consequences and high exposure to disruption of consumption patterns is the same as in full sample in each of the two subsamples. We provide a more formal description of the estimation procedure in the Appendix.

We also study heterogeneity in spending dynamics across groups with different *ex post* realizations of crisis-related unemployment. We compare the spending drop for individuals who lost their job after the shutdown to individuals who did not lose their job while reweighing observations to ensure that each of the two subsamples has the same *ex ante* exposure as the full sample in all four dimensions.

5 Results

Figure 1 illustrates the high-frequency dynamics in consumer spending through the COVID-19 crisis by showing aggregate spending on each day of the window of analysis (red line) and 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 shaded differences.

Figure 2 illustrates our estimates of how the COVID-19 crisis affected aggregate consumer spending. In the left panel ("Aggregate spending"), the first gray bar indicates average excess spending over the pre-shutdown period 2 January – 15 February 2020: consumers spent around 3% more over these days than over the reference days in 2019. The second bar indicates average excess spending over the post-shutdown period 11 March – 3 May 2020: consumers spent around 24% 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 3% absent the crisis, we estimate the effect on aggregate spending at -27%.

The effect on aggregate spending varies over time with the scope of the restrictions, as shown in the middle panel ("Spending by time period"). We estimate a small drop in aggregate spending of around 5% relative to the counterfactual in the period between the first confirmed COVID-19 case in Denmark and the announcement of the shutdown (27 February - 10 March); a larger decrease of around 13% in the stage of the shutdown (11 March - 17 March); a much larger decrease of 32% in the second stage where all restrictions were in place (18 March - 19 April); and a somewhat smaller effect around 22% after the first set of restrictions were lifted (20 April - 3 May).

When we consider heterogeneity in the spending drop across sectors, we also find an intimate link to the restrictions on mobility and activity, as shown in the right panel ("Spending by sector"). Averaged over the full post-shutdown period, spending increased by around 10% in the open sector relative to the counterfactual (roughly half of the economy) whereas spending dropped by around 40% in the constrained sector (roughly one quarter of the economy) and dropped by a staggering 70% in the closed sector (roughly one quarter of the economy). We provide more detail on these results in the Appendix. Figure A3 shows fully dynamic results by sector that confirms the important role of the government restrictions: in all three sectors, spending tracked the reference period closely until shortly before the shutdown and then diverged. Figure A4 shows estimates for more granular spending categories, e.g. spending in grocery shops and pharmacies in the open sector increased modestly whereas spending on travel, restaurants and personal services in the closed sector plummeted. Interestingly, cash withdrawals dropped much more than total spending suggesting that consumers may have moved to alternative modes of payment to reduce the health risk associated with touching coins and bills. Figure A5 reports results on substitution into online shopping. While total online spending decreased considerably less than traditional offline spending (12% versus 32%), these results do not provide support for a massive substitution into online retailing. However, the modest decrease in overall online spending conceals enormous heterogeneity: online spending on travel virtually disappeared whereas online spending on groceries almost doubled.

Figure 3 illustrates how the spending drop varies across individuals with different *ex ante* exposure to the adverse consequences of the crisis in the form of job loss, wealth destruction, severe disease and spending distortions. As explained above, the underlying estimations weigh observations so that the bars can be interpreted as the estimated spending drop for a subsample that has the same characteristics as the full sample in all observable dimensions except the one that is highlighted.

We first compare samples with different exposure to crisis-related unemployment: 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. The results indicate that the spending drop is only slightly larger (+1 percentage point) for individuals with higher exposure to unemployment. Next, we compare samples with different exposure to crisis-related wealth losses: stockholders who were exposed to the global stock market bust following the onset of the pandemic and non-stockholders who were not. The results suggest a somewhat larger spending drop (+4 percentage points) for individuals with exposure to wealth losses. We proceed to compare samples with different exposure to severe health problems: elderly (above 65 years) who are the most likely to suffer serious health consequences if infected with the virus and non-elderly (below 65 years) for whom COVID-19 is rarely lethal. The results indicate a larger spending drop (+8 percentage points) for individuals with more exposure to the health consequences of the virus. Finally, we compare samples with different exposure to the disruption of consumption patterns created by the shutdown: those who spent most in the closed sector before the shutdown and those who spent the least. The results indicate a much larger drop in total spending (+11 percentage points) for individuals with more exposure to the shutdown because of their inherent spending patterns.

The results provide insights into the mechanisms underlying the massive drop in aggregate spending. Differential *ex ante* exposure to unemployment, wealth losses and severe disease can account for some of the heterogeneity in spending dynamics but not nearly all of it. Spending shares on goods and services provided by the closed sector is the strongest correlate of the drop in total spending.

Figure 4 illustrates how the spending drop varies across working-age employees with different *ex post* realizations of the unemployment risk created by the crisis: those who suffered a job loss in April 2020 and those who did not. As explained above, the underlying estimations weigh observations so that the bars can be interpreted as the estimated spending drop for subsamples that have the same *ex ante* exposure to the negative consequences of the crisis, but different *ex post* realizations of the unemployment risk. While the spending drops are similar in the two groups through most of the period we consider, those who became unemployed exhibit a much larger drop in spending in the last subperiod than those who did not (+14 percentage points).

This result illustrates the risks of a negative demand side dynamics whereby laid-off employees cut spending and thus reinforce the contraction of the economy. The differential spending cut of 14 percentage points is around twice as large as recent estimates of spending responses to job losses in normal times (Ganong and Noel, 2019; Andersen et al., 2020a), which may reflect the poor prospects of finding new employment in the midst of an escalating crisis.

6 Conclusion

This paper uses transaction-level bank account data from the largest Danish bank to study the dynamics in consumer spending through the COVID-19 crisis. We present three key results. First, the drop in aggregate spending was around 27%. Second, the spending drop correlates strongly with the severity of government restrictions on mobility and economic activity, both across sectors and over time. Third, the estimated spending drop varies with *ex ante* exposure to the adverse consequences of the pandemic in terms of job loss, wealth destruction, severe health problems and disrupted consumption patterns as well as with the *ex post* realization of crisis-related unemployment.

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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). Details on the construction of the income, industry and spending measures for the analysis sample (Column (1) can be found in the Appendix. Statistics in Column (1) are calculated on an annual basis as of December 2019. Population figures are sourced from the Danish Statistics Agency (DST) online Statistics Bank for the most comparable population available (18+ year olds in 2018). Some differences in variable construction remains:
* Individual-level measure constructed for the 20+ years population in 2018.
** Individual-level measure for the 14+ years population in November 2018, without any tenure requirement.

		Sample (1)	Population (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	37,614*
Stockholder		27.8%	25.2%*
Industry:			
	Private Sector, Closed	3.6%	6.9%**
	Private Sector, Not Closed	34.3%	37.8%**
	Public Sector	19.7%	17.5%**
Total card spending (USD)		19,494	-
Spending by category, %Total:			
	Groceries	23.7%	-
	Pharmacies	1.2%	-
	Retail	18.4%	-
	Entertainment	3.8%	-
	Fuel & commuting	6.4%	-
	Professional & personal services	4.5%	-
	Food away from home	7.7%	-
	Travel	6.5%	-
	Cash	13.3%	-
Online spending, %Total:			
	All online	24.4%	-
Spending by sector, %Non-Cash Total			
	Closed	28.3%	-
	Constrained	27.8%	-
	Open	44.1%	-
Number of individuals		760,571	4,670,227

Figure 1: Daily aggregate spending. The figure aggregate spending for each day in 2020 (red line) and for the reference day in 2019 (gray line) measured as a share of average daily spending in 2019. The vertical dashed line indicates the first stage of the Danish shutdown.

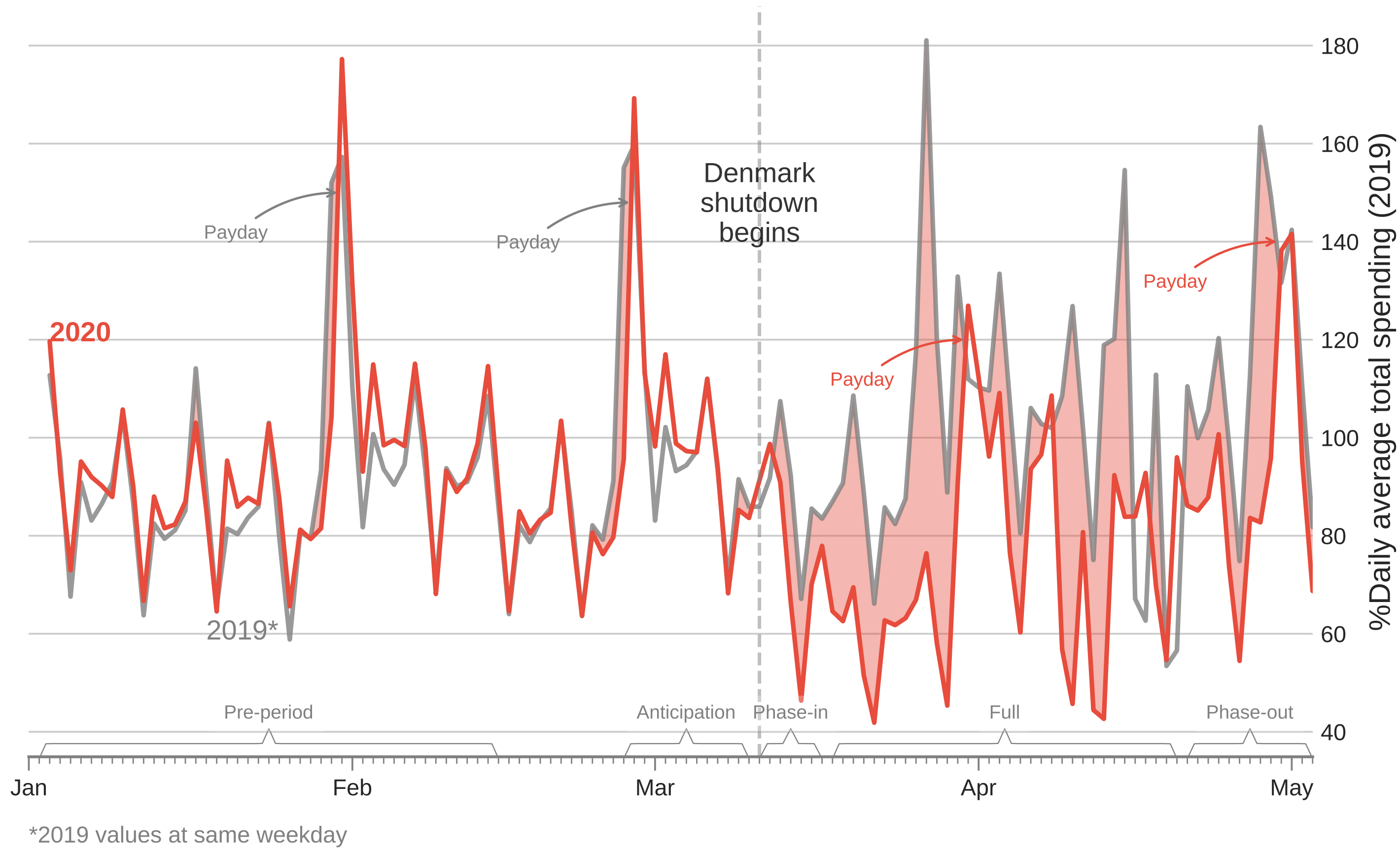


Figure 2: Main results. The left panel of the figure illustrates the headline estimate of the change in aggregate spending as well as the underlying components: the gray bars indicate average spending in the pre-shutdown period and the post-shutdown respectively, both measured relative to the reference period and expressed as a fraction of average daily spending in 2019, whereas the red bar indicates the estimated change relative to the counterfactual, which is just the difference between them. The middle panel shows analogous estimates of the change in aggregate spending for more granular time periods: the period just before the shutdown (”Anticipation”), the first stage of the shutdown (”Phase-in”), the second stage with additional restrictions (”Full”) and the third stage where some restrictions are were lifted (”Phase-out”). The right panel shows analogous estimates of the change in spending by sector: the open sector (”Open”), the constrained sector (”Constrained”) and the closed sector (”Closed”).

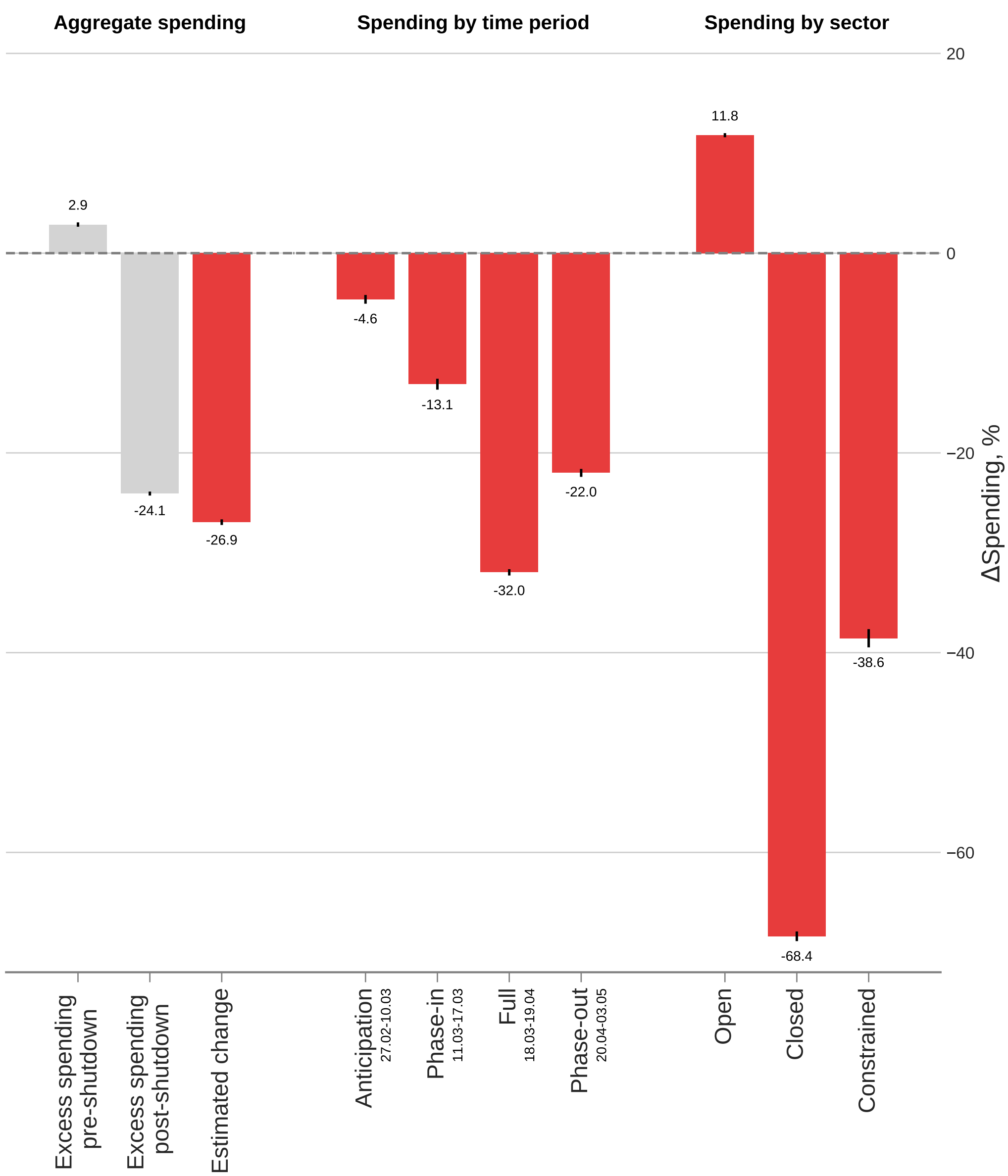


Figure 3: Heterogeneity in *ex ante* exposure to adverse crisis consequences. The figure illustrates how the estimated change in total spending varies across subsamples that are heterogeneous in one dimension of *ex ante* exposure to the adverse consequences of the crisis and homogeneous in other dimensions. The first pair of columns captures exposure to unemployment by comparing employees in the closed sector ("high exposure") and the public sector ("low exposure"); the second pair captures exposure to wealth losses by comparing stockholders ("high exposure") and non-stockholders ("low exposure"); the third pair captures exposure to serious health problems by comparing elderly ("high exposure") and non-elderly ("low exposure"); the last pair captures exposure to disrupted consumption patterns by comparing individuals whose spending share in the closed sector is above the 75th percentile ("high exposure") and below the 25th percentile ("low exposure").

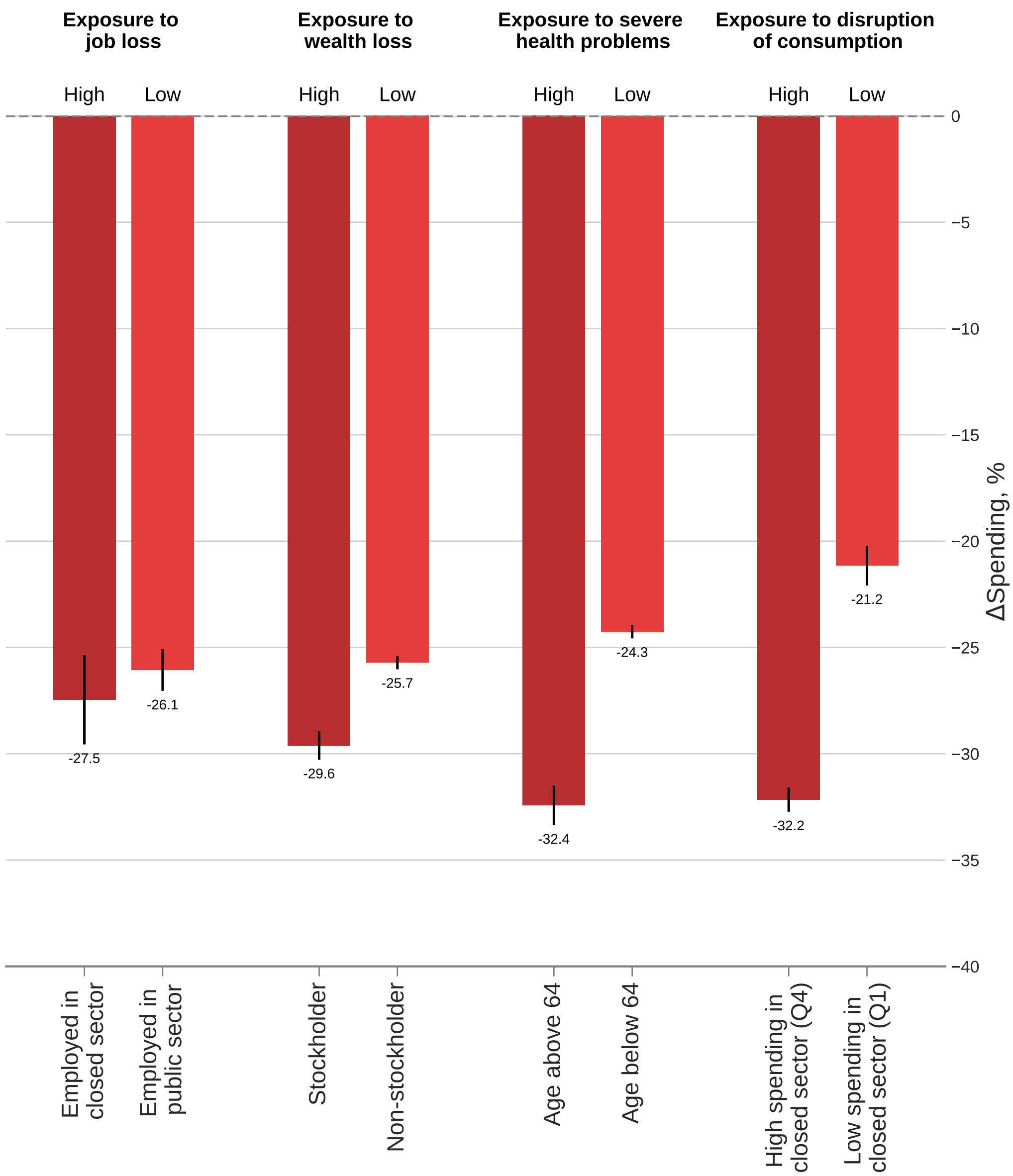
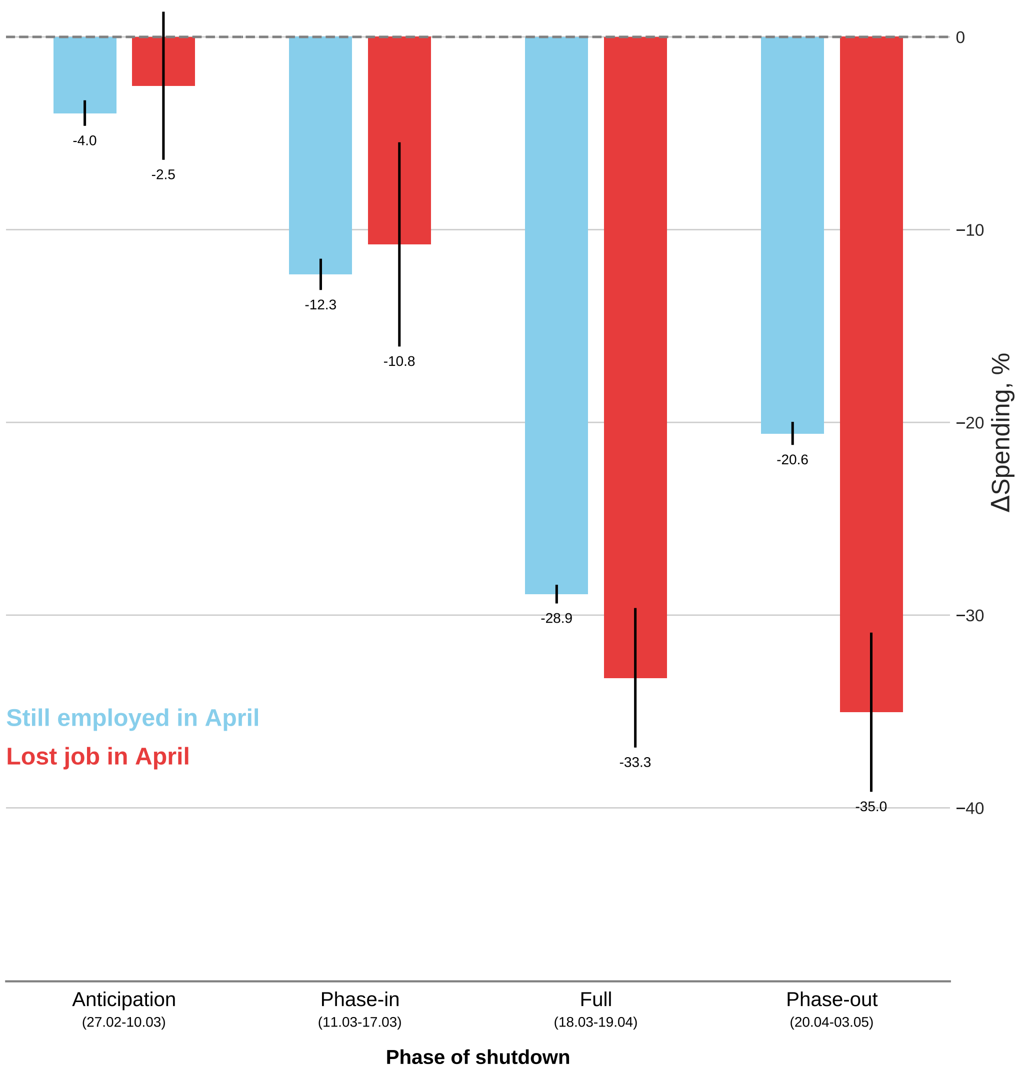


Figure 4: Heterogeneity in *ex post* realization of unemployment risk. The figure illustrates how the estimated change in total spending varies across subsamples who experienced a job loss in April 2020 and individuals who did not. The estimates are by time period: the period just before the shutdown (”Anticipation”), the first stage of the shutdown (”Phase-in”), the second stage with additional restrictions (”Full”) and the third stage where some restrictions are were lifted (”Phase-out”). Observations are reweighed so that the two subsamples have the same *ex ante* exposure to the adverse consequences of the crisis as the full sample.



ONLINE APPENDIX

Figure A1: COVID-19 mortality. The figure shows cumulative mortality due to COVID-19 for Denmark (black line), Italy (green line), the United States (brown line), Germany (red line) and Norway (blue line) over the period 1 February 2020 - 3 May 2020. Source: European Centre for Disease Prevention and Control (2020).

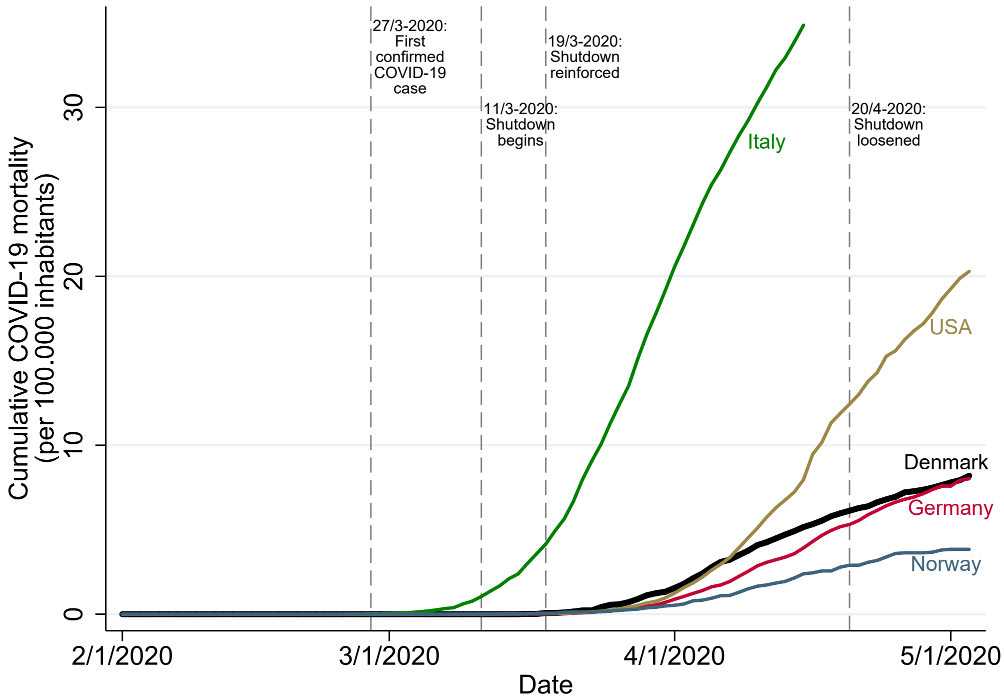


Figure A2: Fiscal stimulus. The figure shows discretionary government spending at the onset of the COVID-19 crisis for Denmark, Italy, the United States, Germany and Norway. Source: IMF (2020).

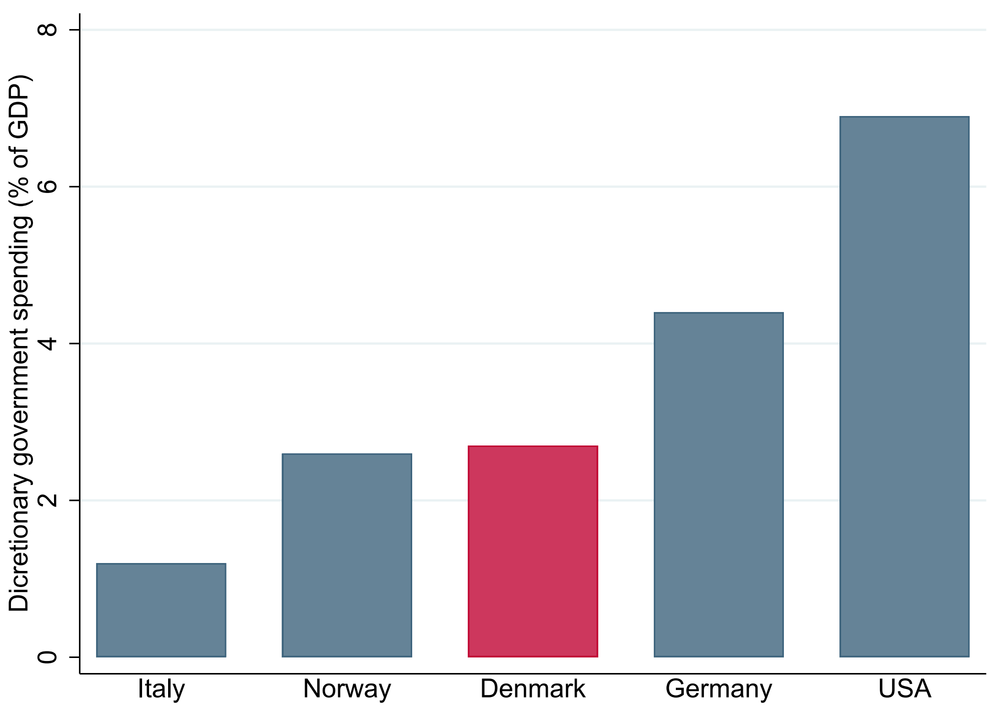


Figure A3: Daily spending by economic sector. The figure shows daily spending relative to the reference period and scaled by average daily spending in 2019 (analogous to Figure 1) in the open sector (top panel), constrained sector (middle panel) and closed sector (bottom panel).

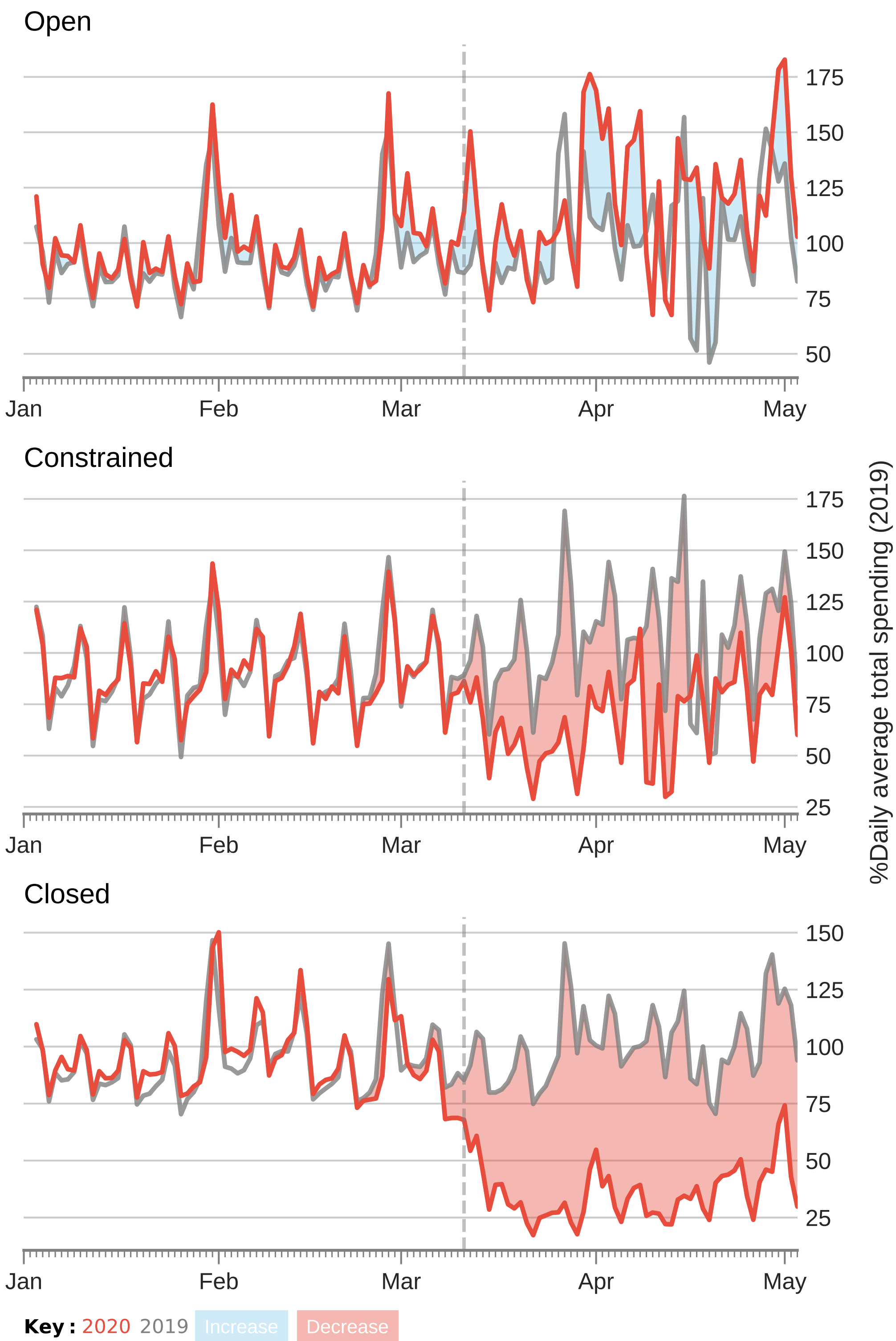


Figure A4: Change in spending by detailed expenditure category. The figure shows the estimated change in spending by detailed expenditure category. The estimates are analogous to the estimates for aggregate spending in Figure 2.

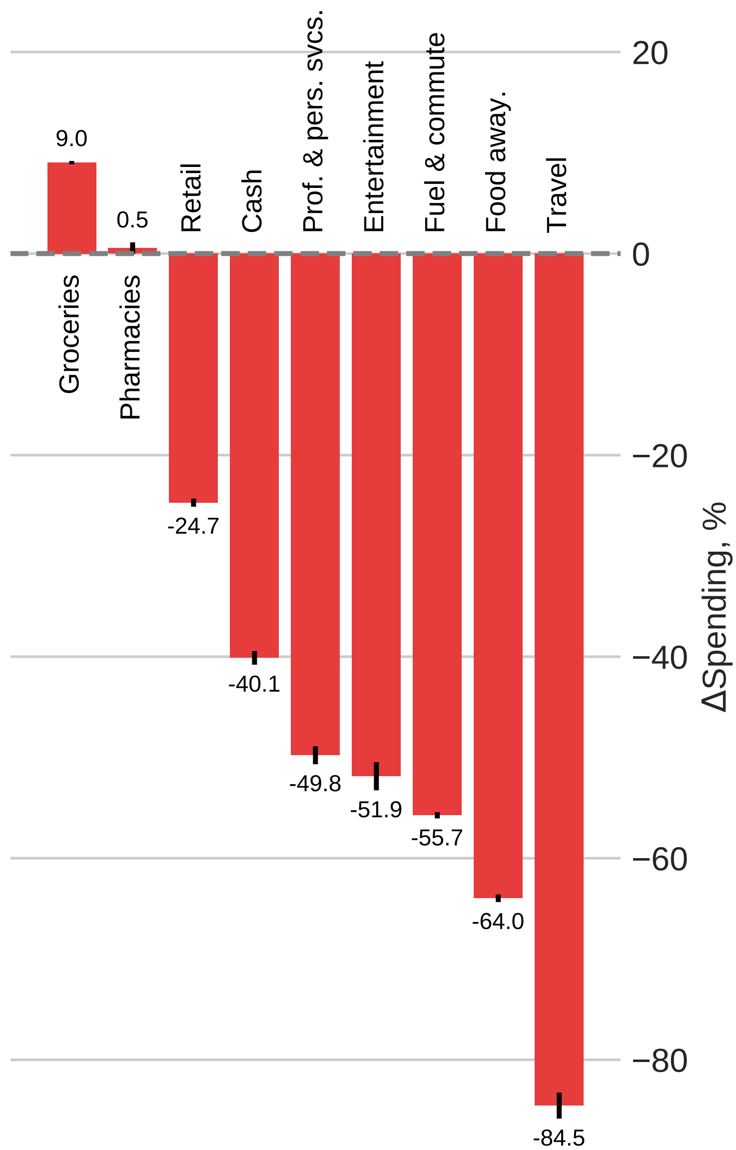


Figure A5: Change in online and offline spending. The figure shows the estimated change in offline and online spending as well as detailed categories of online spending. The estimates are analogous to the estimates for aggregate spending in Figure 2.

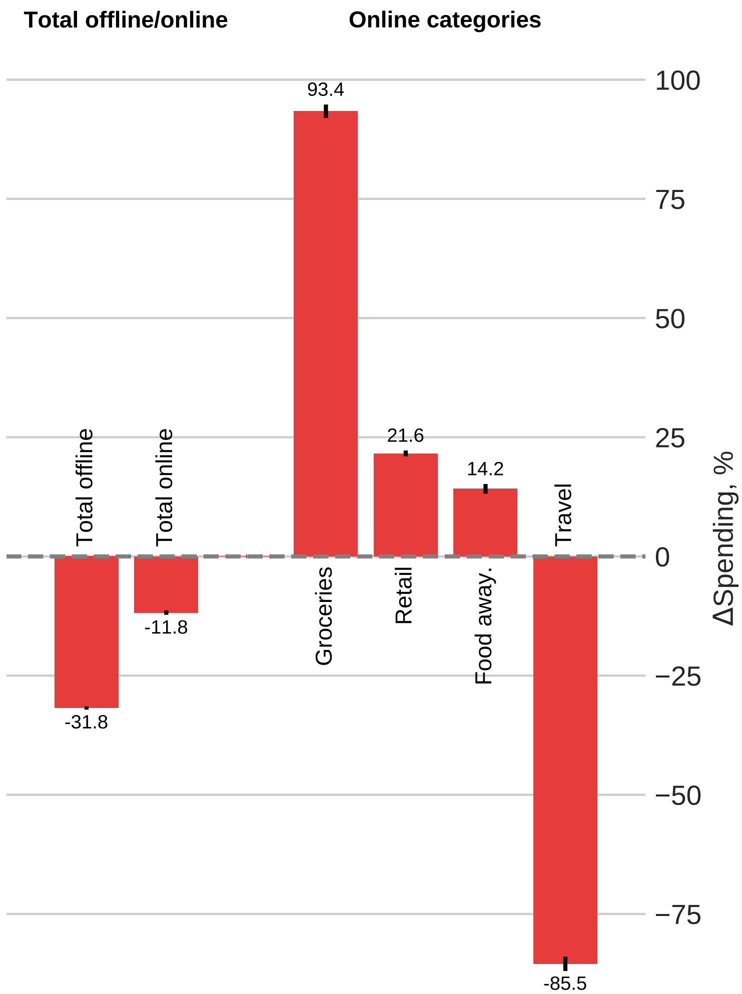


Table A1: Aggregation of spending categories This appendix explains how spending categories obtained from MCCs are aggregated to measures of spending in open, constrained and closed sectors.

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
Private Sector, Closed	Passenger flight and sea transportation, including support services: 493920, 501000, 511010, 511020, 522300 Hotels: 551010, 551020, 552000, 553000, 559000 Restaurants, cafes, bars, etc: 561010, 561020, 562100, 562900, 563000 Travel and reservation agents: 771100, 791100, 791200, 799000 Entertainment, sports, recreation services, etc: 900110, 900200, 900300, 900400, 910400, 920000, 931100, 931200, 931300, 931900, 932100, 932910, 932990, 855100, 855200, 855300, 855900, 889160, 591400 Personal care services: 960210, 960210, 960220, 960300, 960400, 960900, 862200, 862300, 869020, 869030, 869040, 869090, 889990, 477810 Other: 750000
Private Sector, Other	DB07 Sections A, B, C, D, E, F, G, H, J, K, L, M, N, Q, R, S (excluding those already included above) Includes farming, manufacture, logistics, utilities, building and construction, retail, information and communication, financial services, real estate, professional and technical services
Public Sector:	DB07 Sections O and P (excluding private sector activities grouped in recreation services, above), Q (excluding private sector activities grouped in personal care services, above) and 491000, 493110, 493120, 522130, 910110, 910120, 910300, 910200

Heterogeneity in spending drops

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 the estimator $\Delta spending$ to the sample of individuals of type m with characteristic $\widetilde{m}_N$.