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The cost of the COVID-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending

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ABSTRACT

We study how the differential timing of local lockdowns due to COVID-19 causally affects households' spending and macroeconomic expectations at the local level using several waves of a customized survey with more than 10,000 respondents. About 50 % of survey participants reported income and wealth losses due to the corona virus, with the average losses being \$5,293 and \$33,482 respectively. Aggregate consumer spending dropped by 31 log percentage points with the largest drops in travel and clothing. We find that households living in counties that went into lockdown earlier expected the unemployment rate over the next twelve months to be 13 percentage points higher and continued to expect higher unemployment at horizons of three to five years. They also expected lower future inflation, reported higher uncertainty, expected lower mortgage rates for up to 10 years, and had moved out of foreign stocks into liquid forms of savings. The imposition of lockdowns can account for much of the decline in employment during the crisis as well as declines in consumer spending. While lockdowns had pronounced effects on local economic conditions and households' expectations, they had little impact on approval ratings of Congress, the Fed, or the Treasury but led to declines in the approval of the President.

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Consumers in recent years have faced a myriad of large shocks, with the COVID19 crisis being followed by the Russian invasion of Ukraine and the recent inflationary episodes around the world. These large shocks can serve as a valuable magnifying glass to shed more light on how consumers form their expectations about different macro variables jointly but also on how these expectations feed back into consumers' consumption choices.

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Specifically, we zoom into the COVID19 pandemic during and after which we fielded several waves of a customized survey on all households participating in the Kilts Nielsen Consumer Panel (KNCP) to elicit beliefs, employment status, spending, and portfolio allocations.[1] We find that U.S consumers had a very bleak outlook for the U.S. economy. We also use the differential timing of imposing lockdowns at the local level to quantify the effect of lockdowns on households' economic outlook and their spending responses. We find that the cost of lockdowns in terms of reduced spending was very large.

We first report aggregate statistics across survey waves to study how the arrival of COVID19 affected spending patterns and expectations on average between the pre-crisis wave in January 2020 and April 2020. Consistent with earlier work (Coibion et al., 2020a; Bick and Blandin, 2020), we find a massive decline in the employment rate: the rate fell by 5 percentage points which is larger than the cumulative drop in the employment-to-population ratio during and after the Great Recession. Overall spending on non-durables dropped by $1000 per month between January and April which corresponds to a 31 % drop in spending with heterogeneous responses across granular categories. Specifically, we find one of the largest drops in debt payments including mortgages, student, and auto loans. This result raised the concern of a wave of defaults, a slow economic recovery and helped explain the increase in loan provisions by major US banks in subsequent weeks. These dire outlooks did not materialize ex-post, likely due to a strong and immediate fiscal and monetary policy responses. Households also spent substantially less on discretionary expenses such as transportation, travel, recreation, entertainment, clothing, and housing-related expenses. Medical expenses, utilities, education-related expenses, and food expenses also decreased but to a lesser extent. We also document large decreases in planned spending on durables during the crisis. On average, survey participants were 5 percentage points less likely to purchase durables during the crisis wave relative to the pre-crisis wave which translates into an average drop in planned spending on durables of almost $1000.

In line with these negative outcomes at the individual level, households' macroeconomic expectations became far more pessimistic. Subjective expectations are a key driver of consumption and savings decision and the arrival of COVID-19 offered a unique laboratory to study how agents form beliefs and how these beliefs shape behavior (Bordalo et al., 2024). Average perceptions of the current unemployment rate increased by 11 percentage points with similar magnitudes for expectations of unemployment one year later. Unemployment expectations over the next three to five years also increased by an average of 1.2 percentage points, indicating that households expected the downturn to have persistently negative effects on the labor market. Again, from an ex-post perspective, these expectations were too pessimistic relative to realizations, with part of the discrepancy possibly due to the policy response. Inflation expectations over the subsequent twelve months on average dropped by 0.5 percentage points but uncertainty increased by 0.3 percentage points. Current mortgage rate perceptions as well as expectations for the end of 2020 and 2021 dropped on average by about 0.4 percentage points with even larger drops in average expectations over the next five to ten years. Again, these longer run expectations proved to be too low ex post, likely because consumers did not foresee the global surge in inflation that triggered a strong hiking cycle by monetary policy. These changes prior to and during the COVID19 pandemic occurred jointly with dramatic shifts in spending, income and wealth losses and allow us to benchmark our cross-sectional findings to these aggregate statistics. The increased uncertainty at the household level as well the large drop in planned spending indicate the potential role for some form of liquidity insurance to curb the desire for precautionary spending and stimulate demand once local lockdowns were lifted (D'Acunto et al., 2020), consistent with many of the actually implemented policy measures.

To assess the economic damage that households attributed to the virus, we elicited information on the perceived financial situation of the survey participants and possible losses due to the corona virus, both in income and wealth. We measure households' concerns about their financial situation on a ten-point Likert scale with higher levels indicating being more concerned. The average (median) response was 7 (8) indicating that many households were highly concerned about their personal financial situation. We also find large declines both in their income and wealth. Forty-two percent of employed respondents reported having lost earnings due to the virus with the average loss being more than $5000. More than 50 % of households with significant financial wealth reported having lost wealth due to the virus and the average wealth lost was $33,000. Given the important role of wealth effects for consumption, the drop in wealth put further downward pressure on future consumption (Lettau and Ludvigson, 2004), which the fiscal response directly targeted at households and the surge in stock valuations right after the initial collapse at the onset of the COVID19 pandemic partially offset.

What were the economic costs of lockdowns? To answer this question, we compare economic outcomes for households in counties with lockdowns to households in counties without lockdowns. We instrument lockdowns with a dummy variable that equals one if the county had any confirmed COVID cases. Our identification exploits the heterogeneous timing of when the first COVID cases were identified in different counties. As we argue below, most lockdowns occurred when only a handful of COVID cases were reported in a location, which was largely random. By themselves, these few cases were unlikely to change the economic behavior of households (we provide external evidence to support this identifying assumption). We also control for the share of confirmed cases at the county level which proxies for direct health effects on the economy.

In our first set of tests, we study the labor market response to local lockdowns. Individuals living in counties under lockdown were 2.8 percentage points less likely to be employed, had a 1.9 percentage point lower labor-force participation, and were 2.4 percentage points more likely to be unemployed. This degree of variation introduced by lockdowns is large. For example, these results imply that lockdowns account for close to sixty percent of the decline in the employment to population ratio. Furthermore, since we can only estimate the short-run effects of lockdowns on labor markets, these numbers are likely to be a lower bound on the total effects of lockdowns on labor markets, as continued lockdowns were likely to lead to business failures and further job loss.

[1] These surveys build on previous work using the Nielsen panelists to study the formation and updating of economic expectations (see Coibion et al., 2020, 2022, 2023; D'Acunto et al., 2021a,b).

To analyze the degree to which disruptions in labor markets paired with increases in uncertainty and restrictions on spending translated into changes in aggregate demand, we study the spending patterns of survey participants using survey answers on dollar spending in narrowly defined categories during the months from January to April. We find that households under lockdown spent on average 31 log percentage points less than other households, indicating a large drop in aggregate demand due to mobility restrictions and the effect of the pandemic on income and economic expectations. However, the magnitudes of the decline vary dramatically across spending categories.[2] To better understand the effect of the pandemic on subsequent aggregate demand conditions, we analyzed spending plans of households. We first document that lockdowns were not a significant determinant of current financial constraints and durable purchases in the months pre-crisis, thereby ruling out possible concerns that any result we document might be driven by financial constraints or past purchases because purchases of many durable goods are lumpy. At the extensive margin, survey participants under lockdown were 3.5 percentage points less likely to purchases larger ticket items in the next 12 months. At the intensive margin, these survey participants planned to spend almost 26 log percentage points less. Taken together, these results indicate a persistent drop in aggregate demand, possibly due to a mix of lower expected income, heightened uncertainty, and supply restrictions. To the extent that part of the drop in planned spending reflects precautionary savings, our results indicate that tax rebates or other forms of direct transfers to households might be less effective than during normal recessions (Johnson et al., 2006; Parker et al., 2013), consistent with lower impact marginal propensities to consume (MPC) as documented in the literature (Coibion et al., 2020b). At the same time, these lower MPCs resulted in dry gunpowder that then triggered a strong consumption response once supply restrictions eased.

Higher uncertainty should not only result in lower spending due to precautionary motives but might also result in portfolio reallocations out of risky assets and into safe assets (Coibion et al., 2024). Conditional on having savings totaling more than one-month of income, participants under lockdown had a 1.7 percentage point higher portfolio share in checking accounts and a 0.7 percentage point lower share in foreign stocks, consistent with a flight to safety. We do not find a significant reaction for the share of savings held in US equity, possibly because US equity markets already had partially bounced back by the time we fielded the survey in early April of 2020.

We then move on to study the effect of lockdowns on subjective expectations, which can shed light on the speed and shape of the recovery. First, survey participants that were under lockdown expected 0.5 percentage points lower inflation over the next 12 months, which might in part explain the depressed spending response of households. Consistent with the idea that the impact of the pandemic on inflation was not clear, we find that the individual-level uncertainty about future expected inflation increased by more than 0.6 percentage points. Second, we analyze the effect on the expected unemployment rate at different horizons. The pandemic increased concurrent unemployment estimates by staggering 13.8 percentage points, expectations for the unemployment rate in one year increased by 13 percentage points, and long-run expectations over the next three to five years were on average still 2.4 percentage points higher. These results indicate, at least through the lens of household expectations, that consumers did not expect a V-shaped recovery. Moreover, given the length of heightened unemployment according to household expectations, these results justified stimulative fiscal policy targeted directly at households to prevent a large drop in demand once claims expire. Third, we look at the effect on mortgage rate expectations, which are a central transmission mechanism for monetary policy to household consumption. The COVID-19 pandemic resulted in current mortgage rate perceptions that were 0.7 percentage points lower, with similar effects for a forecast horizon until the end of 2020 and 2021 but even larger effects at the long run over the next five to ten years. Hence, the pandemic resulted in a level shift of the term structure of mortgage rates. The negative effect on expectations in the long run suggests that the lower bound on nominal interest rates could have been a binding constraint for monetary policy makers for an extended period of time had the inflation surge not happened.

Finally, to assess the political consequences of lockdowns, we asked respondents to rate several government bodies on a 0 (poor) to 10 (excellent) scale. We find that being under lockdown resulted in a 6.2 point lower rating for the President but a 3.1 point higher rating for the U.S. Center for Disease Control and as such might have played a role in the subsequent change in the White House. Taken together, our findings help us understand the drivers of heterogeneous consumer expectations and spending patterns which is crucial to design policy interventions in an effective way.

Jointly, these findings provided real-time evidence on the economic consequences of the COVID-19 pandemic. Our repeated surveys were able to provide unprecedented detail on how the COVID crisis had affected labor markets, household spending decisions and expectations, and even portfolio reallocations. Strikingly, we found that much of the declines in employment and spending can be attributed to lockdowns rather than to the share of the population infected by the coronavirus. While we cannot speak to the welfare effects of these policies in the absence of knowing to what extent they were successful in slowing the spread of the disease, our results do indicate a direct and large role for the preventative lockdown measures in accounting for the size of the resulting downturn.

[2] These results complement Binder (2020) who shows that 30–40 % of Americans were very concerned about the corona crisis, postponed travel and delayed purchases of larger ticket items as early as March 2020 but became more optimistic about the unemployment situation and revised downward their inflation expectations after being told about the cut in the federal funds target rate on March 3rd. Moreover, Fetzer et al. (2021) show the arrival of the corona virus in a country led to a large increase in internet searches around the world. In a survey experiment on a US population, they find survey participants vastly overestimated the mortality rate and the contagiousness of the virus. Hanspal et al. (2021) study the income and wealth loss in a survey and the impact on expectations about the economic recovery.

1. Data and survey design

This section describes the survey design we use to elicit expectations, plans, and past spending decisions. We first detail the Nielsen Homescan panel on which we ran the survey and then provide more information on the structure of the survey.

1.1. Nielsen panel

Since June 2018, we have been fielding customized surveys inviting participation by all household members in the KNCP on a quarterly frequency. The KNCP represents a panel of approximately 60,000 households that report to AC Nielsen (i) their static demographic characteristics, such as household size, income, ZIP code of residence, and marital status, and (ii) the dynamic characteristics of their purchases, that is, which products they purchase, at which outlets, and at which prices. Panelists update their demographic information at an annual frequency to reflect changes in household composition or marital status.

Nielsen attempts to balance the panel on nine dimensions: household size, income, age of household head, education of female household head, education of male household head, presence of children, race/ethnicity, and occupation of the household head. Panelists are recruited online, but the panel is balanced using Nielsen's traditional mailing methodology. Nielsen checks the sample characteristics on a weekly basis and performs adjustments when necessary.

Nielsen provides households with various incentives to guarantee the accuracy and completeness of the information households report. They organize monthly prize drawings, provide points for each instance of data submission, and engage in ongoing communication with households. Panelists can use points to purchase gifts from a Nielsen-specific award catalog. Nielsen structures the incentives to not bias the shopping behavior of their panelists. The KNCP has a retention rate of more than 80 % at the annual frequency. Nielsen validates the reported consumer spending with the scanner data of retailers on a quarterly frequency to ensure high data quality. The KNCP filters households that do not report a minimum amount of spending over the previous 12 months.

1.2. Survey

Nielsen runs surveys on a monthly frequency on a subset of panelists in the KNCP, the online panel, but also offers customized solutions for longer surveys. Retailers and fast-moving consumer-goods producers purchase this information and other services from Nielsen for product design and target-group marketing. At no point of the survey did Nielsen tell their panelists that the survey they fielded was part of academic research which minimizes the concerns of survey demand effects.

In January and April of 2020, we fielded the two waves of the survey that we exploit in the current paper. Our survey design builds on the Michigan Survey of Consumers, the New York Fed Survey of Consumer Expectations, the Panel on Household Finances at the Deutsche Bundesbank as well as D'Acunto et al. (2021a). The January wave was fielded to 63,732 households. 18,344 individuals responded for a response rate of 26.80 % and an average response time of 16 min 47 s. The response rate compares favorably to the average response rates of surveys on Qualtrics that estimates a response rate between 5 % to 10 %. The April wave had 13,771 unique respondents and a sample of 50,870. Nielsen provides weights to ensure representativeness of the households participating in the survey. We report descriptive statistics for participating households in Appendix Table A.1. The average household income was $68, 000 and the average household size was 2.6. On average, survey participants were 50 years old and 73 % of survey participants were white. These statistics are similar to other studies using the Nielsen panel, such as Coibion et al. (2020b).

The online appendix contains the detailed questions we use in the current paper. We collected information on spending (per month) in the last three months in detailed categories such as debt payments including mortgages, auto loans, and student loans, housing expenses, utilities, food, clothing, gas, medical expenses, transportation costs, travel and entertainment, education and child care, furniture and other small durables, as well as a catch-all category including charitable giving. We also asked participants about purchases of larger durables such as cars or houses over the last 6 months as well as plans to buy these items over the next 12 months. We then elicited financial constraints, and financial portfolios conditional on any savings larger than one month of income.

Subsequently, we elicited inflation expectations. We followed the design in the New York Fed Survey of Consumer Expectations (SCE) and asked specifically about inflation, because asking about prices might induce individuals to think about specific items whose prices they recall rather than about overall inflation (see Crump et al. (2022) for a paper describing and using the SCE data). We elicited a full probability distribution of expectations by asking participants to assign probabilities to different possible levels of the inflation rate. In addition, we also asked about the perception of the current unemployment rate and the expected unemployment rate in twelve months, and the next three to five years and the current rate on a fixed-rate 30-year mortgage as well as the expected rate at the end of 2020, 2021, and in the next five to ten years. Mortgages with a 30-year fixation period represent the most popular mortgage product in the U.S., accounting for more than 70 % of mortgages originated over the period 2013–2016.[3]

To measure labor market conditions, we first asked respondents on whether they had a paid job and if they said no, whether they were actively looking for a job. If they answered no, we classified them as out of the labor force. In case survey participants had a paid job, we asked them whether they had lost any earnings due to the virus and if so, asked them to provide an estimate. Similarly, if respondents had savings of more than one month of income, we also asked them whether they have lost any wealth and if so, how much.

[3] According to data from the National Mortgage Database program, jointly managed by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB).

Regarding the corona virus, we asked participants if they had heard any news about it and if so, how concerned they were about their financial situation with a qualitative scale from 0 to 10. Moreover, we asked them whether they were under lockdown at the time (we also observe their zipcodes), and asked to evaluate how different government bodies were handling the crisis. Finally, we asked households to estimate the expected duration of lockdowns and the amount of time before conditions returned to normal.

One concern with survey data is measurement error and while surveys are the only way to credibly measure subjective expectations, for some of our data alternatives exists. Regarding consumer spending, a leading alternative is account level data such as the JP Morgan Chase Institute data used in Cox et al. (2020). The advantage of these data are that they allow observing individual transactions at high frequency without measurement error. We show below that on average and at the categorical level, our survey-elicited spending data lines up closely with data in the Consumer Expenditure Survey (CEX), which the Census Bureau collects on behalf of the Bureau of Labor Statistics alleviating concerns of measurement error.[4] The CEX is generally considered high-quality data and serves as the official input for the design of consumption bundles in the calculation of the consumer price index. Our data also has potential advantages. First, we can observe overall spending rather than only spending for all accounts at an individual bank such as JP Morgan. Second, we have detailed categorical spending data and do not have to rely on some rough classification based on store identifiers. Third, our data allow us to study spending patterns by income and wealth losses but also subjective expectations which other data do not observe.

2. The COVID19 crisis in the survey data

A major contribution of our study to the literature on the effects of COVID19 on expectations and spending is the panel dimension of our survey. Hence, we can study in detail how spending, perceptions, and expectations changed over time pre and during the pandemic and also benchmark our cross-sectional estimates to the movements in these aggregates over time.

2.1. *Pre-crisis vs. crisis statistics*

Tables 1 and 2 provide average statistics of all the variables we analyze in the paper for the pre-crisis wave in January, the crisis wave in April, as well as the difference. Panel A of Table 1 first documents the labor market statistics. Consistent with Coibion et al. (2020a,b), we find a dramatic (5 percentage point) drop in employment which was larger than the cumulative decrease in the employment-to-population ratio during and after the Great Recession. The unemployment rate only increased by 2 percentage points because more than 4 percent of our survey population dropped out of the labor force which was even larger than the cumulative drop in labor-force participation between 2008 and 2016 of 3 percentage points.[5]

Panel B of Table 1 studies differences in liquidity and financial constraints across survey waves. Surprisingly, the fraction of survey participants that was able to cover an unexpected expense equal to one month of income slightly increased.[6] In a similar spirit, the fraction of households reporting significant financial wealth (more than one month of income) increased slightly.[7] Given the collapse of employment and financial markets, one may have expected that households should have less liquidity and access to credit. However, there was an offsetting factor. Because consumer spending declined dramatically, household could have greater (precautionary) savings and hence, on balance, there was little change in liquidity and access to credit.[8]

Panel C focuses on portfolio reallocations for the subsample of survey participants that had savings larger than one months of income. In the aggregate, we find small decreases in portfolio shares for cash, foreign assets, and gold but increases in US bonds and stocks. Overall, the portfolio reallocations were small however, consistent with many savers not trading frequently (Giglio et al., 2021).

Finally, Panels D to G report average statistics for inflation expectations and uncertainty, unemployment and mortgage rates, both current, over the near future, as well as in the longer run. Inflation expectations on average dropped by 0.5 percentage points but uncertainty increased by 0.3 percentage points. Average perceptions of current unemployment rates increased by 11 percentage points with similar magnitudes for expectations in one year. Unemployment expectations over the next three to five years also increased by an average of 1.2 percentage points. These results are qualitatively similar (i.e., a large, short-run increase in unemployment with unemployment rates elevated by one percentage point in 3–5 years) when we drop observations for unemployment rates larger than 40 % but economic magnitudes of the average differences across waves are about half the size. Current mortgage rate perceptions as well as expectations for the end of 2020 and 2021 also dropped on average by about 0.4 percentage points with even larger drops in average expectations over the next five to ten years. The change in average expectations show some dramatic differences across waves before and during the crisis and allow us to benchmark our cross-sectional estimates below to movements in the aggregate. From an ex-post

[4] For more information on the CEX, please see https://www.bls.gov/cex/.

[5] Unemployment is defined as the ratio of those respondents that currently do not have a paid job but are looking for one. We define labor-force participation as the fraction of the overall survey population that is either employed or looking for work.

[6] The survey question is “Suppose that you had to make an unexpected payment equal to one month of your after-tax income, would you have sufficient financial resources (access to credit, savings, loans from relatives or friends, etc.) to pay for the entire amount?”

[7] The survey question is “Does your household have total financial investments (excluding housing) worth more than one month of combined household income?”

[8] Another possibility is that income declined so much that more households could find credit to cover this correspondingly reduced amount of spending.

Table 1
Descriptive statistics by wave.

	Pre-crisis mean/(st.dev) (1)	Crisis mean/(st.dev) (2)	Difference mean/[s.e.] (3)
Panel A. Employment statistics			
Employment	0.577	0.527	−0.050***
	(0.494)	(0.499)	[0.006]
Labor force participation	0.631	0.590	−0.041***
	(0.483)	(0.492)	[0.006]
Unemployment rate	0.086	0.106	0.020***
	(0.280)	(0.308)	[0.005]
Panel B. Liquidity and access to credit			
Ability to make an unexpected payment of one-month income	0.639	0.652	0.013**
	(0.480)	(0.476)	[0.006]
Share of households with significant financial wealth	0.504	0.517	0.013**
	(0.500)	(0.500)	[0.006]
Panel C. Share of financial wealth in:			
Checking account	44.152	43.619	−0.533
	(34.811)	(34.528)	[0.601]
Cash	14.342	13.591	−0.751**
	(21.532)	(20.514)	[0.367]
US Bonds	5.127	5.769	0.641***
	(11.578)	(12.466)	[0.205]
US Stocks	21.391	22.517	1.126***
	(27.193)	(27.524)	[0.472]
Foreign stocks and bonds	3.124	2.677	−0.446***
	(8.014)	(6.900)	[0.133]
Gold and precious metals	1.233	1.088	−0.145*
	(4.896)	(4.717)	[0.084]
Bitcoin and other cryptocurrencies	0.429	0.415	−0.014
	(3.615)	(3.426)	[0.062]
Other	10.203	10.323	0.120
	(23.082)	(23.366)	[0.401]
Panel D. 12-month-ahead inflation, distributional question			
Implied Mean	2.231	1.708	−0.524***
	(4.457)	(5.868)	[0.061]
Uncertainty (standard deviation)	4.107	4.385	0.278***
	(3.546)	(3.607)	[0.044]
Panel E. Unemployment rate, point prediction			
Current	10.466	21.783	11.317***
	(13.388)	(21.861)	[0.205]
One-year-ahead	10.704	20.747	10.043***
	(12.979)	(19.397)	[0.189]
In the next 3–5 years	11.827	13.049	1.222***
	(14.475)	(14.839)	[0.181]
Panel F. Unemployment rate, point prediction, response restricted to be less than 40 %			
Current	7.856	12.055	4.199***
	(7.716)	(9.547)	[0.112]
One-year-ahead	8.152	12.863	4.712***
	(7.644)	(8.949)	[0.108]
In the next 3–5 years	8.436	9.371	0.936***
	(7.572)	(7.927)	[0.099]
Panel G. Mortgage rate, point prediction			
Current	6.553	6.164	−0.389***
	(7.372)	(7.735)	[0.093]
End of 2020	7.311	6.836	−0.475***
	(8.441)	(8.965)	[0.107]
End of 2021	7.759	7.362	−0.397***
	(8.690)	(9.012)	[0.109]
In the next 5–10 years	8.644	8.039	−0.606***
	(9.443)	(9.273)	[0.116]

Notes: Column (1) reports moments for the pre-crisis wave. Column (2) reports moments for the crisis wave. Column (3) reports the difference between crisis and pre-crisis averages. Standard errors for the difference are in square parentheses. Standard deviations are reported in parentheses in columns (1) and (2). ***, **, * indicate statistical significance at 1, 5 and 10 percent.

perspective, consumers at the onset of the COVID19 pandemic were too pessimistic regarding their outlook for the unemployment rate but underestimated both future inflation and mortgage rates. These patterns are consistent with many consumers overestimating the duration of the pandemic and its economic ramifications as well as not foreseeing the subsequent surge in inflation.

We now move on to study the change in average monthly spending in the three months before the two survey waves. One concern

Table 2
Pre-crisis vs. crisis consumer spending.

	Spending			Extensive margin			Intensive margin		
	Pre-crisis Mean (st. dev) (1)	Crisis Mean (st. dev) (2)	Diff. Mean [s. e.] (3)	Pre-crisis Mean (st. dev) (4)	Crisis Mean (st. dev) (5)	Diff. Mean [s. e.] (6)	Pre-crisis Mean (st. dev) (7)	Crisis Mean (st. dev) (8)	Diff. Mean [s. e.] (9)
Consumer non-durable spending									
Total spending	3999	3033	−0.310***						
	(3485)	(2805)	[0.013]						
Debt payments	1288	905	−0.917***	0.703	0.584	−0.119***	1832	1549	−0.148***
	(1836)	(1446)	[0.042]	(0.457)	(0.493)	[0.006]	(1948)	(1607)	[0.020]
Housing (rent, maintenance, home insurance)	616	524	−0.881***	0.810	0.661	−0.149***	791	826	0.000
	(906)	(853)	[0.034]	(0.392)	(0.473)	[0.005]	(1132)	(1137)	[0.020]
Utilities	429	361	−0.474***	0.956	0.891	−0.064***	467	417	−0.103***
	(403)	(362)	[0.020]	(0.206)	(0.311)	[0.003]	(550)	(463)	[0.011]
Food	532	454	−0.266***	0.984	0.963	−0.021***	561	486	−0.140***
	(511)	(452)	[0.016]	(0.127)	(0.189)	[0.002]	(664)	(579)	[0.011]
Clothing, footwear, persona care	126	81	−1.106***	0.850	0.627	−0.223***	166	138	−0.168***
	(168)	(132)	[0.025]	(0.357)	(0.484)	[0.005]	(373)	(248)	[0.016]
Gasoline	174	125	−0.538***	0.919	0.859	−0.060***	207	154	−0.286***
	(186)	(151)	[0.021]	(0.273)	(0.348)	[0.004]	(361)	(269)	[0.012]
Other transport (public transport, car maintenance)	58	36	−0.788***	0.465	0.293	−0.172***	154	151	−0.241***
	(128)	(107)	[0.027]	(0.499)	(0.455)	[0.006]	(413)	(414)	[0.028]
Medical	220	175	−0.544***	0.745	0.644	−0.101***	329	288	−0.082***
	(402)	(349)	[0.031]	(0.436)	(0.479)	[0.006]	(697)	(556)	[0.021]
Travel, recreation, and entertainment	162	94	−1.500***	0.641	0.328	−0.312***	300	342	−0.020
	(336)	(280)	[0.031]	(0.480)	(0.470)	[0.006]	(726)	(798)	[0.027]
Education and child care	79	53	−0.290***	0.174	0.121	−0.053***	609	566	−0.145**
	(280)	(235)	[0.025]	(0.379)	(0.326)	[0.004]	(1209)	(1071)	[0.068]
Furniture, jewelry, small appliances and other small durable goods	50	39	−0.471***	0.325	0.215	−0.110***	218	251	0.001
	(146)	(136)	[0.026]	(0.468)	(0.411)	[0.006]	(688)	(640)	[0.036]
Other spending	159	84	−1.004***	0.519	0.323	−0.196***	364	280	−0.140***
	(353)	(249)	[0.032]	(0.500)	(0.468)	[0.006]	(821)	(516)	[0.029]
Purchases of durables in the previous 6 months	4426	4830	−0.004	0.907	0.925	0.018***	10,416	10,917	0.236***
	(21,477)	(22,689)	[0.043]	(0.291)	(0.264)	[0.007]	(44,474)	(46,830)	[0.059]
Plans to buy durables goods in the next 12 months	9949	9002	−0.304***	0.236	0.189	−0.048***	46,939	52,024	0.226***
	(44,362)	(42,244)	[0.046]	(0.425)	(0.391)	[0.005]	(86,891)	(89,879)	[0.069]

Notes: Columns (1), (4), and (7) report moments for the pre-crisis wave. Columns (2), (5) and (8) report moments for the crisis wave. Columns (3), (6) and (9) report the difference between crisis and pre-crisis averages. Standard errors for the difference are in square parentheses. Standard deviations are reported in parentheses in columns. In column (3), the difference is computed for averages of $\log(1 + \textit{Spending})$. In column (6), the difference is computed as a simple difference in the shares between the crisis and pre-crisis waves. In column (9), the difference is computed for averages of $\log(\textit{Spending})$. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

with survey data is that participants might only partially recall their past expenditure. To benchmark our survey data, we first compare the reported average monthly spending in the January wave to the monthly spending in the 2018 CEX. To do so, we take the annual data from the CEX, divide it by 12 to get monthly averages, and match the survey categories to the categories in the CEX. Some differences are expected for at least two reasons. First, no one-to-one mapping exists between categories in the different datasets. Second, consumer spending is seasonal and the CEX survey is a monthly average over a year, while the Nielsen survey covers a specific part of a year. Despite these inconsistencies, consumer spending in the Nielsen survey is reasonably close to consumer spending in the CEX (Appendix Table A.2). Overall monthly spending in our survey was $3999 which is smaller than the average monthly spending in the CEX of $5102. This is expected because the CEX also includes additional categories which we did not elicit in the survey as well as larger durables such as car purchases and larger appliances. Excluding these categories moves the two averages closer to each other. As for debt payments which include student loans we see larger expenditures in the January wave than in the CEX which does not have a separate category for student loans. Housing related expenses including rent and maintenance among other expenses compare closely with monthly expenses of $616 in our survey and $535 in the CEX. Similarly, for utilities which also includes phone and internet, and food which includes groceries, dine out, and beverages, both surveys report spending of $429 and $532 (KNPC) and $455 and $709 (CEX), respectively. As for clothing and footwear, we find averages of $126 in the KNCP and $220 in the CEX. For expenditures on gasoline, the category which matches closest across surveys, we indeed find almost identical averages, \$174 versus \$176. Overall, we conclude that the survey-elicited expenses line up reasonably closely to averages we can find in the CEX and suggest our subsequent analysis provides meaningful insights. Another advantage of our survey design relative to repeated cross-sections is the fact that we can do comparisons across survey waves in the same sample population which allows us to difference out systematic misreporting (i.e., some survey respondents systematically over- or underreporting certain categories).

Table 2 reports the overall monthly dollar spending as well as the split down by categories.[9] Note that households could report zero spending for a given category in a wave and average spending in columns (1) and (2) includes households with zero spending. To make descriptive statistics more comparable to the results we report below, we also compute the growth rate of $\log(1 + \mathit{Spending})$, that is, $\overline{\log(1 + \mathit{Spending})}_{April} - \overline{\log(1 + \mathit{Spending})}_{January}$. We do this particular transformation of the data to handle the skewness of consumer spending and to take into account variation in the extensive margin, that is, some households stop spending on some categories. We see that overall spending over the last three months dropped by \$1000 per month between January and April. The decline in the averages corresponds to a drop of 31 log percentage points in spending. Across categories, we see the largest average drops for travel, clothing, debt payments, and housing with decreases of 150, 110, 92, and 88 log percentage points, respectively. These figures correspond to 77.8, 66.7, 60.1, and 58.5 percentage point declines. To better understand the nature of these declines, we also report extensive and intensive margins of each spending category in columns (4)–(6) and (7)–(9) respectively. The extensive margin measures whether a survey participants had spent any money in a given category, whereas the intensive margin reports average dollar spending conditional on any spending. We observe large declines in the extensive margin not only for travel (the share of household reporting spending on this category declines by 31 percentage points) and clothing (22 percentage points) but also for debt payments and housing (which includes rent), by 12 and 15 percentage points, respectively. Hence, households mainly curbed their discretionary spending and adjusted their non-discretionary spending by less, which is consistent with D'Acunto et al., 2024. Furthermore, we observe that even for those that had positive debt payments, the size of the payment declined by approximately 15 log percentage points, while for housing (rent) the change in the intensive margin was zero (i.e., conditional on paying rent, households pay the full rent). These results suggest that constrained households stopped servicing their debt and housing payments.[10] Results for the intensive margins of other categories suggest that households downsized their purchases conditional of buying goods/services in a category. Given the importance of mortgage defaults for the severity of the Great Recession, these results raised the concern of a sluggish recovery and substantial defaults in the subsequent months, which were likely muted due to adequate policy interventions (Mian et al., 2013).

Table 2 also reports spending on durables over the previous six months, both at the extensive margin, any durable purchase, and the intensive margin, the realized dollar spending. The survey question specified durables as a house (apartment), a car, or a large appliance. We see a slight increase in the frequency of spending on durables over the last six months in our April survey wave but no difference in the intensive margin. Because the reference period is the previous six months and the speed at which the COVID crisis had been unfolding, we are less likely to capture material variation between the pre-crisis and crisis periods.

The last row of Table 2 focuses on planned durable purchases (intensive and extensive margins) over the next twelve months. Here, we find large decreases in planned spending on durables during our crisis wave. On average, survey participants were 5 percentage points less likely to purchase durables during the crisis wave relative to the pre-crisis wave but conditional on a purchase the average amount was higher, which indicates possibly strong selection effects. When we measure the decline using $\log(1 + \mathit{Spending})$ which combines both margins, the planned purchases of durable goods declined by 30 log percentage points.

In short, we observe a massive decline in consumer spending and consumers anticipated reduced spending in the subsequent months, which is consistent with other data. For example, Baker et al. (2020) observe subsets of spending through a FinTech app and find decreases of restaurant spending of one third with overall average daily spending decreasing by two thirds between January and March but sharp increases in groceries early in the pandemic due to stockpiling with a decline during the end of March. Chen et al. (2021) use data from the largest bankcard acquiring and professional service supplier in China and find spending on goods and services decreased by 33 %, whereas spending on entertainment and travel plummeted by about 60 %. Andersen et al. (2022) uses transaction-level customer data from the largest bank in Denmark and documented that overall spending dropped by 25 % with the largest decreases for food away from home and travel with more than 60 % and almost 80 %, respectively. Hence, our survey-based estimates are consistent with transaction-based analysis for several countries. Our analysis, though, has the potential advantage that we can observe overall spending and not only subsets of spending via credit cards or QR codes. From a historical perspective, these drops were large. De Nardi et al. (2012) use real personal consumption expenditure data and argue that overall consumption grew 15 percentage points less over the five years following 2007Q4 compared to historical averages with even larger declines in services consumption.

2.2. Direct COVID19 impacts

Table 3 reports several descriptive statistics for variables measuring welfare of survey participants in the context of the COVID crisis. First, we find that respondents had high levels of concerns about their household's financial situation. On a scale from 0 (not

[9] Andersen et al. (2022), Chen et al. (2020), and Baker et al. (2020) also study the consumption response to the COVID19 pandemic using a variety of data sources from Fintech apps to bank account data.

[10] It's unlikely that these patterns are driven by young adults moving back in with their parents for two reasons. First, our sample is on average older and second, rent contracts and mortgage payments typically cannot be terminated on short notice.

Table 3
COVID19-related economic concerns and losses.

	Mean	St.dev.	Percentiles				
			10	25	50	75	90
Concerned about your household's financial situation (10 = extremely concerned, 0 = no concerned at all)	7.18	2.96	2	5	8	10	10
Lost earnings							
Extensive (yes = 1)	0.42						
Intensive	$5293	$8358	$200	$500	$1500	$5000	$20,000
Lost financial wealth							
Extensive (yes = 1)	0.54						
Intensive	$33,482	$54,920	$300	$1250	$9000	$40,000	$100,000
Time before conditions return to normal in your location, days	186.3	140.5	61.0	91.5	152.5	227.5	366.0
The duration of lockdown in your location, days	83.0	47.7	30.5	45.5	66.0	101.5	181.5

Notes: the survey question for the first variable is "How concerned are you about the effects that the coronavirus might have on the financial situation of your household? Please choose from 0 (Not at all concerned) to 10 (Extremely concerned)". The survey question for lost earnings is "Have you lost earnings due to coronavirus concerns?" and conditional on responding "yes" the follow up question is "Could you provide an estimate of lost income? (Please round to the nearest dollar)". This question is only asked for people who are employed in the April wave of the survey. The survey question for lost financial wealth is "Have you lost any financial wealth due to coronavirus concerns?" and conditional on responding "yes" the follow-up question is "Could you provide an estimate of lost wealth? (Please round to the nearest dollar)". This question is asked only for people who reported having financial wealth (excluding housing wealth) greater than his/her household's one-month income. *The duration of lockdown in your location* is only asked for respondents who reported to be a lockdown. The survey question is "How long do you think the lockdown in your location will last?". Time before condition return to normal in your location is asked for all respondents. The survey question is "How long do you think it will be before conditions return to normal in your location?".

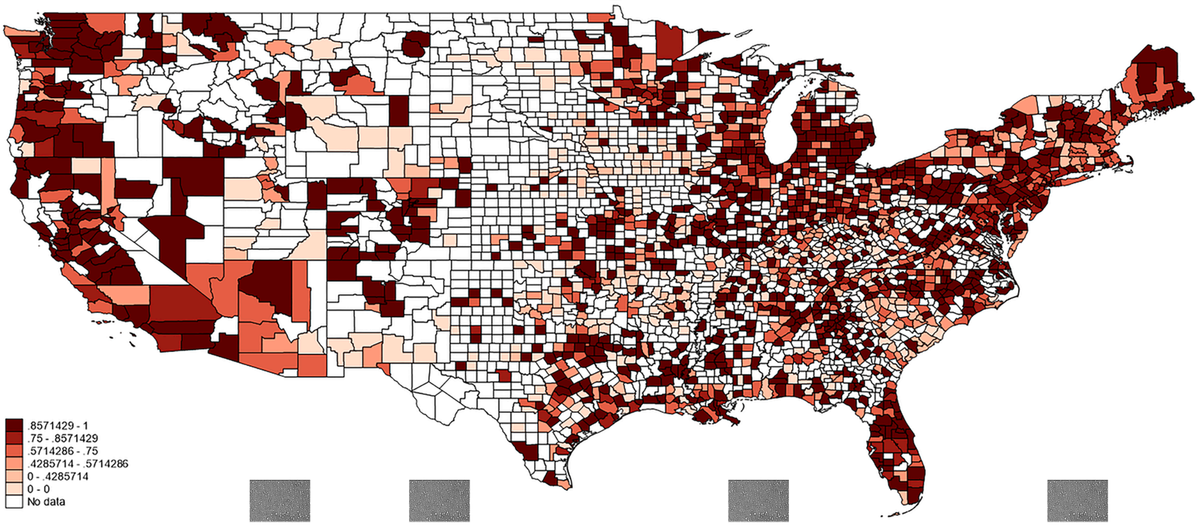

Fig. 1. Share of population reporting a lockdown.
Notes: The figure shows the distribution of lockdowns as reported by respondents in the Kilts Nielsen Consumer Panel. Hawaii is a part of the sample but is not shown in the figure.

concerned) to 10 (extremely concerned), the mean response was 7.2 and the median response was 8. A third of respondents chose the maximum score of 10. Second, we find that even employed households reported a considerable loss of labor earnings. Approximately 40 percent of the employed reported lost earnings because of COVID concerns. Conditional on losing earnings, the median loss was $1500 but the mean loss was much higher at more than $5000. Third, 54 percent of respondents with materially important financial wealth (worth more than one-month of household income) reported losses in financial wealth because of COVID. Because the distribution of wealth was highly skewed, the mean loss (approximately $33,500) was much greater than the median loss ($9000). These statistics suggest that the COVID crisis had a significant impact on income and wealth of households. These numbers are similar to Hanspal et al. (2021) who report average income losses of about $3000 and wealth losses of about $50,000.

We also asked respondents to report the expected duration of lockdowns in their locations and the expected time before conditions return to normal in their locations. On average, lockdowns were expected to last 83 days and consumers expected to return to normalcy in approximately six months. However, there was significant variation in these estimates: the standard deviation was 48 days for the lockdown duration and 140 days for the return time. In reality, most states that had implemented stay at home orders had lifted lockdowns by the end of May 2020. It took at least until the first quarter of 2021, though, until vaccines started to become available and some form of normalcy started again for many people.

2.3. Lockdowns and COVID19 infections

Fig. 1 graphically illustrates the geographic spread of lockdowns at the county level according to our survey. The darker the color, the higher the fraction of the survey participants reporting being under lockdown. White represents counties without any data. We see substantial variation in the lockdown status with intensive lockdowns in the West, North East, and northern Midwest, which is consistent with the data reported in Baek et al. (2021).

To provide a sense for time variation in the distribution of lockdowns and COVID cases, Fig. 2 shows the evolution of the fraction of counties with a lockdown as well as the fraction of counties with reported COVID cases above various thresholds. We take the timing of lockdowns at the county level from Baek et al. (2021) and the time series of confirmed COVID infections from Barrios and Hochberg (2021). We observe a significant spread of COVID cases before counties started to introduce lockdowns. Indeed, the fraction of counties with at least one confirmed COVID case led the fraction of counties with a lockdown. For example, on March 22, 2020, more than 30 percent of counties had at least one confirmed COVID case, but only 10 percent of counties had a lockdown. Note that the fraction of counties with 10+ cases or with 100+ cases grew at a slower rate and as we increase the threshold for the number of confirmed cases, the fraction of counties with cases above a higher threshold generally lags the fraction of counties with lockdowns.

Given that lockdowns deterred social mobility substantially (Barrios and Hochberg, 2021), we now study how the COVID-induced lockdowns causally determine employment, consumer spending and expectations and whether lockdowns can account for aggregate economic conditions.

3. Econometric framework for measuring the lockdown effects

To estimate the effect of lockdowns on economic activity, we need to address two related identification concerns. First, COVID infections may have a direct effect on the local economy. For example, workers may fail to show up at work because they fell sick with the virus or may have to take care of sick family members. Second, lockdowns were not applied randomly by policymakers and it could be that the same factors that lead policymakers to implement lockdowns also induce behavioral changes on the part of the population. For example, people concerned about the virus may have self-quarantined thus depressing the economy before a shelter-at-home order was announced. Because of this behavioral response, a lockdown may appear to have a larger effect on the economy than its actual direct effect. In short, estimates of lockdown effects may be confounded by omitted variables.[11]

To tackle these concerns, we estimate the following econometric specification:

$$Y_{ijt} = \kappa_i + \psi \times Lockdown_{ijt} + \eta \times ShareCOVID_{jt} + error \tag{1}$$

$$Lockdown_{ijt} = \alpha_i + \beta \times \mathbb{I}\left\{COVID_{j,t-s} > 0\right\} + \gamma \times ShareCOVID_{jt} + error \tag{2}$$

where i, j index persons and counties and t and s index time. t are the January and April survey waves, $t-s$ shows the time of exposure to COVID s periods before wave t to determine variation in lockdowns in county j. Y is an outcome variable. κ_i is a person fixed effect. *Lockdown* is a dummy variable equal to one if person i in county j reports being under lockdown at time t. $\mathbb{I}\left\{COVID_{js} > 0\right\}$ is a dummy variable equal to one if county j reported a positive number of COVID infections at time s. There was no lockdown or confirmed COVID case for any county in the January wave. $ShareCOVID_{jt}$ is the share of the population with confirmed COVID infection in county j at time t, the share is measured in percent (i.e., from 0 to 100). *ShareCOVID* proxies for the first concern that COVID infections can have a direct effect on the economy by influencing the health of workers and consumers, thus addressing the first identification concern. Data on local COVID infections are from Barrios and Hochberg (2021). Because variation in policy is at the county level, we cluster standard errors at the county level.

Eq. (2) is the first-stage regression for *Lockdown*. Our identifying assumption is that local public health authorities were likely to impose a lockdown as soon as a *single* case of a COVID infection in a location was confirmed. The timing of this first case was largely random and can reflect idiosyncratic travel of local individuals, the ability or willingness of local authorities to do COVID tests, etc. Because the number of confirmed cases initially was very low (which we can achieve by choosing an appropriate date s), it is unlikely to generate a large public concern about contracting the virus or to have a direct health effect on the local population. Instead, the response of the local population to COVID concerns was more likely to reflect the prevalence of the disease locally, which would be captured by the *ShareCOVID* variable. Note that with this identifying assumption, we effectively measure the effect of lockdowns by comparing late and early adopters of lockdown policies and therefore we may miss general equilibrium effects.

While we cannot statistically validate this identifying assumption, we can assess its quality indirectly by examining external data.

[11] The effect of first confirmed COVID infections on the decision to introduce a lockdown can be heterogeneous across locations. For example, locations with a higher density of population could be more vulnerable to a fast dissemination of the virus and thus may implement lockdowns earlier than locations with lower densities. The public media also suggested that locations with a large share of Trump supporters appeared to have a lower propensity to introduce lockdowns in response to COVID. We find some support for these hypotheses in the data (Appendix Table A.3), but introducing heterogeneity in the propensity to adopt lockdowns has no material effect on our second-stage estimates and thus we consider a simple specification for the first stage.

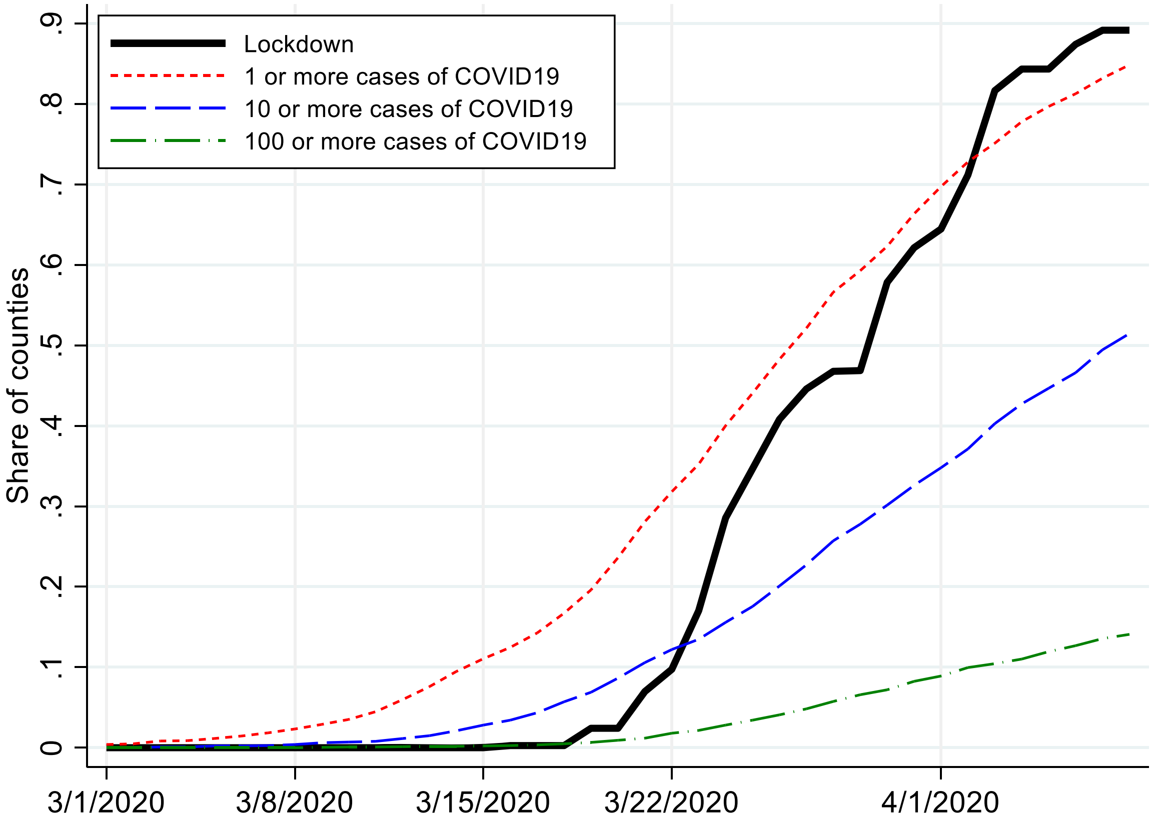

Fig. 2. Evolution of COVID19 cases and lockdowns over time.
Notes: The figure shows time series for the fraction of counties adopting lockdown policies and the fraction of counties with confirmed COVID cases above a certain threshold.

First, we examine the distribution of COVID cases at the time when a lockdown was implemented. Fig. 3 shows that approximately 75 percent of counties had less than 10 confirmed COVID cases at the time when a lockdown was implemented. Furthermore, going from zero cases to one case is associated with a 15 percent higher probability of a lockdown. Thus, it took only a handful of cases—which was hardly enough to have a discernable direct health effect on the local economy—before a county was under a lockdown.

Second, we use event analysis to investigate how lockdowns and first reported COVID cases influence dynamics for proxies of economic activity. In particular, we use the insight of Baek et al. (2021) and estimate the following specification:

$$\begin{aligned} Mobility_{j\tau} &= \alpha_j + \phi_\tau + \sum_{\varsigma=-8}^{14} \beta_\varsigma \times Lockdown_{j,\tau+\varsigma} \\ &+ \sum_{\varsigma=-8}^{14} \psi_\varsigma \times \mathbb{I}\{First\ COVID\ at\ \tau\}_{j,\tau+\varsigma} + error. \end{aligned} \tag{3}$$

j indexes counties, τ, ς index time in days, *Mobility* is the daily Google's Community Mobility Report (retail mobility),[12] $Lockdown_{j,\tau}$ is a dummy variable if county j has a lockdown at day τ (these data are from Baek et al., 2021), and $\mathbb{I}\{First\ COVID\ at\ \tau\}_{j\tau+\varsigma}$ is a dummy variable equal to one if county j reports its first confirmed COVID infection on day τ and zero otherwise. α_j and ϕ_τ are county and time fixed effects.

Estimated coefficients $\{\beta_\varsigma\}_{\varsigma=-8}^{14}$ and $\{\psi_\varsigma\}_{\varsigma=-8}^{14}$ provide event analysis of lockdowns and first confirmed infections. Our identification assumption predicts that the behavioral response to first infections should be small relative to the lockdown response. We report the estimates for $\{\beta_\varsigma\}_{\varsigma=-8}^{14}$ and $\{\psi_\varsigma\}_{\varsigma=-8}^{14}$ in Fig. 4. We find weak (if any) pre-trends in the data for lockdowns (we replicate Figure 5 in Baek et al., 2021) or first COVID cases. Each event reduces mobility but mobility declines by an order of magnitude more to a lockdown than

[12] These data are described in https://www.google.com/covid19/mobility/. In short, Google uses anonymized sets of data from users who have turned on their location History setting. We use the retail mobility index which covers places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.

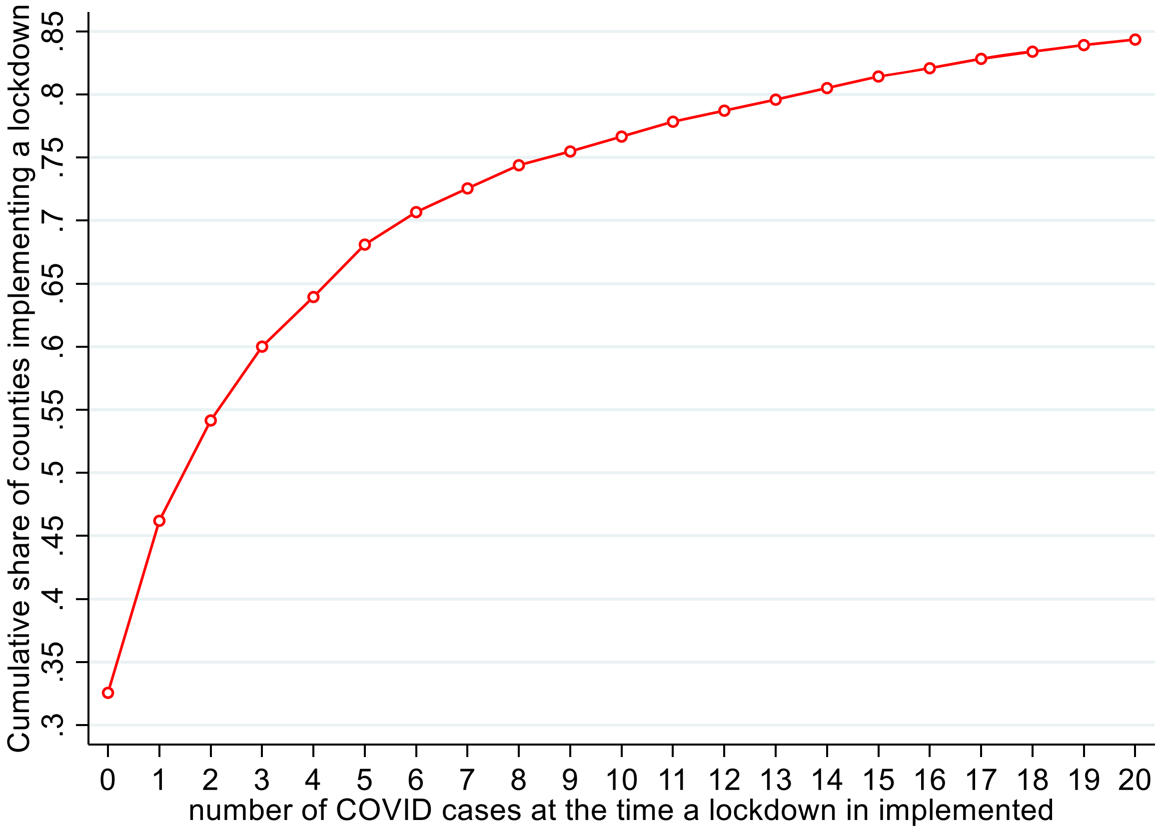

Fig. 3. CDF of the number of confirmed COVID cases at the time a lockdown is implemented.
Notes: The figure show the distribution of COVID cases at the time when a county implements a lockdown.

to a first COVID case. Given consumer spending and/or employment are highly correlated with mobility (Baker et al., 2020), economic activity was unlikely to be materially affected by reports of a first confirmed COVID case. We conclude that our identifying assumption is plausible.

Table 4 reports estimates for the first stage regression (Eq. (2)) for various choices of s, the date that we use to determine whether a county had confirmed COVID cases. We see that the dummy variable for confirmed COVID cases is a strong predictor of lockdowns at the local level across different time periods. The t-statistic on $\mathbb{I}\{COVID_{js} > 0\}$ is well above 10 thus suggesting a strong first stage. Note that the coefficient on $ShareCOVID_{jt}$ is statistically significant only when we use s equal to March 22, 2020 or later, while the survey was fielded in the first week of April (i.e., the lockdown dummy in the "crisis" wave refers to April 2–23, 2020). This pattern suggests that the intensity of infections has predictive power roughly one week before a lockdown was implemented. To ensure that our results are not driven by direct health effects, we set s so that $t - s$ refers to March 15, i.e., two weeks before the survey.

4. Perceptions, expectations, and choices during lockdowns

We now causally study the effect of lockdowns on outcomes Y_{it} such as spending, employment, expectations, and perceptions via instrumental variable regressions.[13] These results were possibly an important input into policy discussions about adequate measures of fiscal and monetary policy to stabilize local economies but are also important to measure the economic costs of lockdowns that constituted one key determinants for discussions about re-opening the economy.

4.1. Employment status

We first analyze the effect of lockdowns on labor-market statistics. Column (1) of Table 5 shows individuals in counties under lockdown were 2.8 percentage points less likely to be employed relative to other survey participants. Compared to the overall drop in

[13] In general, we find that OLS estimates (not reported) are smaller than IV estimates but the qualitative results are similar.

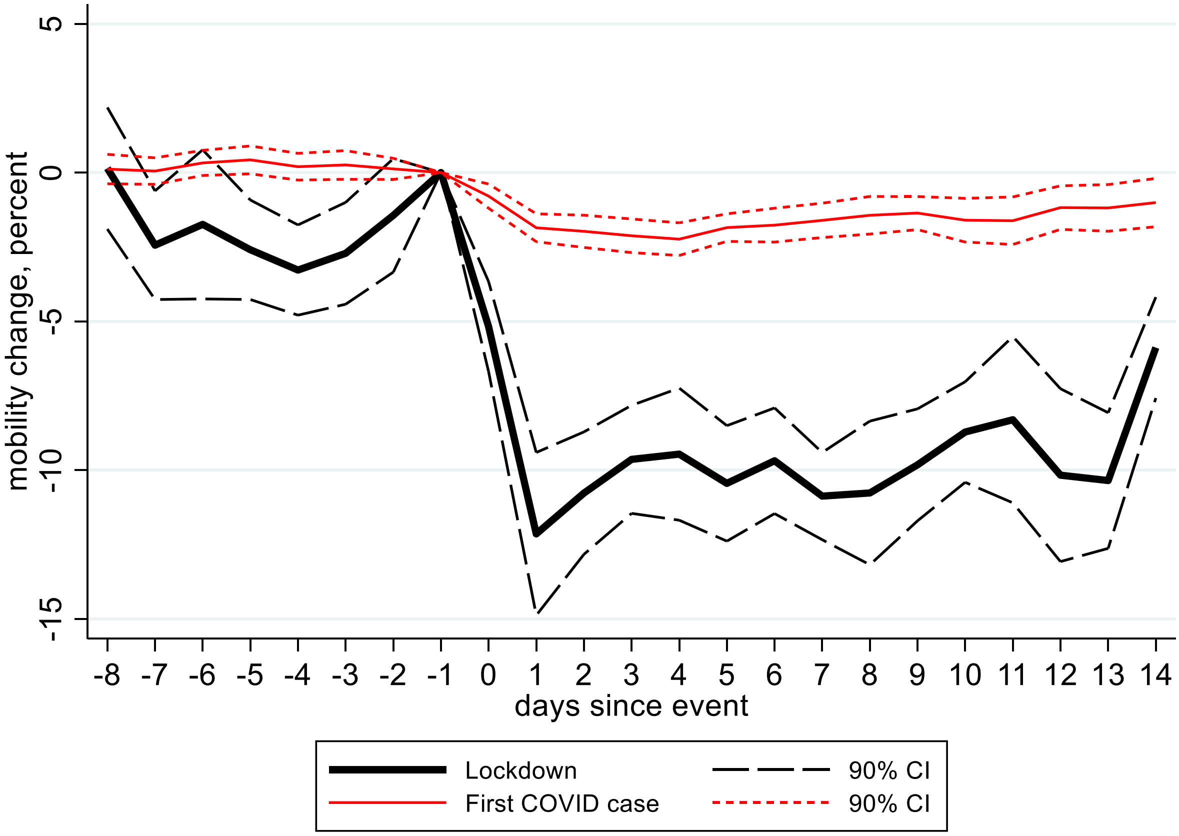

Fig. 4. Retail mobility response to lockdown and the first COVID case.
Notes: the figure shows event analysis for lockdowns and first confirmed COVID infections. The estimates are based on specification (3). Standard errors are clustered by county and day. The outcome variable (vertical axis) is Google's retail mobility index which covers restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. because of high coverage. The estimation sample is February 29, 2020 to April 3, 2020.

Table 4
First stage by the time of COVID19 exposure.

Dependent variable: *Lockdown* reported by person i in county j at time t	Date $t-s$ in $\mathbb{I}\{COVID_{j,t-s}>0\}$ in the April 2020 wave				
	March 1 (1)	March 8 (2)	March 15 (3)	March 22 (4)	April 1 (5)
$\mathbb{I}\{COVID_{j,t-s}>0\}$	0.746***	0.766***	0.793***	0.777***	0.769***
	(0.057)	(0.043)	(0.018)	(0.014)	(0.013)
$ShareCOVID_{jt}$	0.957	0.545	0.156	0.083*	0.076**
	(0.863)	(0.510)	(0.121)	(0.043)	(0.035)
Constant	0.301***	0.234***	0.114***	0.040***	0.012**
	(0.023)	(0.010)	(0.005)	(0.006)	(0.006)
Number of households	6064	6064	6064	6064	6064
R^2	0.307	0.427	0.636	0.753	0.795

Notes: The table reports estimated coefficients for Eq. (2). Standard errors clustered by county are reported in parentheses. The results for the corresponding first-stage regressions are reported in Appendix Table A.3. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

employment we document, we find that 60 % of the overall decline was driven by survey participants in early lockdown counties. Column (2) studies the effect on labor-force participation and column (3) on unemployment. Lockdowns had a sizeable effect on both variables. Individuals under lockdown had a 1.9 percentage point lower labor-force participation and a 2.4 percentage point higher unemployment rate. The difference in the unemployment rate between individuals in counties under lockdowns and other counties corresponds to a third of the overall rise in unemployment during the Great Recession, whereas the difference in the labor-force participation corresponds to almost 80 % of the decline between 2008 and 2016. Moreover, the rise in unemployment corresponds to even more than 100 % of the overall average rise we document in Panel A of Table 1 suggesting redistributive effects across counties. In short, lockdowns appear to have immediate and large consequences on employment and can account for much of the deterioration

Table 5
Employment status.

	Dependent variable: Dummy variables for employment status		
	Employment (1)	Labor force participation (2)	Unemployment (3)
$Lockdown_{ijt}$	−0.028***	−0.019**	0.024**
	(0.008)	(0.009)	(0.009)
$ShareCOVID_{jt}$	−0.016	−0.018	0.002
	(0.015)	(0.015)	(0.018)
Number of households	6064	6064	2927
R-squared	0.012	0.006	0.012
1st stage *F*-stat	1968	1968	1281

Notes: The table reports estimated coefficients for Eq. (1) with employment status variables as the regressands. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

in the labor market that occurred in the U.S. in 2020.

4.2. Consumer spending

Did this dramatic change in labor market conditions due to COVID19-induced lockdowns translate into changes in spending patterns? Table 6 reports the second-stage results for $\log(1+spending)$ for overall spending and for granular subcategories in the previous three months. We see that lockdowns are associated with a drop in overall spending equal to 31 log percent which is even

Table 6
Consumer spending.

Dependent variable:	$Lockdown_{ijt}$ Coef./(s.e.) (1)	$ShareCOVID_{jt}$ Coef./(s.e.) (2)	Number of households (3)	R^2 (4)	1st stage *F*-stat (5)
Panel A. log(1+Spending)					
Total spending	−0.313***	0.002	6064	0.050	1968
	(0.036)	(0.072)			
Debt payments	−0.708***	0.399	6064	0.037	1968
	(0.103)	(0.243)			
Housing (rent, maintenance, home insurance)	−1.091***	0.168	6064	0.069	1968
	(0.130)	(0.267)			
Utilities	−0.447***	0.205	6064	0.030	1968
	(0.081)	(0.131)			
Food	−0.228***	−0.047	6064	0.015	1968
	(0.054)	(0.067)			
Clothing, footwear, persona care	−1.275***	−0.202	6064	0.126	1968
	(0.091)	(0.298)			
Gasoline	−0.541***	0.221***	6064	0.049	1968
	(0.058)	(0.071)			
Other transport (public transport, car maintenance)	−0.916***	0.225	6064	0.072	1968
	(0.097)	(0.182)			
Medical	−0.626***	−0.186	6064	0.028	1968
	(0.103)	(0.266)			
Travel, recreation, and entertainment	−1.846***	−0.143	6064	0.165	1968
	(0.108)	(0.176)			
Education and child care	−0.183***	0.085	6064	0.011	1968
	(0.061)	(0.142)			
Furniture, jewelry, small appliances and other small durable goods	−0.632***	−0.012	6064	0.035	1968
	(0.101)	(0.309)			
Other spending	−1.210***	−0.291	6064	0.094	1968
	(0.102)	(0.613)			
Panel B. Purchases of durable goods					
Extensive margin	−0.008	0.010	6064	0.001	793
	(0.016)	(0.032)			
Intensive margin, $\log(1+Spending)$	−0.069	−0.203	6064	−0.000	1968
	(0.116)	(0.206)			
Panel C. Plans to buy durable goods					
Extensive margin	−0.035**	−0.029	6064	0.008	1968
	(0.015)	(0.035)			
Intensive margin, $\log(1+Spending)$	−0.259**	0.025	6064	0.006	1968
	(0.128)	(0.290)			

Notes: The table reports estimated coefficients for Eq. (1) with consumer spending (actual and planned) variables as the regressands. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

slightly larger than the overall drop we document in Panel A of Table 2. Recreation, travel, and entertainment expenses, clothing and footwear, housing expenses including rent and maintenance, transportation, and debt payments including mortgages, auto, and student loans saw the largest declines in spending with 184, 128, 110, 92, and 71 log percentage points, respectively. Gasoline also had a large decrease in dollar spending which could partially be driven by the large decrease in oil prices. Instead, for utilities, food, or education and childcare, we only observe modest drops consistent with findings in Andersen et al. (2022), and intermediate drops for small durables such as furniture and medical expenses. These heterogeneous responses in spending across categories to local lockdowns are consistent with supply restrictions, individuals no longer being able to travel and non-essential businesses being closed but also in part reflect differences between discretionary and non-discretionary spending (D`Acunto et al., 2020c). Moreover, these results suggest different sectors in the economy were differentially exposed to drops in consumer spending. These heterogeneous exposures were important for the design and implementation of government programs such as loans programs as well as for the overall speed and the differential speed of the recovery across sectors of the economy and geographic partitions. Our results were therefore informative for the debate on federal help for local economies and states.

We move on to study the effect of lockdowns on durable purchases that are the most cyclical component of consumption. Durable purchases are lumpy and occur infrequently and financial constraints might be an important impediment for these purchases. Hence, we first study whether survey respondents differ systematically in their financial constraints and past purchases of durables by lockdown status. We find that no systematic difference exists in the degree to which individuals were able to cover an unexpected expense equal to one month of income (see Panel B of Table 7). Similarly, no difference exists in the degree to which survey respondents purchased durable goods in the last six months (Panel B of Table 6). Panel C of Table 6, instead, indicates large drops in plans to spend on durables both at the extensive margin and the intensive margin. Survey participants under lockdown were more than 3.5 percentage points less likely to purchase durable goods in the next 12 months and planned to spend almost 26 log percentage points less. This drop in planned spending is almost 100 % of the aggregate drop in planned spending in Table 2 across the survey waves in January and April 2020.

4.3. Liquidity and portfolio allocations

During times of crisis and uncertainty, a flight to safety and quality often occurs, reflected in a surge in treasuries and the US dollar. To study whether similar phenomena also happened at the individual portfolio level, we now examine the sample of individuals that had savings larger than one month of income in Panel A of Table 7. Consistent with the macro trends, we find that survey participants in lockdown counties had a portfolio share in liquid savings that was 1.7 percentage points higher than other participants, although the difference is not statistically significant. The increase in portfolio shares in checking accounts is of the opposite sign to the average in Panel C of Table 1 suggesting that survey participants in late lockdown counties actually decreased their portfolio share by more. Moreover, we find a decrease in the share of foreign assets by 0.7 percentage points. Gold is often portrayed as a store of value and safety but only few households in our sample have any savings in gold and no difference existed in portfolio shares across survey participants by lockdown status. Panel B shows that no systematic variation existed in liquidity, that is, the ability to cover an unexpected payment equal to one-month of income. This result is important because it indicates that differentially binding financial constraints were an unlikely driving force for our spending results. We also find no difference in financial wealth, that is, savings larger than one month of income, by lockdown status. This null result is plausible because it was unlikely that the checking account balance, or the value of stock and bond portfolios should be differentially affected by local lockdown conditions.[14]

4.4. Macroeconomic expectations

To what extent do local lockdowns spill over to subjective expectations? After all, most economic decisions are forward looking and therefore directly depend on individuals' expectations. Moreover, the effectiveness of fiscal and monetary policy measures crucially depends on the expectations of households Bernanke (2010) and Binder (2020) finds systematic revisions of GDP growth and inflation expectations due to news about COVID. Ex-ante, it was unclear whether the COVID crisis would have resulted in higher or lower inflation. On the one hand, supply-chain disruptions could have increased marginal costs and resulted in higher future inflation. On the other hand, depressed demand as reflected in low oil prices during the time of the survey in April 2020 could instead put downward pressure on inflation. To shed more light on this matter, we first study the effect on inflation expectations and report results in Table 8. During the binding lower bound on nominal interest rates, inflation expectations translate one-to-one into changes in real interest rates (Euler equation) which can directly impact current and future consumption choices (Coibion et al., 2022; D'Acunto et al., 2022). We see in Panel A that survey participants under lockdown had on average 0.5 percentage point lower inflation expectations over the next twelve months. Lower inflation expectations imply higher perceived real interest rates which suggests additional downward pressure on household consumption. Household consumption, however, responds not just to the level of real interest rates but also to the dispersion in inflation expectations due to precautionary savings (Coibion et al., 2024). We use the distribution question for inflation expectations and create a measure of uncertainty in expected inflation at the individual level as the standard deviation in one-year

[14] The null effect for US equity shares could also be consistent with individuals in early lockdown counties selling their domestic stocks and consumers in late lockdown counties experiencing valuation losses resulting in a similar decrease in portfolio shares across both groups. We consider this alternative as less likely because then we should also see larger increases for other portfolio shares reflecting the sale of domestic equity for consumers in early lockdown counties, which we don't see.

Table 7
Liquidity and portfolio allocation.

Dependent variable:	$Lockdown_{ijt}$ Coef./(s.e.) (1)	$ShareCOVID_{jt}$ Coef./(s.e.) (2)	Number of households (3)	R^2 (4)	1st stage F-stat (5)
Panel A. Share of financial wealth in					
Checking account	1.713	−0.044	2995	0.003	1439
	(1.723)	(1.961)			
Cash	−0.506	0.599	2995	0.000	1439
	(1.057)	(1.478)			
US Bonds	0.654	0.395	2995	−0.002	1439
	(0.661)	(1.477)			
US Stocks	−0.016	−0.898	2995	0.000	1439
	(1.285)	(2.770)			
Foreign stocks and bonds	−0.651**	−1.936***	2995	0.010	1439
	(0.318)	(0.395)			
Gold and precious metals	−0.033	−0.036	2995	0.000	1439
	(0.271)	(0.248)			
Bitcoin and other cryptocurrencies	−0.104	0.090	2995	−0.004	1439
	(0.074)	(0.095)			
Other	−1.056	1.831	2995	−0.001	1439
	(1.427)	(4.234)			
Panel B. Liquidity					
Ability to make an unexpected payment of one-month income	−0.013	0.014	5398	0.002	1895
	(0.013)	(0.042)			
Significant financial wealth	−0.018	0.016	6064	−0.001	1968
	(0.013)	(0.018)			

Notes: The table reports estimated coefficients for Eq. (1) with liquidity, access to credit, and portfolio allocations as the regressands. Standard errors clustered by county are reported in parentheses. Shares in Panel A are measured in percent from 0 to 100. Share are elicited only for household who report significant financial wealth. *Significant financial wealth* is equal to one if a respondent reports that his/her household has financial wealth (excluding housing) that is greater than combined monthly household income. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

Table 8
Macroeconomic expectations.

Dependent variable: Macroeconomic expectations	$Lockdown_{ijt}$ Coef./(s.e.) (1)	$ShareCOVID_{jt}$ Coef./(s.e.) (2)	Number of households (3)	R^2 (4)	1st stage F-stat (5)
Panel A. 12-month-ahead inflation, distributional question					
Implied Mean	−0.545**	−0.738	5602	0.006	2108
	(0.238)	(0.678)			
Uncertainty (standard deviation)	0.586***	0.261	5602	0.017	2108
	(0.123)	(0.299)			
Panel B. Unemployment rate, point prediction					
Current	13.751***	−0.162	5973	0.205	1887
	(0.848)	(1.194)			
One-year-ahead	12.952***	0.425	5998	0.218	1906
	(0.638)	(2.360)			
In the next 3–5 years	2.394***	−0.439	6025	0.016	1922
	(0.453)	(0.971)			
Panel C. Unemployment rate, point prediction, response restricted to be less than 40 %					
Current	7.067***	0.243	4885	0.208	1682
	(0.453)	(0.954)			
One-year-ahead	8.194***	0.043	5085	0.246	1635
	(0.396)	(1.118)			
In the next 3–5 years	1.789***	0.211	5516	0.028	1767
	(0.259)	(0.655)			
Panel D. Mortgage rate, point prediction					
Current	−0.686***	0.190	6045	0.005	1966
	(0.240)	(0.458)			
End of 2020	−0.730***	0.148	6046	0.007	1956
	(0.270)	(0.399)			
End of 2021	−0.607**	0.164	6048	0.006	1980
	(0.297)	(0.564)			
In the next 5–10 years	−0.745**	0.666	6045	0.007	1970
	(0.322)	(0.551)			

Notes: The table reports estimated coefficients for Eq. (1) with macroeconomic expectations as the regressands. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

Table 9
Approval of policies.

Dependent variable: Approval of policies (10 = extremely helpful, 0 = not helpful at all)	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of respondents	R^2	1st stage *F*-stat
	(1)	(2)	(3)	(4)	(5)
President	−6.247***	−0.113	9247	−0.414	16
	(2.425)	(0.225)			
Congress	1.067	0.109	9247	−0.016	16
	(1.503)	(0.125)			
US Treasury	0.710	0.003	9247	−0.002	16
	(1.901)	(0.170)			
Federal Reserve	2.402	−0.078	9247	−0.072	16
	(1.958)	(0.175)			
U.S. Center for Disease Control	3.134*	−0.226	9247	−0.138	16
	(1.851)	(0.173)			

Notes: The table reports estimated coefficients for Eq. (4) with political approval variables as the regressands. The first stage is given by Eq. (5). State fixed effects are included but not reported. Standard errors clustered by county are reported in parentheses. Political approval data are collected only in the April 2020 wave. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

ahead expected inflation. Indeed, local lockdowns increased the uncertainty for future inflation by more than half a percentage point which might translate into increasing precautionary savings demand. These cross-sectional estimates for inflation expectations and uncertainty are large and correspond to about 100 % of the difference across survey waves in Panel D of Table 1. Yet, from a historical perspective these changes are not unprecedented. During the Great Recession, median inflation expectations decreased from a peak of 5.2 % in May of 2008 to a trough of 1.7 % in December 2008. We need to also recall, however, that high prices at the pump partially explain the elevated level of consumers' inflation expectations at the onset of the Great Recession (Coibion and Gorodnichenko, 2015).[15]

The remaining Panels of Table 8 study the perceptions of current unemployment and mortgage rates as well as the expectations for the next 12 months, or the end of 2020 and 2021 and the longer horizon (three to five years for unemployment and five to ten years for mortgage rates, respectively). Unemployment rates are a key indicator for the state of the economy and mortgage rates are the key transmission mechanism of monetary policy for many households and also directly shape the economic recovery given the importance of housing for business cycles (Mian et al., 2017). The perceived unemployment rate spiked up by more than 13 percentage points in lockdown counties and the expected unemployment rate stayed at elevated levels for the next 12 months and only slowly decreased to an increase of 2 percentage points over the longer horizon (Panel B). These increases in cross-sectional estimates are even larger than the aggregate increases in expectations that we document in Panel E of Table 1. Results are similar in terms of persistence, albeit slightly smaller in magnitude, once we exclude extreme observations with perceptions and expectations larger than 40 % (Panel C). These expectations suggest a rather sluggish and slow recovery, resembling a U shape in terms of policy discussions at the time of the survey. These expectations were again too negative compared to ex-post realizations, likely reflecting the fact that consumers did not anticipate the large fiscal response. As for mortgage rates, we see survey participants perceived a decrease of about two-thirds of a percentage point which persisted until the longer horizon (Panel D). These expectations correspond to a level shift in the term structure of mortgage rates and are also consistent with a depressed economy for an extended period of time. Again, we find that the decrease in mortgage rates across counties was larger than the aggregate decreases across survey waves (Panel G of Table 1) but also too persistent and negative, likely because consumers did not anticipate the inflationary surge that triggered one of the fastest interest rate hiking cycles in recent history.

4.5. Political outcomes

Finally, we study whether local lockdowns affect the qualitative rating of several government institutions in Table 9 which we measure on a ten-point Likert scale with higher values reflecting higher approval ratings. We only elicited approval ratings in the April wave of the survey which is why our two-stage least squares estimation now exploits purely cross-sectional variation:

$$Y_i = \psi \times lockdown_i + \eta \times ShareCOVID_j + StateFE + error \tag{4}$$

$$lockdown_i = \beta \times \mathbb{1}\{COVID_{js} > 0\} + \gamma \times ShareCOVID_j + StateFE + +error, \tag{5}$$

where we use the same notation as in Eqs. (1) and (2) and both equations include state fixed effects.

U.S. officials increasingly referred to the pandemic as a war situation[16] and typically, incumbents have tended to experience a surge in support during war times. At the same time, the 'current war' also reflected a major economic hardship for many individuals and

[15] These numbers can be accessed online here: https://fred.stlouisfed.org/series/MICH.

[16] For example, Treasury Secretary Steven Mnuchin noted, "This is a war, and we need to win this war and we need to spend what it takes to win the war."

typically support for the president decreases during poor economic times. We see in Table 9 that survey respondents in lockdown counties had a 6 point lower approval rating of the President than other survey respondents on a ten-point scale. No heterogeneity existed for other government institutions (the Congress in row (2), the U.S. Treasury in row (3), the Federal Reserve in row (4)). The approval for the U.S. Center for Disease Control in row (5), though, was 3 points higher for survey participants in lockdown.

5. Conclusion

The arrival of the COVID19 pandemic resulted in major economic downturns around the world with large drops in employment, equity markets, and personal income. To slow the spread of the pandemic, many governments imposed restrictions on movement to slow the spread of the virus. We fielded large-scale customized surveys on a representative US panel of households to document the extent of economic damage and to study the impact of local lockdowns on realized and planned spending, income and wealth losses, macroeconomic expectations and approval ratings of political institutions. We observe a dramatic decline in employment and consumer spending as well as a bleak outlook for subsequent years. Our estimates suggest that this economic catastrophe can be largely accounted for by lockdowns.

It is beyond the scope of this paper to establish whether this economic cost was sufficiently small to justify lockdown policies that may have saved lives. However, our analysis can inform policymakers about at least one part of the tradeoff they faced because these costs are relevant in thinking about how long to maintain lockdown policies, especially since the costs are likely increasing with duration. The significant costs that we identified suggest that policymakers should be wary of focusing only on the benefits of lockdown policies and not carefully weighing them against their costs. Our analysis also provides input for policies aimed to mitigate the consequences of the COVID recession. For example, we document that many households effectively defaulted on their debt payments and rents which could have started a wave of bankruptcies and evictions and thus delayed the recovery. Low expectations for inflation and mortgage interest rates likely limited the power of monetary policy. Households expected normalcy to return within six months and as such on average were on the optimistic side, because it took more than 12 months for most Americans until they had access to vaccines from the time of our survey. To avoid adverse hysteresis-like scenarios, policymakers considered and partially implemented less conventional measures such as extended periods of fiscal stimulus, debt forgiveness, taking stakes in businesses (including financial institutions), and more aggressive quantitative easing.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2024.106846.

Appendix

Table A.1
Descriptive statistics for households in the Nielsen Survey, January 2020 wave.

	Mean (1)	Standard deviation (2)
Household income, annual, $	68,370	37,667
Household size	2.58	1.32
Age of the respondent	50.1	15.0
Share of white respondents	0.73	0.44

Table A.2
Consumer spending in the Nielsen Survey and the Survey of Consumer Expenditures.

Spending category	Nielsen survey (KNCP) (1)	Survey of consumer expenditures (2)
Total spending	3999	5102
Debt payments	1288	250
Housing (rent, maintenance, home insurance)	616	535
Utilities	429	455
Food	532	709
Clothing, footwear, persona care	126	220
Gasoline	174	176
Other transport (public transport, car maintenance)	58	142
Medical	220	414

(*continued on next page*)

Table A.2 (*continued*)

Spending category	Nielsen survey (KNCP) (1)	Survey of consumer expenditures (2)
Travel, recreation, and entertainment	162	269
Education and child care	79	117
Furniture, jewelry, small appliances and other small durable goods	50	64
Other spending	159	1715

Notes: Columns (1) reports monthly spending in the January wave of the Nielsen survey. Column (2) reports monthly spending (annual divided by 12) from the 2018 Survey of Consumer Expenditures.

Table A.3
First stage by the time of COVID-19 exposure with heterogeneous responses to COVID infections.

Dependent variable: *Lockdown* reported by person *i* in county *j* at time *t*	Date $t-s$ in $\mathbb{I}\{COVID_{j,t-s}>0\}$ in the April 2020 wave				
	March 1 (1)	March 8 (2)	March 15 (3)	March 22 (4)	April 1 (5)
$\mathbb{I}\{COVID_{j,t-s}>0\}$	−0.674	0.600***	0.964***	1.072***	1.088***
	(1.082)	(0.220)	(0.096)	(0.079)	(0.073)
$\mathbb{I}\{COVID_{j,t-s}>0\}\times\log\left(PopDensity_j\right)$	−0.190	−0.036	0.012	0.025**	0.028***
	(0.146)	(0.033)	(0.014)	(0.011)	(0.010)
$\mathbb{I}\{COVID_{j,t-s}>0\}\times TrumpShare_j$	−0.043	−0.328	−0.165	−0.180*	−0.150*
	(1.222)	(0.310)	(0.121)	(0.094)	(0.088)
$ShareCOVID_{jt}$	1.139	0.575	0.116	0.002	−0.019
	(0.732)	(0.523)	(0.121)	(0.035)	(0.031)
Constant	0.301***	0.234***	0.114***	0.040***	0.012**
	(0.023)	(0.010)	(0.005)	(0.006)	(0.006)
Number of households	6064	6064	6064	6064	6064
R^2	0.312	0.427	0.637	0.755	0.799

Notes: The table reports estimated coefficients for Eq. (2) with $\mathbb{I}\{COVID_{j,t-s}>0\}$ interacted with the share of Trump votes in the 2016 Presidential elections and log population density. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

Data availability

The authors do not have permission to share data.

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