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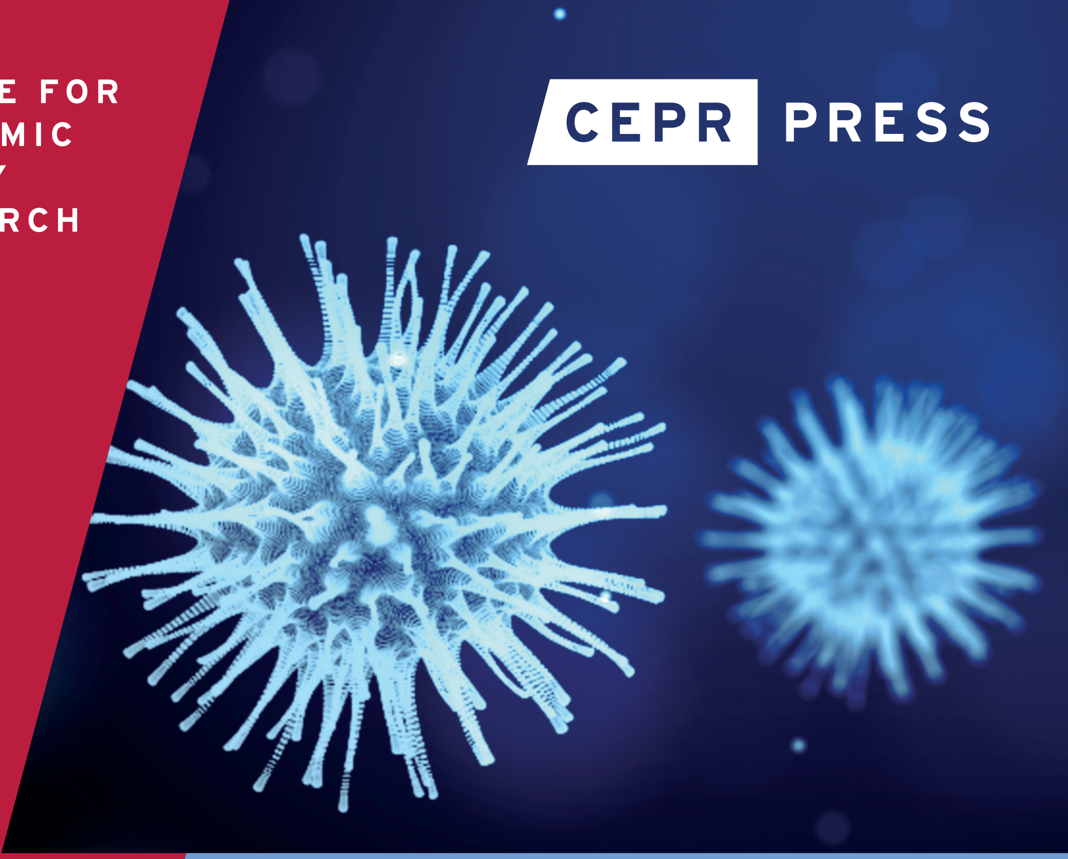

CEPR PRESS

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 59
27 NOVEMBER 2020

CONSUMPTION AND SAVINGS ACROSS INCOME GROUPS
David Bounie, Youssouf Camara, Etienne Fize, John Galbraith, Camille Landais, Chloe Lavest, Tatiana Pazem and Baptiste Savatier

CONSUMPTION AFTER THE PANDEMIC
Alexander Hodbod, Cars Hommes, Stefanie J. Huber and Isabelle Salle

STATE GUARANTEE AND CONNECTED LOANS
Ran Duchin, Xiumin Martin, Roni Michaely, and Ivy Wang

HOW EFFECTIVE IS SOCIAL DISTANCING?
Difang Huang

Covid Economics
Vetted and Real-Time Papers

Covid Economics, Vetted and Real-Time Papers, from CEPR, brings together formal investigations on the economic issues emanating from the Covid outbreak, based on explicit theory and/or empirical evidence, to improve the knowledge base.

Founder: Beatrice Weder di Mauro, President of CEPR
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Covid Economics will feature high quality analyses of economic aspects of the health crisis. However, the pandemic also raises a number of complex ethical issues. Economists tend to think about trade-offs, in this case lives vs. costs, patient selection at a time of scarcity, and more. In the spirit of academic freedom, neither the Editors of *Covid Economics* nor CEPR take a stand on these issues and therefore do not bear any responsibility for views expressed in the articles.

Submission to professional journals

The following journals have indicated that they will accept submissions of papers featured in *Covid Economics* because they are working papers. Most expect revised versions. This list will be updated regularly.

American Economic Review
American Economic Review, Applied Economics
American Economic Review, Insights
American Economic Review, Economic Policy
American Economic Review, Macroeconomics
American Economic Review, Microeconomics
American Journal of Health Economics
Canadian Journal of Economics
*Econometrica**
Economic Journal
Economics of Disasters and Climate Change
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Journal of Economic Growth
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Journal of Finance
Journal of Financial Economics
Journal of International Economics
*Journal of Labor Economics**
Journal of Monetary Economics
Journal of Public Economics
Journal of Public Finance and Public Choice
Journal of Political Economy
Journal of Population Economics
Quarterly Journal of Economics
*Review of Corporate Finance Studies**
Review of Economics and Statistics
*Review of Economic Studies**
Review of Financial Studies

(*) Must be a significantly revised and extended version of the paper featured in *Covid Economics*.

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Consumption dynamics in the COVID crisis: Real-time insights from French transaction and bank data[1]

David Bounie,[2] Youssouf Camara,[3] Etienne Fize,[4] John Galbraith,[5] Camille Landais,[6] Chloe Lavest,[7] Tatiana Pazem[8] and Baptiste Savatier[9]

Date submitted: 19 November 2020; Date accepted: 20 November 2020

We use anonymised transaction and bank data from France to document the evolution of consumption and savings dynamics since the onset of the pandemic. We find that consumption has dropped very severely during the nation-wide lockdown but experienced a strong and steady rebound during the Summer, before faltering in late September. This drop in consumption was met with a significant increase in aggregate households' net financial wealth. This excess savings is extremely heterogenous across the income distribution: 50% of excess wealth accrued to the top decile. Households in the bottom decile of the income distribution experienced a severe decrease in consumption, a decrease in savings and an increase in debt. We estimate marginal propensities to consume and show that their magnitude is large, especially at the bottom of the income and liquidity distributions.

1 We would like to thank the Groupement des Cartes Bancaires CB and Crédit Mutuel Alliance Fédérale for providing access to the data. We thank Marion Brouard for research assistance. We thank Philippe Martin and Hélène Paris at the French Council of Economic Analysis, under whose authority this work was performed. Finally, we would like to thank seminar participants at the CEPR New Consumption Data Seminar 2020 for helpful comments.
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1 Introduction

The explosive dynamics of the coronavirus shock has created a new historic need for "extreme nowcasting" to monitor the impact of the shock on the economy. This in turn requires access to new data that are quickly available (for reactivity), representative (for robustness) and granular (to allow for rich distributional analysis, as well as quasi-experimental analysis to learn about mechanisms).

Furthermore, the covid shock is unprecedented in both its magnitude and its nature. This poses a series of original issues to policy-makers in their response to the crisis. How is the economic shock distributed in the population? What is the causal role of health risk in explaining behaviors? How much are consumption and savings behavior driven by precautionary savings in response to the significant rise in uncertainty regarding future income and employment dynamics? Etc.

In this work, we offer insights coming from the use of original anonymous and de-identified transaction and bank data in the French context. The data comes from two unique sources. First, from the universe of card transactions from the French consortium of card providers "Groupement Cartes Bancaires CB" (CB thereafter). Second, from a large balanced panel of 300,000 households randomly sampled from the clients of the French Bank Credit Mutuel Alliance Federale (CM thereafter).[1]

We first investigate the dynamics of aggregate transactions. We find that card transaction expenditures experienced a severe decline of about 50% during the nation-wide lockdown period that started in mid-March in France, and lasted until mid-May. Interestingly, we find that after that initial phase, expenditures bounced back almost immediately to their 2019 levels, and remained steady throughout the summer. In that sense, the French recovery in terms of consumption has been much stronger than in other countries such as the US or the UK. There is nevertheless an extreme amount of sectoral heterogeneity in the dynamics of expenditures, which is a unique feature of the covid-induced recession. Furthermore, there are clear signs that consumption expenditures have been faltering in the last weeks of September, as a second epidemic wave was gaining momentum in France.

Using the richness of the CM data, we also explore the dynamics of financial wealth and savings behavior during the crisis. We find that aggregate financial wealth has increased by about €50 billions since the onset of the crisis, compared to the counterfactual of a prolongation of the 2019 trend. Interestingly, most of this excess financial wealth is accounted for by an increase in liquid savings. Moving to distributional

[1] All data is de-identified, and accessed through secure internal IT servers. We provide all details on the data, and on the procedures for data access and for preserving data privacy in the Data section of this paper, as well as in the Appendix.

analysis, we find that more than 50% of this excess "savings" accrued to households in the top decile of the income distribution. At the bottom of the distribution, consumption and savings have both decreased since the start of the pandemic, indicative of severe income shocks experienced by these households, despite the social insurance and welfare transfer policies put in place by the French government since the start of the crisis.

Finally, we also show how this unique source of data can be used to explore the respective role of three potential drivers of consumption dynamics. We investigate the importance of income dynamics and income expectations by estimating marginal propensities to consume, taking advantage of the granularity of the CM data, combined with quasi-experimental variation in welfare transfer payments. We find large but heterogeneous MPCs, with households at the bottom of the liquid savings distribution being particularly sensitive to additional cash-on-hand. We then turn to exploring the role of health risk, vis-a-vis that of lockdown and restriction policies. We find relatively little role of health risk perceptions on consumption dynamics on average, but a strong role for lockdown policies.

The remainder of the paper is organized as follows. Section 2 presents the data, Section 3 analyzes the evolution of aggregate consumption and savings. Section 4 documents sectoral heterogeneity, while section 5 delves into the distributional impact of the crisis. Finally, section 6 explores the mechanisms driving consumption dynamics since the beginning of the covid crisis.

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2 Data

2.1 Carte Bancaires

Cartes Bancaires CB is one of the leading consortium of payment service providers, banks and e-money institutions. It was created by the French banks in 1984, and by 2019 had more than 100 members. As of 2019 there were more than 71.1 million CB cards in use in the CB system, and 1.8 million CB-affiliated merchants.

Thanks to a partnership with Cartes Bancaires CB, we are able to observe the universe of CB card transactions at a very granular level. A CB card transaction is characterized by its amount, the precise time and date of the transaction, the geographical location of the merchant, the statistical classification of the type of purchase, and the type of purchasing channel used during the transaction, i.e. off-line or online. By definition, all other card transactions carried out with payment card schemes such as Visa or MasterCard are not covered and part of the analysis, unless they are co-branded with

CB. Similarly, the payments made by checks, direct debits and credit transfers are not transactions covered by the CB card network.

The coverage of the CB card transactions dataset is exceptional, allowing us to capture a significant proportion of all consumer expenditure in France. To appreciate the richness of the Cartes Bancaires CB data, consider a few comparisons with national statistics provided for the full year 2019 by the National Institute of Statistics and Economic Studies (INSEE). GDP in France in 2019 was estimated as €2,427 billion, with €1,254 billion (52 percent of GDP) representing household consumption expenditure. Excluding fixed charges (rents, financial services, insurances) from household consumption expenditure, as these are typically paid by checks, direct debits and credit transfers, the remaining part of consumer expenditure amounts to €828 billion (34 percent of GDP). Comparing these figures with total CB card payments (€494 billion), the value of CB card payments represents 20 percent of French GDP, 39 percent of total household consumption expenditure, and finally 60 percent of total household consumption expenditure excluding fixed charges. CB card transactions thus captures the most cyclical part of household consumption expenditure, which is very useful for economic nowcasting.

The real-time and detailed information on timing and location of the transaction, the nature of the merchant, allows us to provide fine-grained descriptions of consumption fluctuations, and to contrast consumption patterns along the geographical and sectoral dimensions.[2] For more details on the CB data, see Bounie, Camara and Galbraith [2020], who provide a detailed analysis of consumption dynamics in the early months of the crisis.

2.2 Credit Mutuel Alliance Fédérale

Sampling

The data used in this paper comes from a balanced panel of 300,000 randomly selected clients of the French National retail bank CIC, a subsidiary of Crédit Mutuel Alliance Fédérale. As opposed to the Crédit Mutuel which is deeply rooted in the East of France, the CIC is less regionally concentrated and has more than 2,000 agencies spread across the country.

The sampling procedure was the following. We selected customers according to their age and department (French administrative geographical area called “département”) of residency. We defined 6 age groups (18-25, 26-35, 36-45, 46-55, 56-65 and 66+). From

[2] We limit the sample to Metropolitan France, which excludes the overseas territories.

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each of the 94 departments and age groups we randomly selected a certain number of customers. For the 31 most populated departments in France we selected 1,000 customers per cell (age-groupe - department). For the next 26, we selected 500, for the next 13 300 and finally 100 for the last 24 departments. This sampling procedure ensured a better representativity of the sample but also guaranteed anonymity, by making sure that the fraction of sampled customers in each cell did not exceed a specific threshold.

Furthermore, the customers were chosen out of a sub-sample of all CIC clients. The customers had to be "principal customers", meaning that the CIC is their main bank where they domiciliate their income and main assets and credits. They had to be a physical entity and alive. We do have self-employed individuals in our sample but no firms. All customers in our sample had to be customers at least before January 2019. We excluded residents of Corsica, French overseas territories and customers outside of France. Finally we also excluded employees of Crédit Mutuel Alliance Fédérale and individuals banned from holding a bank account.

The sampling resulted in a little over 300,000 customers defined at the group level (i.e household level) which amounts to approximately 550,000 individuals. In cases where the household composition changed (marriage, divorce ...), we kept in the sample all of the initial members of the groups. The sampling was performed in June 2020.

Reweighting

In order for our sample to better match national data, we reweight each age-group department cell to match French census data from INSEE. Note that for now, we only use age and geography as observables characteristics in our reweighting approach, but more sophisticated approaches can be used, to match other aggregate or distributional statistics in the French population.

Data structure

We use pseudo-anonymized data located on a secure distant server.[3]

We were granted access of three tables containing information on card expenditures, cash withdrawals, check payments, bank balances, savings accounts, equities, life insurances and household debts. Moreover we have some information on wire transfers and for the year 2020 we have information on direct debits and daily information on card expenditures that allows us to know in which sector (MCC classification) the spending was made.

[3]See appendix for more detail information on data access and the partnership with Crédit Mutuel Alliance Fédérale.

We also have access to some information regarding the account owner and household members : department, age, socio-professional category (PCS)[4], marital status and whether or not the individual is self-employed. Note that the definition of households in the CM data is different from the standard INSEE definition usually retained in French survey data.[5].

Descriptive statistics

Our sampling strategy led to an overrepresentation of young people and an underrepresentation of older people. Appendix Table 1 provides descriptive statistics for our original sample, as well as our reweighted sample, and then compares these statistics to external INSEE data on the universe of the French population. The reweighting procedure allows us to get a more representative sample of the French population. But we still slightly underrepresent retirees.[6]

[4]"Nomenclature des Professions et catégories socio-professionnelles" which can translate to "Nomenclature of Professions and Socioprofessional Categories"

[5]Indeed, whereas INSEE considers that a household is defined by a shared home, and not by kinship, allowing roomates, for example, to form a unique household, this is not the case in the Crédit Mutuel Alliance Fédérale databases. Their definition of a household is much more restricted: only blood or marriage related people are considered to be a unit. Moreover, children turning 18 are by default transferred to a new household unit even though they may still be living with their parents.

[6]Our interpretation of this deviation is that even though the sample has been reweighted and does better at comparing with the actual percentage of older people in the French population (66+ people attainted 21.13% after the weighting procedure against 16.70% before it for a total of 24.61% as reported by the INSEE census in 2018), because the Crédit Mutuel Alliance Fédérale data must be updated by the account owners themselves, few of them actually declare their retirement right away, hence PCS variables are often updated with significant delay at retirement.

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3 Aggregate Consumption & Savings Dynamics

3.1 Consumption

We start by documenting the evolution of aggregate consumption dynamics in France since the beginning of the pandemic. We focus on aggregate credit card expenditures measured in the CB data. We aggregate transactions at the weekly level. To deal with seasonality, we divide aggregate transactions in week t of 2020 by aggregate transactions in the exact same week t in 2019: C_t^{2020}/C_t^{2019}. We further take away the general trend in aggregate consumption between 2019 and 2020. To this effect, we normalize these expenditure ratios by the average ratio between week 2 and week 6 in 2020: $\bar{C}_{t\in[2;6]}^{2020}/\bar{C}_{t\in[2;6]}^{2019}$. In other words, we assume that the overall trend observed in expenditures between the first weeks of 2020 and the first weeks 2019 would have continued absent the COVID crisis. We then report $c_t = \frac{C_t^{2020}/C_t^{2019}}{\bar{C}_{t\in[2;6]}^{2020}/\bar{C}_{t\in[2;6]}^{2019}}$, which measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occured between 2019 and 2020 absent the pandemic.

Sharp Decline & Steep Recovery Figure 1 shows the evolution of credit card transactions from the CB data since the start of 2020. The first red line corresponds to the start of the nation-wide lockdown in France (week 12) and the second red line corresponds to the end of the lockdown at the end of week 19. The figure shows that aggregate transactions did not experience much of a decline before the start of the lockdown. But the lockdown was associated with a brutal and severe decline in transactions, of about 50%. Transactions remained extremely depressed throughout the seven weeks of lockdown despite a small improvement after the initial sharp contraction of week 13. Interestingly, aggregate consumption bounced back immediately to pre-crisis levels as soon as the lockdown ended, and has been stable at this level ever since. There does not seem to be signs of a decrease in expenditures since late August, as a second wave of covid infections has been quickly spreading across the country.

A few important lessons emerge from these patterns of aggregate consumption dynamics. First, the overall contraction in spending during the lockdown has been massive in France. If we cumulate the aggregate amount of spending "lost" from week 12 to week 19 (the light grey area in Figure 1), this corresponds to a 6.3% loss in annual spending. Second, although the recovery in credit card transactions has been quick and steady since the end of the lockdown, transactions have reached their pre-crisis level, but did not overshoot: there is no sign of intertemporal substitution at the aggregate level. In other words, the 6.3% loss in annual spending during the lockdown is a permanent loss. Third, there does not seem to be strong signs of correlation in the

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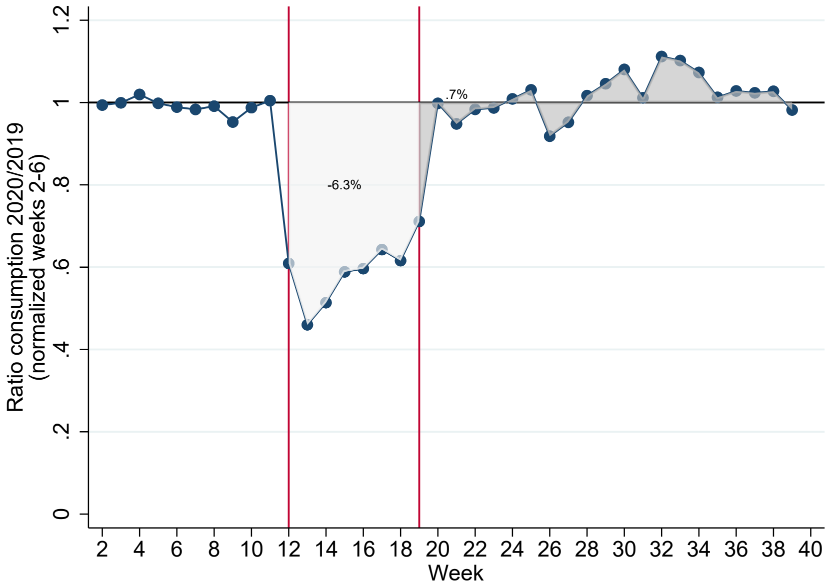
time series between credit card expenditures and the dynamics of the epidemic since the end of the lockdown.

Figure 1: Evolution of Aggregate Weekly Credit Card Expenditures in the CB Data



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data. The graph plots $c_t = (C_t^{2020}/C_t^{2019})/(\bar{C}_{t\in[2;6]}^{2020}/\bar{C}_{t\in[2;6]}^{2019})$, where C_t^{2020} corresponds to aggregate expenditures in week t of 2020 and $\bar{C}_{t\in[2;6]}^{2020}$ corresponds to the average aggregate expenditures in week 2 to 6 of 2020. This normalization procedures deals with both seasonality in expenditures, and the overall trend in expenditures over time. The graph therefore measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occurred between 2019 and 2020 absent the pandemic.

Accounting for Substitution Across Payment Types While the CB data has the advantage of capturing the universe of credit card transactions, it does not account for expenditures that are done using other payments types such as cash, cheques, or wire transfers for instance. We now turn to the CM data to evaluate the dynamics of expenditures for these different payment methods and assess whether the pandemic has caused a substitution across payment types.

Appendix Figure 17 shows the evolution of monthly aggregate expenditures for different payment methods, where we use the same normalization methodology as in Figure 1 above. Panel A reports the evolution of aggregate credit card expenditures in the CM data. For comparison, we also plot on the same graph the series from the exhaustive CB data. The two series display similar dynamics, although the CM series is a little more volatile. Panel B focuses on payments by cheque and shows that such payments have decreased more than credit card payments during the lockdown. Furthermore, they are still at a level that is 5 to 10% lower than pre-crisis level. Panel C shows similar patterns for cash withdrawals, which are currently 15% below their pre-crisis levels. This suggests that consumers have significantly moved away from cash payments in response to the pandemic. In panel D, we show the dynamics of total expenditures, that is credit card transactions, cash withdrawals, cheques. The graph confirms that accounting for all payment methods, the level of consumer expenditures has bounced back vigorously after the sharp contraction of the lockdown. However, the level of total expenditures is, after the lockdown, about 2 to 3% lower than what it would have been absent the pandemic.

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International Comparisons We now compare the evolution of consumption dynamics in France and in a series of countries for which similar data is available. The data for Denmark and Sweden comes from Andersen et al. [2020], the data for the US comes from Chetty et al. [2020] and the data from the UK is from Hacioglu, Känzig and Surico [2020].[7] For all countries, we use the same normalization as in Figure 1. Note that all five countries experienced a roughly similar timing for their first wave of the covid epidemic.

Several important insights transpire from this comparison. First, in the second half of March 2020, all five countries witnessed a sudden drop in spending, and this drop was of roughly similar magnitude. This happened despite the drastically different levels of severity of the restrictions put in place at that time across these five countries. This evidence prompted the interpretation that this is the epidemic, and not policies, that caused the severe contraction in spending (e.g. Andersen et al. [2020]). Interestingly though, after this initial phase that saw remarkably similar dynamics across countries, consumer transactions have been experiencing drastically different patterns across countries. These differences suggest that the policy paths chosen by the different countries have had a significant impact on the dynamics of aggregate consumption. We see for instance that, countries like France, which entered a strict nation-wide lockdown, had a much more severe decrease in aggregate transactions, than countries that did not mandate nation-wide lockdowns like Sweden or the US. But we also see that after this initial phase of severe decline in consumption, the recovery in credit card transactions has been much more rapid in France than anywhere else. In the UK for instance, overall consumption remained heavily depressed throughout May and June. In panel B, we focus on the comparison between France and the US. Due to its

[7] The UK data is only normalised relative to the levels in weeks 1-3 in 2020.

severe lockdown, France experienced until May a decline in expenditures relative to the US equivalent to 2.6% in annual term (i.e. light grey area in panel B). But since the end of the lockdown, the quick recovery has made up for all this loss: French expenditures have recovered 2.6% in annual term relative to the US. As a consequence, so far, the cumulated decline in consumption expenditures over the year 2020 appears equivalent in both countries despite drastically different trajectories.

Overall, evidence from Figure 2 confirms that policies do actually matter, and that their impact must be measured by taking into account their full long run dynamic effects.

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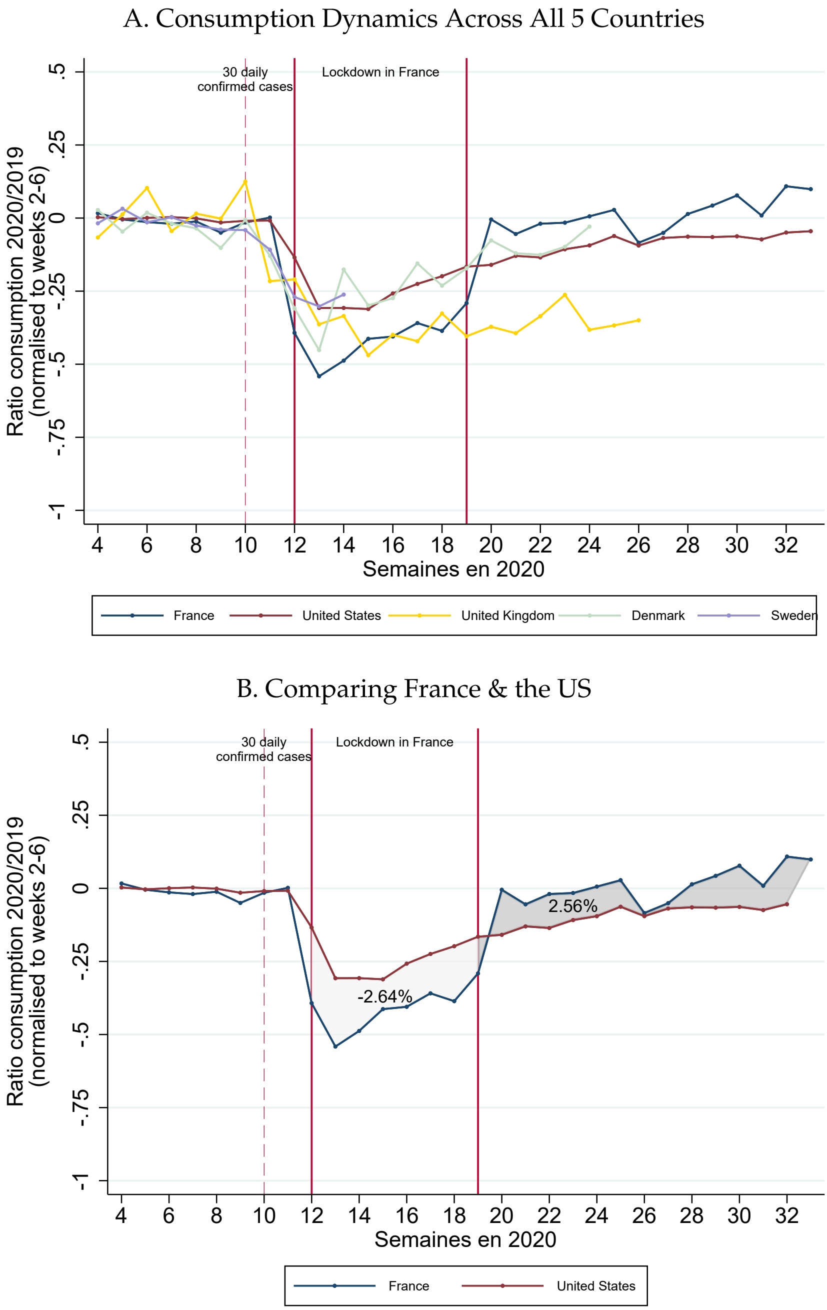
Figure 2: Evolution of Aggregate Weekly Credit Card Expenditures: International Perspective



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data following the same methodology as in Figure 1 in France and in four other countries. The normalization procedures deals with both seasonality in expenditures, and the overall trend in expenditures over time. The graph therefore measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occurred between 2019 and 2020 absent the pandemic. Data from Denmark & Sweden comes from Andersen et al. [2020]. Data from the US comes from Chetty et al. [2020] and data from the UK comes from Hacioglu, Känzig and Surico [2020].

3.2 Household Balance Sheet & Savings Dynamics

The household balance-sheet data from CM allows us to also investigate the dynamics of household savings during the pandemic. We start by explaining the content of the household balance-sheet data currently available. What we observe in the data are:

- W^B_{it}: balances of all bank accounts held with CM in month t
- W^S_{it}: balances on all liquid savings accounts held with CM in month t (e.g. "comptes sur livret", PEL, etc)
- W^M_{it}: balances of all mutual funds held with CM in month t (e.g. "comptes titres")
- D_{it}: balance of all household debt held with CM in month t (e.g. consumer loans, credit card debt, etc.) also including mortgage

From this information, we create a measure of household financial wealth net of debt

$$W_{it} = W^B_{it} + W^S_{it} + W^M_{it} - D_{it} \tag{1}$$

It is important to acknowledge a couple of important limitations of this measure. First, we do not observe the balance of accounts or assets held outside the bank. Second, there are important components of the household balance sheet that we do not observe. In particular, at this point, we do not observe the value of real estate wealth W^R_{it} owned by households.In that sense, our measure is not a comprehensive measure of household wealth, but a measure of net financial wealth.

We start by documenting the evolution of our measure of household financial wealth. But we are also interested in measuring savings, that is, in separating what, in the dynamics of household wealth, is driven by the dynamics of asset prices, and what is due to active savings behaviors of household.

To define households' active savings, it is useful to start from the definition of the household budget constraint:

$$C_{it} = Z_{it} - \underbrace{\sum_k p_{kt}\left[A_{ikt} - A_{ikt-1}\right],}_{\text{Savings}} \tag{2}$$

where Z_{it} captures all sources of income net of taxes and transfers, $\mathbf{A}_{it} = A_{i1t}, .., A_{iKt}$ denotes the portfolio of assets and $\mathbf{p}_t = p_{i1t}, .., p_{iKt}$ the corresponding vector of prices at which they are traded. We can re-write the asset component of the identity in (2) as

$$p_{kt}\Delta A_{ikt} = \Delta W_{ikt} - \Delta p_{kt} A_{ikt-1},$$

where we use the difference notation $\Delta X_t = X_t - X_{t-1}$. The above expression highlights that only the active rebalancing of assets participates in the flow of active savings. To measure active savings, we therefore need to substract from the change in the value of the portfolio (ΔW_{it}) the passive gains on assets induced by changes in the price of these assets.

In practice, we do not observe the prices for each individual asset held by each household to offer a household-specific measure of passive capital gains on each asset class. We therefore operationalize our measure of savings in the following way:

$$S_t = \Delta W_{it} - \overbrace{\frac{\Delta p_t}{p_{t-1}} \cdot W^M_{it-1}}^{\text{Passive K gains}} - Y^S_{it} + \underbrace{r_t \cdot D_{it}}_{\text{Interests on debt}}$$

That is, we use the evolution of average prices of stocks to measure passive capital gains on wealth held in mutual funds (W^M_{it}), and the average interest rate on debt to measure the contribution of the change in the price of household debt. Y^S_{it} is the observed interest income on liquid savings accounts.

Kolsrud, Landais and Spinnewijn [2020] and Eika, Mogstad and Vestad [2020] provide a detailed discussion of the measurement error created by using average (rather than individual-specific) price indices to retrieve savings and consumption flows from household balance-sheet data.

Dynamics of Net Financial Wealth W_t. In Figure 3, we present the evolution of total net financial wealth, normalized to zero at the end of January 2020. Note that aggregate wealth is computed using our designed sample weights, so that we interpret this total as representative of total net financial wealth (as defined in (1)) in the population living in the French Metropolitan area. The Figure shows that, after a sharp initial dip in March 2020, W_t rebounded strongly. Overall, W_t has grown by about €90 billions between January 2020 and beginning of September 2020. The Figure also highlights that W_t was already trending strongly upwards in 2019. We report in red on the graph the linear trend in W_t computed over the period January 2019 to January 2020. We measure the effect of the pandemic shock on wealth W_t as the deviation from this trend. We find that total net financial household wealth has increased by €47 billions in the aftermath of the covid crisis, relative to the counterfactual of what would have happened if it had continue to grow according to its 2019 trend.

In Figure 4, we decompose the evolution of net financial wealth W_t into its different components. For each component W^k_t observed in month t, we deal with both seasonality and trend using the same methodology as in Figure 1. That is, we report the ratio

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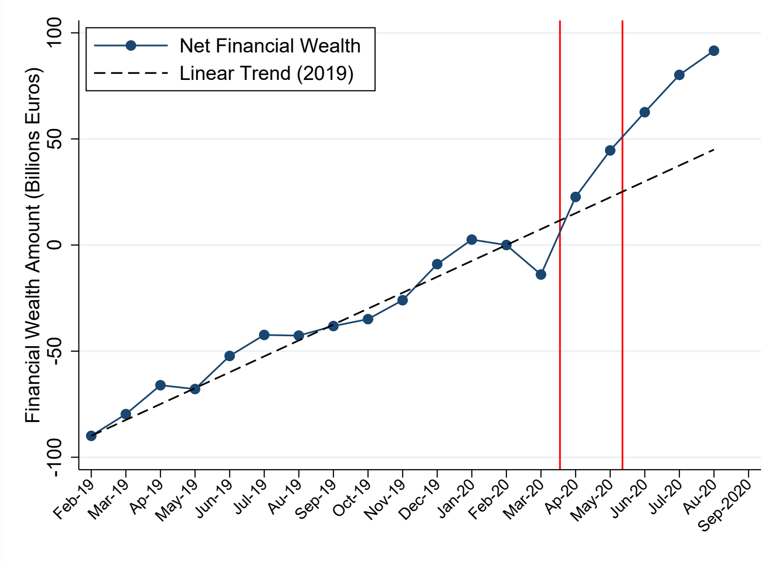
Figure 3: Estimated Evolution of Total Net Financial Wealth W_t



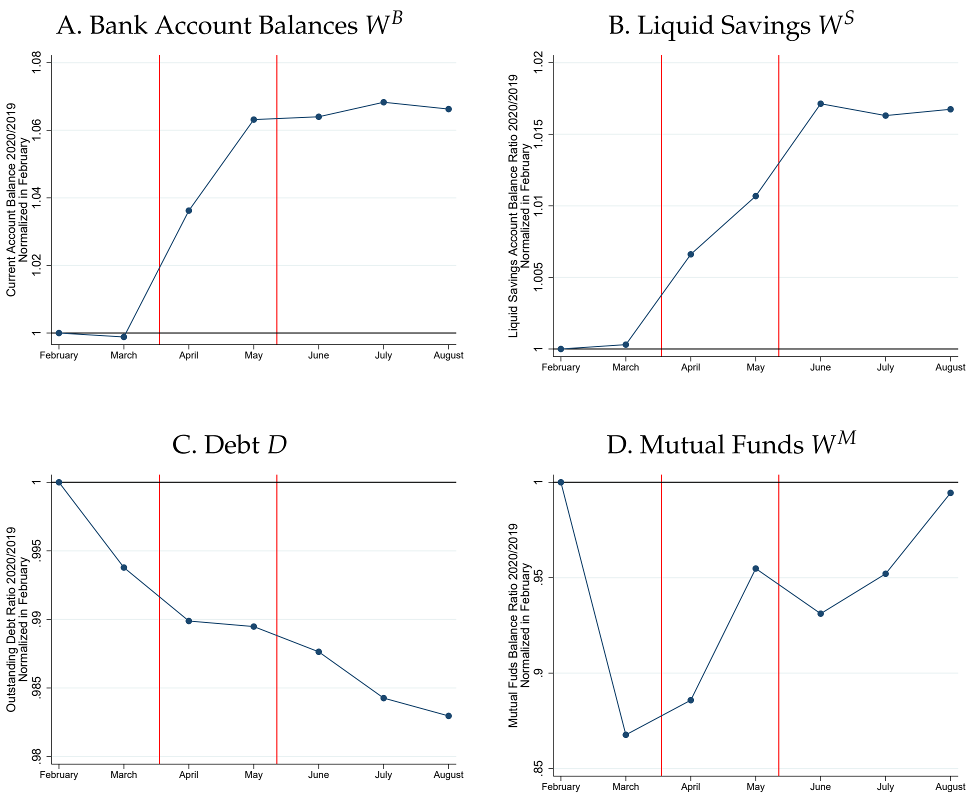
Notes: The Figure reports the evolution of total net financial wealth W_t as defined in equation (1), and normalized to zero at the end of January 2020. The total is weighted by our sample weights to reflect total net financial wealth in the whole population living in the French metropolitan area. Net financial wealth does not include real estate wealth, but includes mortgage debt. See text for more details on our measure of W_t and its potential limitations. The figure also reports in red the overall linear trend in W_t computed over the period January 2019 to January 2020. We measure the effect of the pandemic shock on wealth as the deviation from this trend.

$(W_t^{k,2020}/W_t^{k,2019})/(W_{Jan}^{k,2020}/W_{Jan}^{k,2019})$. Panel A shows the evolution of bank account balances. Bank account balances experienced a sharp increase during the lockdown period, increasing by more than 6% in two months, compared to the counterfactual of what would have happened if they had remained on their 2019 trend. After the lockdown, balances have remained stable, showing no sign of dissaving or reallocation towards other asset classes. Panel B shows a very similar pattern for liquid savings accounts: their balances have increased by 1.75% during the lockdown period and have not decreased after.[8]. In panel C, we report the evolution of total household debt: we see that the stock of household debt has decreased significantly, by about 2% in the aftermath of the covid crisis. This reflects the fact that household have used liquidity to pay back their debt. But it also driven by a decrease in the evolution of new credit lines, due to decreased consumption opportunities and the slowdown in the number of transactions in housing market. Finally panel D displays the evolution of mutual fund balances. It shows that the pandemic was initially met by a sharp de-

[8]Note that these balances are far larger than bank account balances. The overall contribution of each asset class to the evolution of total net financial wealth is given in Figure 5

cline in the value of mutual funds held by households, but that mutual funds balances have reached back their pre-crisis level by the end of August. These brutal evolutions are clearly driven by the evolution in asset prices. The pandemic shock triggered a sudden and global drop in stock prices and other asset prices. Interestingly there has been a quick recovery in asset prices following this initial crash: stock price indices are almost back to their pre-crisis level. This means that, once removing the effects of passive capital gains, there has not been much extra active savings in mutual funds so far.

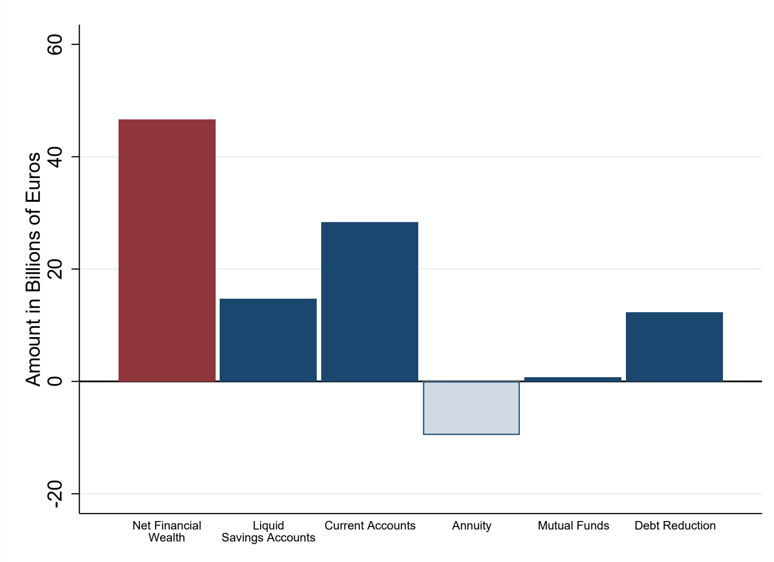
Figure 4: Detrended Evolution of the Different Components of Net Financial Wealth (2020)



Notes: The Figure reports the evolution of the different components of net financial wealth W_t as defined in equation (1). For each component W_t^k observed in month t, we deal with both seasonality and trend using the same methodology as in Figure 1. That is, we report the ratio $(W_t^{k,2020}/W_t^{k,2019})/(W_{Jan}^{k,2020}/W_{Jan}^{k,2019})$, and therefore, we measure the effect of the pandemic shock as the deviation from the 2019 trend. Panel A shows the evolution of bank account balances W_t^B. Panel B focuses on liquid savings, panel C reports the evolution of total debt including mortgage, panel D reports the evolution of mutual fund balances. See text for details.

In Figure 5, we summarize these findings by computing the contribution of each asset class to the evolution of total net financial wealth over the period January 2020 to August 2020. The left bar on the histogram corresponds to the excess net financial wealth of €47 billions generated during the covid crisis. The histogram shows that the bulk of this extra financial wealth has been held in liquid accounts (bank and liquid savings accounts). It also shows that the reduction in household debt has been an important contributor to the increase in aggregate net financial wealth of French households during the pandemic.

Figure 5: Contribution of Each Asset Class to Excess Total Net Financial Wealth Created Over the Period January 2020 to August 2020



Notes: The Figure reports the contribution of each asset class to the evolution of total net financial wealth W_t over the period January 2020 to August 2020. For each component W_t^k observed in month t, we deal with both seasonality and trend using the same methodology as in Figure 1. That is, we report the ratio $(W_t^{k,2020}/W_t^{k,2019})/(W_{Jan}^{k,2020}/W_{Jan}^{k,2019})$, and therefore, we measure the effect of the pandemic shock as the deviation from the 2019 trend. Panel A shows the evolution of bank account balances W_t^B. Panel B focuses on liquid savings, panel C reports the evolution of total debt including mortgage, panel D reports the evolution of mutual fund balances. See text for details.

4 Sectoral Heterogeneity

The richness of the CB data allows to document the large sectoral heterogeneity in the severity of the covid shock.

4.1 Durables

We start by focusing on expenditures on durable goods. We define durable goods as cars, motorcycles, home appliances, IT, furniture, and jewelry.[9] The dynamics of expenditures on durables is in important signal regarding the underlying mechanisms driving consumption dynamics. First, because, contrary to other goods or services, durables allow for intertemporal substitution. If the effect of the severe lockdown on consumption was entirely driven by incapacitation effects, then we should see almost perfect intertemporal substitution. And durable expenditures would catch up post lockdown the losses made during the lockdown period. But durable consumption is also an important signal regarding households' expectations and is often strongly correlated with cyclical variation in economic activity, dipping strongly in recessions. The reason is that durables are an important means of consumption insurance against the expectations of future shocks. In the face of a future expected shock, one can use durables to smooth consumption over time without having to incur new expenditures.

In Figure 6 below, we report in panel A the evolution of consumption expenditures on durables observed in the CB data following the same approach as in Figure 1 to account for trends and seasonality. The Figure shows that, after a very large decline during the lockdown period, expenditures on durable goods have bounced back significantly right after lockdown and have been at a significantly higher level than in 2019 ever since. Overall, this strong pattern of intertemporal reallocation of expenditures has enabled to recoup almost two thirds of the losses made during the lockdown period.

4.2 Hospitality & Recreation

In panel B of Figure 6, we report, following a similar methodology, the evolution of expenditures in the hospitality and recreational sectors, defined as sector codes "56", "90", "91" and "93" in the French NAF classification. The patterns are markedly different compared to panel A. We see that the hospitality sector has been severely impacted by the lockdown, but did not experience a quick rebound after. Various administrative

[9] This corresponds to the following sectors in the French NAF classification of sectors: "451", "453","454", "474", "475", "4777".

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restrictions have remained in place in these sectors throughout the summer months, such that in annual terms it has lost 6.6% of annual expenditures since the end of the lockdown. When added to the 13% annual expenditures already lost during the lockdown, this makes for a historic and dramatic loss for 2020. Furthermore, hospitality expenditures have been declining since the end of August, as new cases started to rise in France, prompting new administrative measures restricting consumption in these sectors.

4.3 Overall Heterogeneity Across Sectors

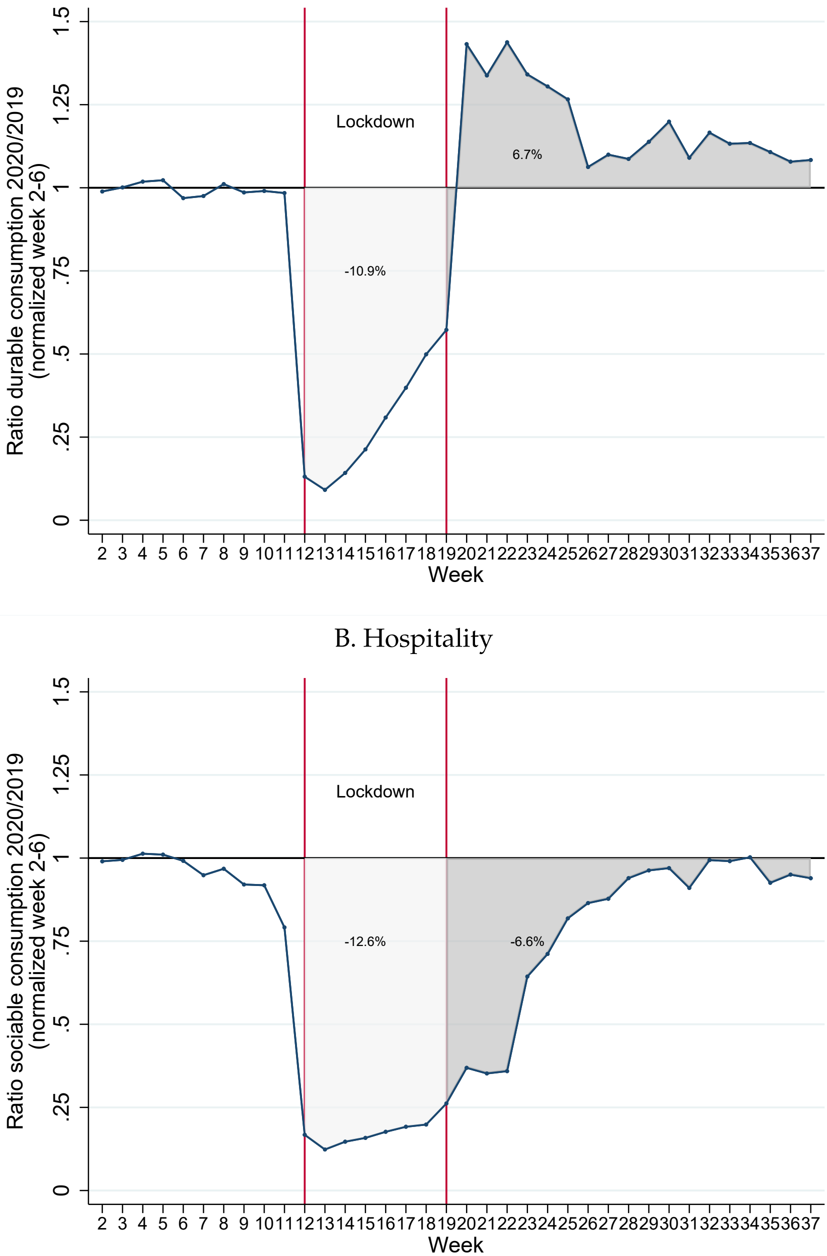
In Figure 7, we report the total annualized gains or losses in expenditures made by each sector during the lockdown period, and the post-lockdown period. Results provide a clear picture of the extreme heterogeneity in the severity of the shock across sectors, something that is quite unique compared to previous recessions. Overall, the majority of sectors was confronted with heavy losses in expenditures during the lockdown period, with only a few sectors doing better than in 2019. But interestingly, some sectors did compensate for these losses during the post-lockdown period with a significant rebound in expenditures (hardware stores, bookshops, etc). In contrast, some sectors continued to face extremely depressed expenditures (travel agencies, museums, leisure centers, etc).

These results indicate that sectors face extremely heterogeneous prospects in terms of recovery, and different needs in terms of public policies. While some sectors have experienced temporary losses that did affect their liquidity but not their solvency in the near future, others have faced permanent losses, and cannot anticipate a recovery in terms of expenditures as long as the epidemic is not brought into control. These sectors are now facing extremely severe solvency issues, and their needs can only be addressed via targeted sectoral policies.

Figure 6: Evolution of Consumption Expenditures By Sector

A. Durables

B. Hospitality



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data following the same methodology as in Figure 1 for different sectors. The normalization procedures deals with both seasonality in expenditures, and the overall trend in expenditures over time. The graph therefore measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occurred between 2019 and 2020 absent the pandemic. Durables correspond to sectors "451", "453","454", "474", "475", "4777" according to the French NAF classification of sectors. The hospitality sector corresponds to sectors "56", "90", "91" and "93".

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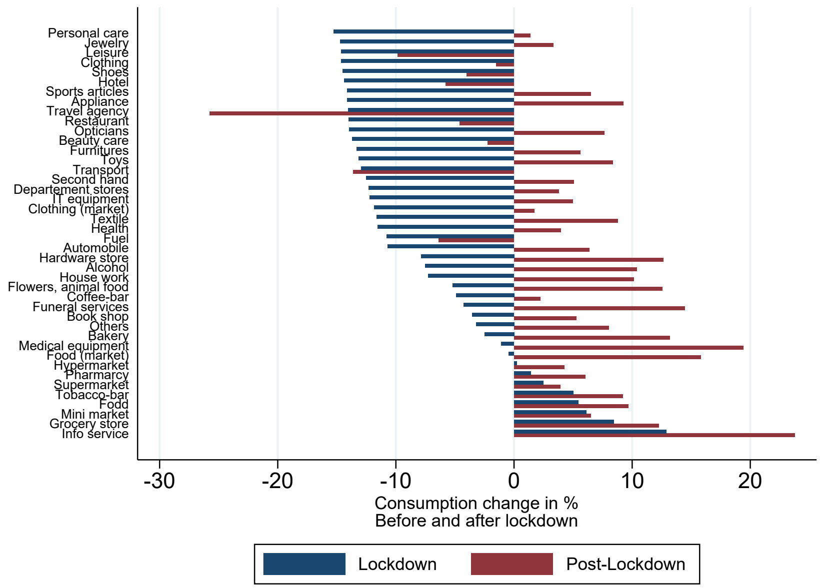
Figure 7: Total Expenditure Change in Annual Terms by Sector During the Lockdown and Post-Lockdown Periods



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data by sector during the lockdown period (in blue) and post-lockdown period (in red). We follow the same normalization methodology as in Figure 1 to control for both seasonality and the overall trend in expenditures over time. We cumulate the difference between 1 and these normalized expenditures for each week during the lockdown and post lockdown periods. We then convert the cumulated difference in annual terms, to measure the overall losses or gains made during each period as a fraction of annual 2019 expenditures in each sector.

5 Distributional Effects

We now turn to documenting heterogeneity in the responses of household consumption and savings to the crisis.

We first rank households in the CM panel according to their level of total expenditures in 2019. The CM data does not enable us yet to measure income flows precisely, and total consumption expenditures offer a good proxy for the standard of living of a household pre-crisis.[10] In Figure 8, we show in panel A the evolution of total consumption expenditures for different deciles of the distribution of pre-crisis expenditures. The graph shows that households in the bottom of the distribution of pre-crisis expenditures experienced a smaller decrease in consumption during the lockdown, and a steeper rebound during the summer months. This finding of an overall larger decline in consumption for richer households is reminiscent of the results in Chetty et al. [2020]. Note that their results are based on correlations between aggregate card expenditures and average income across zip codes, while our approach is based on individual level variation in "income" levels.

Interpreting these differential consumption patterns is not straightforward. They may first reflect differential variations in income or in income expectations. But they may also be due to differential perceptions regarding the risk of getting infected or severely ill, perceptions which may ultimately affect consumption behaviors. Finally, they may also simply reflect differential incapacitation in the face of the restrictions (e.g. lockdowns, etc) put in place by the the government: individuals at the top end of the income distribution have usually a much larger share of their expenditures in sectors that have been shut down by the pandemic (travels, leisure, hospitality, etc.). It is important to understand which of these three main channels is driving consumption patterns to understand the distributional and welfare effects of the shock.

We start here by focusing on the role of income fluctuations and income expectations. Ideally, of course, we would like to be able to observe income, and its differential evolution across households. Unfortunately, we do not have (yet) a robust measure of income in the CM data. But by combining the patterns of evolution of consumption and household financial wealth in the CM data, we can get a good indication of what has happened to income, using households' budget constraint identity (2). In panel B of Figure 8, we report the evolution of total gross savings, defined as the sum of current account balances, all liquid savings account balances, and of all mutual funds balances held in the bank, for different deciles of the distribution of 2019 total expenditures. Once again, we take care of trends and seasonality, using the same approach as in panel A. The graph shows that the crisis has caused a decline of about 2% of

[10] Total expenditures are defined as credit card transactions, check payments and cash withdrawals.

the total gross financial wealth for the "poorest" households (i.e. the bottom deciles of the distribution of pre-crisis expenditures). For households in the middle of the distribution (5th decile), the crisis has created a small increase of about 1% of their gross financial wealth, after an initial dip in March, due to the crash in asset prices. Interestingly, households at the top end of the distribution saw a larger dip than other households in gross financial wealth in March, due to the larger fraction of their financial wealth held in risky assets. But after this dip, the situation reversed: as of August, households in the 10th decile have experienced the largest increase in financial wealth in percentage terms (i.e. of about 4%). This rebound reflects both the rebound in asset prices following the initial crash, but also the steady flow of savings maintained by these households since the start of the pandemic.

In panel C, we investigate the evolution of outstanding debt by deciles, and use the same approach as before to detrend the data and take care of seasonality. We find that poorest households have seen a significant increase in their outstanding debt since the start of the crisis. To the contrary, households at the top end of the distribution of pre-crisis expenditures have experienced a large decrease in the stock of their outstanding debt, reflecting movements both at the intensive margin (debt repayments), and extensive margin (fewer new debt contracts). Overall, the patterns reported in all three panels of Figure 8 suggest that households at the bottom of the distribution, experienced both a decline in consumption and a decline in their net financial wealth. Inverting their budget constraint's identity, this is direct evidence that they experienced a significant drop in income. Clearly, these households have been strongly affected by the pandemic crisis, and, contrary to households at the top end of the distribution, have not been able to create a buffer of savings during the lockdown.

In Figure 9, we compute the contribution of each decile of pre-crisis expenditures to the excess growth in net financial wealth over the period February to August 2020. The graph shows that the contribution of the poorest deciles was negative, as they experienced a decline in their net financial wealth. It also shows that more than 70% of the €47 billions in excess wealth have accrued to the top two deciles. And 55% alone of this excess wealth went to the top decile. Given these top two deciles accounted for a little less than 45% of total net financial wealth before the pandemic, this suggests that the crisis has generated an increase in wealth inequality.

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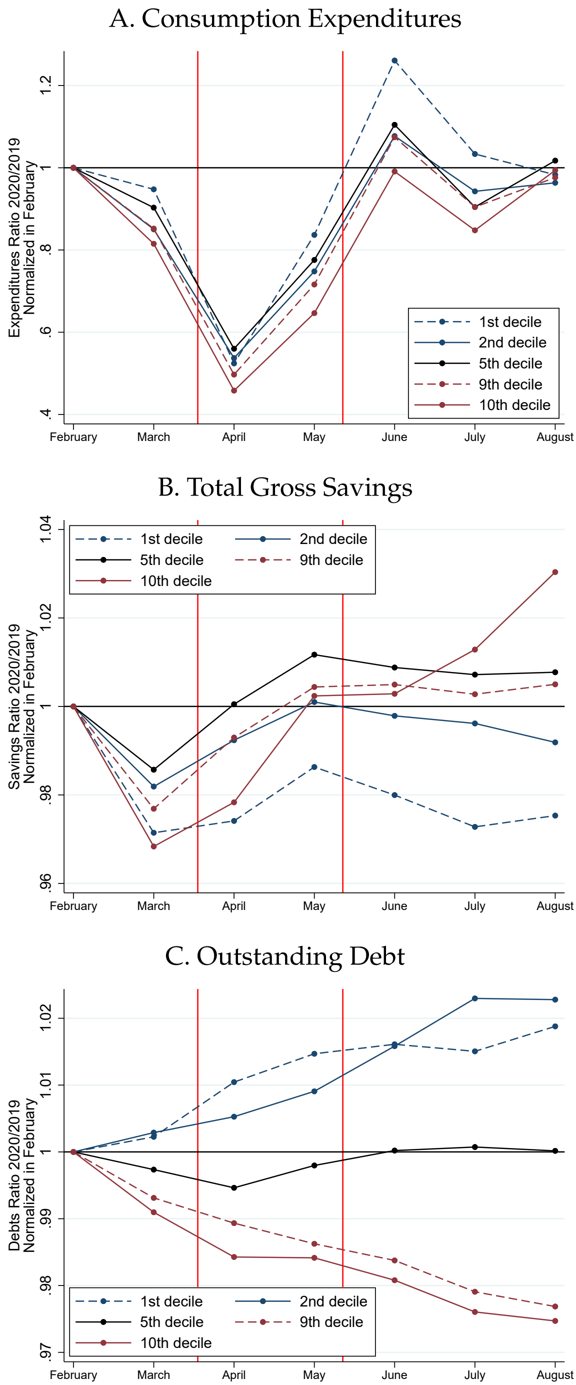
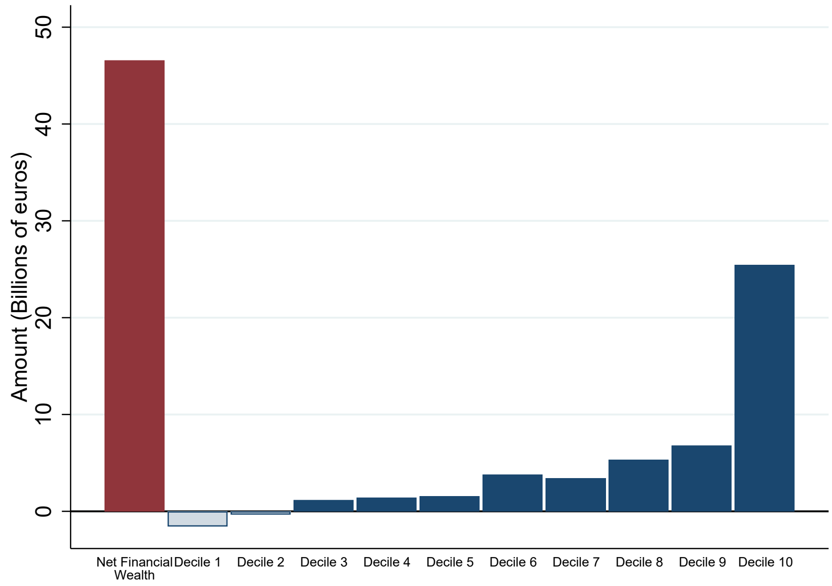
Figure 8: Dynamics of Consumption, Liquid Savings and Debt by Deciles of 2019 Total Expenditures



Notes: The figure reports the evolution of total expenditures (panel A), total gross savings (panel B) and outstanding debt (panel C) from the CM data. We break down the sample by deciles of 2019 total expenditures to proxy for differences across households in terms of income. In each panel, and for each decile, we detrend the data and take care of seasonality using the same methodology as in Figure 1. Total gross savings are defined as the sum of current account balances W_{it}^{B}, all liquid savings account balances W_{it}^{S}, and of all mutual funds balances W_{it}^{M} held in the bank.

Figure 9: Contribution to the "Excess" Growth in Net Financial Wealth by Deciles of Expenditures in 2019



Notes: The figure reports the contribution of each decile of pre-crisis expenditures to the excess growth in net financial wealth over the period February to August 2020, computed from the CM data. Excess growth is computed in Figure 3 as the deviation in observed net financial wealth compared to the counterfactual of the 2019 linear trend. It amounts to about €47 billions.

6 What Is Driving Consumption Dynamics?

We now investigate the role of three potential drivers of consumption dynamics during the pandemic. First, we focus on the role of income dynamics and income expectations. For this, we estimate marginal propensities to consume using the granularity of our data. Second, we explore the role of health risk. Finally, we measure the impact of restriction policies.

6.1 Income Dynamics & Marginal Propensities to Consume

To evaluate the role of income dynamics in explaining consumption and savings dynamics, we focus on estimating marginal propensities to consume (MPC). MPCs measure the sensitivity of consumption to income changes and are therefore important to understand the aggregate demand effects of transfer and stimulus policies put in place during the crisis. Furthermore, MPCs reveal households' expectations about the future. The presence of strong precautionary saving motives for instance would translate into low MPCs, indicative that households prefer to use any extra income to build a buffer stock of savings in the face of uncertain income and employment dynamics. Finally and importantly, MPCs also help capturing the social value of transfers. Landais and Spinnewijn [forthcoming] show that, under particular assumptions, heterogeneity in MPCs can identify heterogeneity in the underlying price of raising an extra € of consumption. As a result, while consumption dynamics alone is a poor guide to evaluate the welfare consequences of a shock, heterogeneity in MPCs is key to measure the differential welfare impacts of such shocks, and determine the redistributive and social value of transfers.

Identifying MPCs To identify MPCs, we exploit eligibility criteria for a specific welfare transfer called the "Allocation de Rentree Scolaire" (ARS). This welfare transfer is a one-time payment made in August, just before the start of the school year, to families with children above 6 years old. The transfer is means-tested. This year, the regular amount was topped-up by an extra €100 payment, so that eligible families received €470 per child for children between six and ten years old. We focus on households in the CM panel with one or two children meeting the means-test requirement to receive the payments. We then create two groups from this subsample. The treatment group comprises households with just one child, whose age is between 6 and 10 years old, as well as families with two children, with one of them being between 6 and 10 years old and the other between 3 and 5 years old. The control group is made of households with just one child, whose age is between 3 and 5 years old, as well as families with

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two children, both of them being between 3 and 5 years old. The treatment group receives a €470 ARS payment on August 18th, while the control group does not receive any payment on this date. Identification relies on a standard difference-in-difference assumption of parallel trends.

Figure 10 shows the difference in average weekly expenditures between households in the treatment and control group, normalized to zero in week 33. The difference was extremely stable in the weeks preceding the ARS payment, lending credibility to our diff-in-diff identifying assumption. We see a sudden and sharp increase in consumption expenditures by households in the treated group in week 34, just after they receive the ARS welfare payment. When scaled by the value of the transfer (i.e. €470), this sharp increase in expenditures translates into a MPC estimate of .15 for the first two weeks. These findings are consistent with estimated expenditures responses to CARES Act stimulus payments in the US, from Chetty et al. [2020] (who use aggregate card transaction data), as well as from Baker et al. [2020] and Karger and Rajan [2020] who use individual transaction data. Note that the estimated MPCs from the latter two studies are slightly higher (around .2 to .25) but they both rely on samples primarily made of lower-income individuals (compared to the population eligible to ARS).

In Figure 11, we show the presence of strong heterogeneity in estimated MPCs. We split the estimation sample by quartiles of liquid savings, defined as the sum of current account balances W_{it}^{B}, and of all liquid savings account balances W_{it}^{S}. The graph shows that estimated MPCs are three times larger for households in the bottom quartile of liquid savings compared to households in the top quartile.

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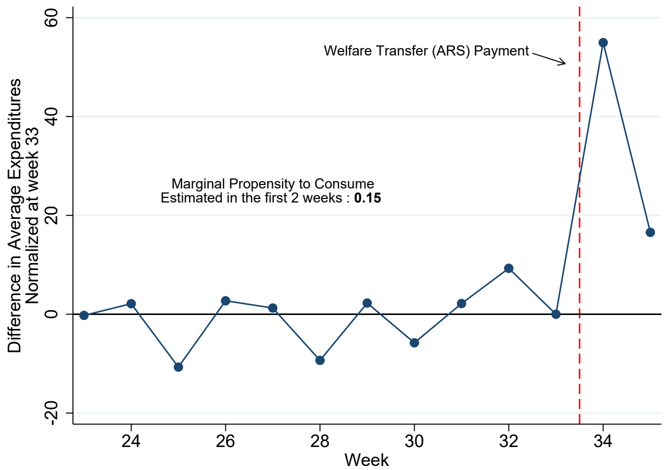
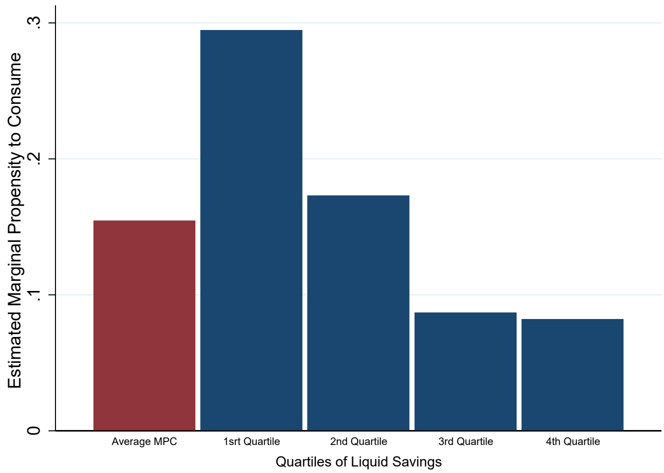
Figure 10: Estimating Marginal Propensity to Consume: Difference in Average Weekly Total Expenditures Between Households Eligible to ARS and Households Ineligible to ARS Based on the Child Age Cutoff



Notes: The graph reports the difference in average weekly expenditures between households in the treatment and control groups, normalized to zero in week 33. The treatment group is made of households with just one child above 6 years old and eligible to the ARS payment of €470 on August 18th. The treatment group is made of households with the same number of children, but with children below the 6 years old age cutoff to benefit from the payment. See text for details.

Figure 11: Estimated Marginal Propensity to Consume from the ARS Payment By Level of Liquid Savings



Notes: Panel reports the diff-in-diff estimate of the marginal propensity to consume from the ARS payment using the CM data. We split the estimation sample by quartiles of liquid savings, defined as the sum of current account balances W^B_{it}, and of all liquid savings account balances W^S_{it} held in the bank.

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6.2 Health Risk

Time Series & Cross-sectional Geographical Evidence How much is consumption dynamics impacted by the increased health risk that people face due to the pandemic? The first natural approach is to look at time series and cross-sectional variation in the severity of the epidemic, and use this variation to estimate correlation with consumption expenditures. In Figure 12, we plot the evolution of ICU admissions in France against the evolution of aggregate daily card transactions in the CB data, using a 7-day moving average.[11] The graph shows the presence of a strong negative correlation in the time series between virus dynamics and aggregate consumption behaviors. In particular, the graph shows that aggregate consumption has started to falter since mid-September, as the second wave of the epidemic was gaining strength in France. Cross-sectional variation confirms the presence of a strong correlation between virus spread and aggregate consumption: in panel B, we display an binscatter of aggregate log CB consumption in September 2020 (relative to log aggregate CB consumption in September 2019) by "departement", against the number of average daily new confirmed cases in September by "departement".[12] The binscatter is residualized on a series of controls for observable characteristics at the departement level, including population size, occupational structure of the workforce, age structure of the population. The graph indicates clearly that departements in which the number of cases is the highest in September are also facing the lowest level of aggregate card transactions.

Evidence from Figure 12 clearly indicates that the steady and quick rebound of aggregate consumption observed in France during the Summer months is now at risk, and there is a clear slowdown of expenditures since mid-September, as the second wave is looming. However, it is hard to interpret the correlations from Figure 12 as direct evidence of a causal link between health risk and consumption dynamics, as there is a strong correlation in the time series and in the cross-section between the severity of the epidemic and restriction policies. To counter the rapid spread of the virus, the French government has indeed strengthened restrictions since early September, and enabled local jurisdictions to take targeted restrictions and lockdown measures.

[11]ICU admissions come from the official data series released by the French government on the "Sante Publique France" web portal.

[12]A "departement" is a French political jurisdiction. There are about 100 "departements" in France. Numbers of daily new confirmed cases by departement come from the "Sante Publique France" web portal.

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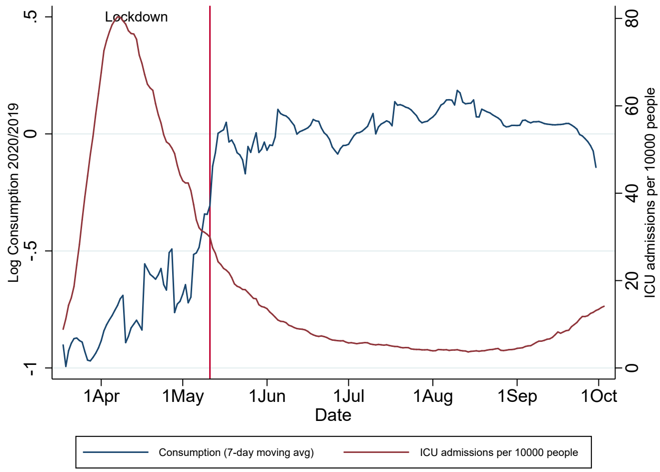
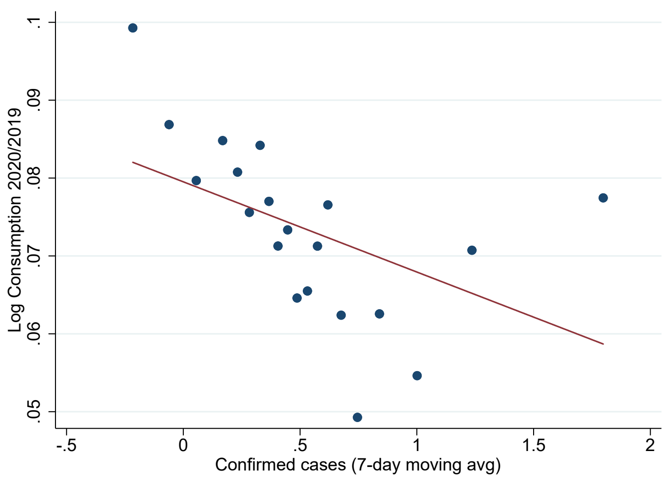
Figure 12: Health Risk & Consumption Dynamics

A. Time Series of CB Card Transactions & ICU Admissions



B. Cross-sectional Variation in New Cases & CB Card Transaction by "Departement"



Notes: Panel A reports the evolution of ICU admissions (right axis) and of consumption in the CB data (left axis). Panel B is a binscatter of aggregate log CB consumption in September 2020 (relative to log aggregate CB consumption in September 2019) by "departement", against the number of average daily new confirmed cases in September by "departement". The data is first residualized on a series of observable characteristics at the departement level, including population size, occupational structure of the workforce, and age structure of the population. The health data comes from the dashboard of the web portal "Sante Publique France" of the French government.

Age Variation To try to identify the causal relationship between health risk and consumption dynamics, we examine heterogeneity in patterns of consumption across age groups. There has not been any age-specific restriction policies put in place during the pandemic, that may confound the correlation observed between age and consumption. Furthermore, there is a clear gradient in health risk by age, as older people are more likely to die from the new coronavirus. To identify first how risk perceptions varied by age, and correlate with actual risk, we use elicited risk perceptions of dying from the coronavirus from the DataCovid survey, which was conducted in June on a random representative sample of 5,000 individuals. Three insights emerge from this panel. First, the overall average elicited risk of dying strongly overstates the true actual risk of dying from the virus. Second, we find a strong gradient in elicited risk, with older people clearly perceiving their higher likelihood of dying from the virus. But thirdly, the gradient is smaller than the actual gradient in true risk. Epidemiological studies suggest that individuals above 65 years old are 4 to 5 times more likely to die from the virus than individuals below 40 years old. In the survey, we see that this gradient is only of about 2: older individuals believe on average to be about 2 times only more likely to die than 18-34 years old. This indicates that there is strong upward bias in risk perception in younger individuals, compared to older individuals.

In panel B, we investigate to what extent these differential percpetions translate into consumption dynamics. We use the CM data and plot the evolution of total expenditures for three age groups. We see that during the lockdown period, consumption of the elderly decreased significantly more than that of younger age groups. But interestingly, we see that as soon as the lockdown ended, consumption patterns reverted back to their 2019 levels for all age groups, without significant differences in consumption dynamics during the summer months. Note that if we break down consumption by sectors, we do find that the consumption structures of the elderly changed compared to younger age groups: the elderly are less likely to engage in consumption involving social interactions (restaurants, etc). Yet, these differences in structure do not seem to impact aggregate consumption levels, suggesting the presence of strong substitution across consumption types.

These results suggest that health risk perceptions may have been less consequential than restriction policies to explain, in the French context, the strong correlation between the dynamics of the epidemic, and that of consumption. To confirm this, we now turn to identifying the effect of restriction policies more directly.

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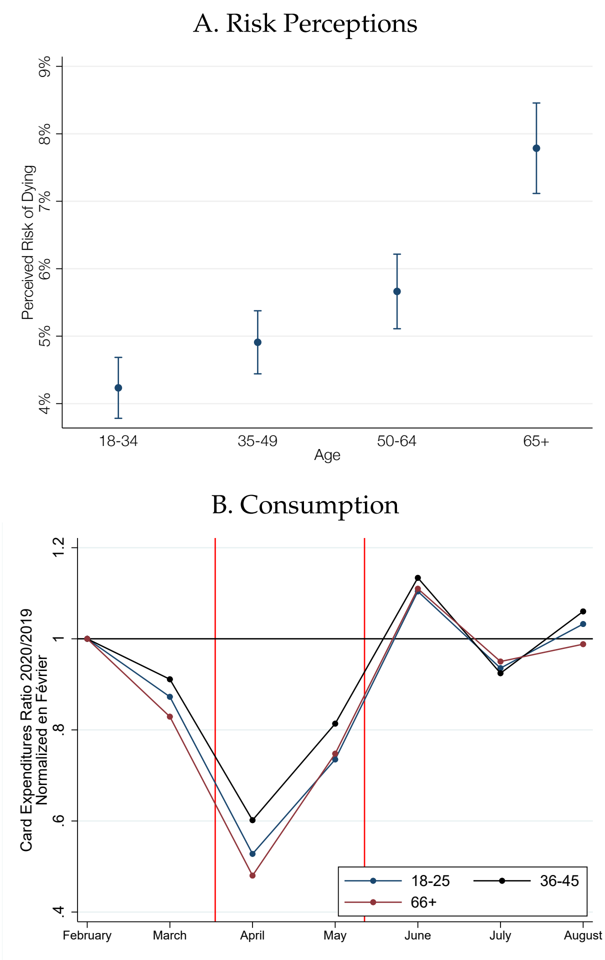
Figure 13: Elicited Risk Perceptions and Consumption Dynamics By Age Groups



Notes: Panel A reports average elicited risk perceptions of dying from the coronavirus by age group. The data comes from the 8-th wave of the DataCovid survey, which took place in June, and surveyed a random representative sample of 5,000 French individuals. Panel B shows the evolution of consumption expenditures by age group in the CM data. We follow the same methodology as in Figure 1 to take care of seasonality and detrend the data.

6.3 Lockdown & Restriction Policies

To investigate the effect of restriction and lockdown policies, we exploit geographical variation in the severity of the lockdown based on the structure of expenditures pre-crisis. For each sector, we compute an indicator variable equal to 1 if that sector ended up being closed by an administrative decree during the lockdown period.We compute for each ZIP code, using the CB data, the fraction of total expenditures made in 2019 in sectors that ended up remaining opened (i.e. not closed by decree) during the lockdown. This fraction represents our measure of exposure to the lockdown shock. In panel A of Figure 14, we correlate, using a binscatter, the change in average weekly card expenditures observed in the CB data during the lockdown period, in percentage term relative to 2019, and our measure of exposure to the lockdown shock, by ZIP code. We do residualize the data first on series of observable characteristics at the ZIP code level, including population size, density, occupational structure of the workforce, and age structure of the population.[13] We find a strong positive correlation between the two, indicating that in ZIP codes where the structure of expenditures was heavily tilted towards sectors that did close during the pandemic, the drop in expenditures has been more severe. Importantly, the estimated correlation is not statistically significantly different from 1, and the overall relationship lies almost exactly on the 45 degree line, which suggests an almost one for one mechanical relationship between consumption and sectoral closures. In panel B, we use detailed ZIP code level measures of unemployment available from the French Public Employment Service (Pole Emploi), and correlate the change in unemployment from February to June 2020 with our measure of exposure to lockdown policies. The binscatter is again residualized on ZIP code level characteristics. We find a strong relationship between lockdown exposure and unemployment growth: a ten percentage point increase in the pre-crisis share of total consumption expenditures in sectors that remained open during the lockdown correlates with a .2 percentage point decrease in the local unemployment rate. This large effect seems driven by the fact that sectors closed during the lockdown are predominantly labor intensive sectors (restaurants, retail, etc). Taken together this evidence suggests that restriction policies have a significant and first-order effect on consumption dynamics and as a consequence on labor market dynamics.

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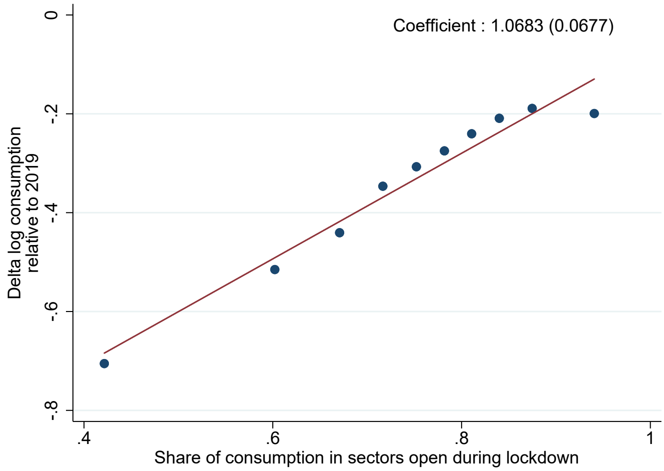
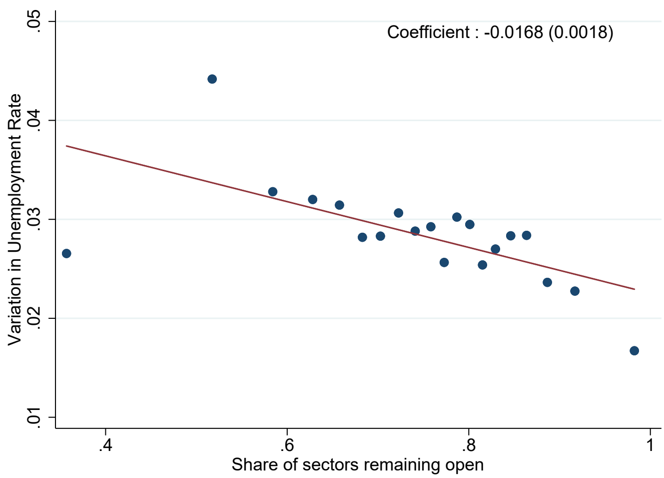
[13]These data come from the office of national statistics (INSEE) and are available at the municipality level.

Figure 14: The Impact of Lockdown Policies

A. Expenditures vs Exposure to Lockdown by ZIP Code



B. Unemployment vs Exposure to Lockdown by ZIP Code



Notes: Panel A is a binscatter of aggregate log CB consumption in the lockdown period in 2020 (relative to log aggregate CB consumption in the same weeks in 2019) by ZIP code, against our measure of exposure to lockdown policies, i.e. the fraction of total expenditures in the ZIP code in 2019 that was made in sectors that will not be closed by administrative decree during the lockdown period. Panel B is a binscatter of unemployment rate change between February and June 2020 by ZIP code, against our measure of local exposure to lockdown policies. In both binscatters of panels A and B, the data is first residualized on a series of observable characteristics at the ZIP code level, including population size, density, occupational structure of the workforce, and age structure of the population.

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APPENDIX

Data

Groupement des Cartes Bancaires CB Le Groupement des Cartes Bancaires CB, Groupement d'Intérêt Economique qui définit les modalités de fonctionnement du schéma de paiement par carte CB (physique ou dématérialisée dans le mobile) a également contribué Ã cette étude par la fourniture de ses données (agrégées) et par la possibilité de solliciter des traitements sur des données individuelles anonymisées dans un espace strictement sécurisé et dans le cadre de son partenariat avec la Chaire Finance Digitale. "Le partenariat entre CB et le monde académique va permettre de développer de nouvelles filières de compétence. Il reflète aussi la démarche citoyenne et responsable de CB, qui a pour volonté de servir l'intérêt général et favoriser l'inclusion sociale et sociétale", déclare Philippe Laulanie, Directeur Général de CB.

Crédit Mutuel Alliance Fédérale Première banque à adopter le statut d'entreprise à mission, Crédit Mutuel Alliance Fédérale a contribué à cette étude par la fourniture de données dans le cadre des missions qu'il s'est fixé :

- contribuer au bien commun en oeuvrant pour une société plus juste et plus durable : en participant à l'information économique, Crédit Mutuel Alliance Fédérale réaffirme sa volonté de contribuer au débat démocratique ;
- protéger l'intimité numérique et la vie privée de chacun : Crédit Mutuel Alliance Fédérale veille à la protection absolue des données de ses clients. Toutes les analyses réalisées dans le cadre de cette étude ont été effectuées sur des données non identifiantes (pas de nom, prénom ou adresse de résidence) sur les seuls systèmes d'information sécurisés du Crédit Mutuel en France.

Representativeness of CM Sample

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Table 1: Descriptive Statistics: Comparison Between the CM Sample (with and without reweighting) and the French Metropolitan Population

	(1) Raw Sample Mean	(2) Reweighted Sample Mean Mean	(3) Full Population (INSEE Data) Mean
Age (Percentage) :			
18-25	17.6	12.2	11.65
26-35	16.2	16.3	14.96
36-45	17	17.2	15.85
46-55	16.7	17.3	17.06
56-65	15.7	15.8	15.87
66+	16.7	21	24.61
Occupation (Percentage) :			
Farmers	0.3	0.6	0.8
Craftsmen, Traders and Company Head	4.6	9.1	3.5
Executives	8.9	13.8	10.1
Intermediate Professions	11.6	12.9	13.6
Employees	21.4	19.4	15.0
Workers	13.8	9.4	11.4
Retired	13.0	16.4	32.5
No Professional Activity	26.3	18.3	12.9
Family Status (Percentage) :			
Single	35.1	30.5	40.9
Married	36.6	39.4	43.0
Widower	4.7	6.3	7.5
Divorced	7.4	8.4	8.6
Civil Partnership	3.4	3.4	NA
French Department Code (The 3 most populated) :			
Nord (59)	2.1	3.99	3.99
Bouches du Rhone (13)	2.1	3.27	3.13
Seine Saint-Denis (93)	2.2	2.34	2.57

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Figure 15: Aggregate Dynamics of Card Expenditures in CB & CM Data

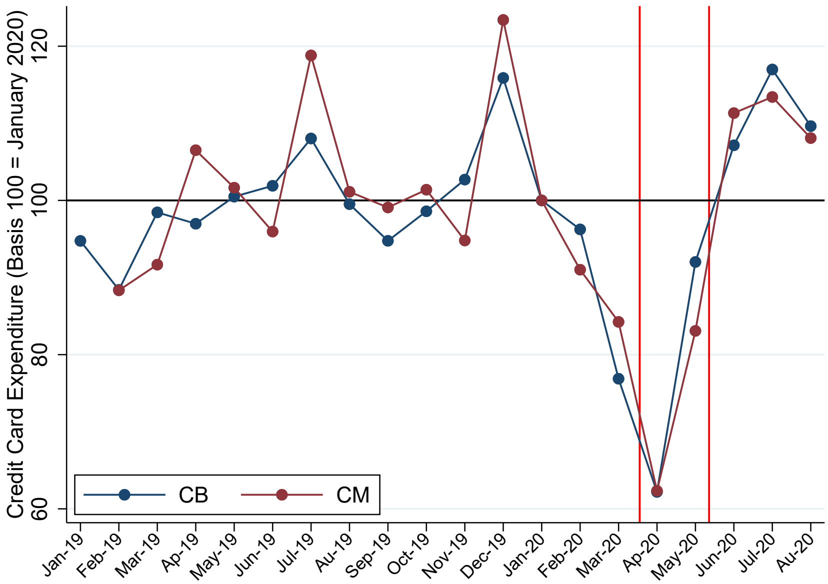
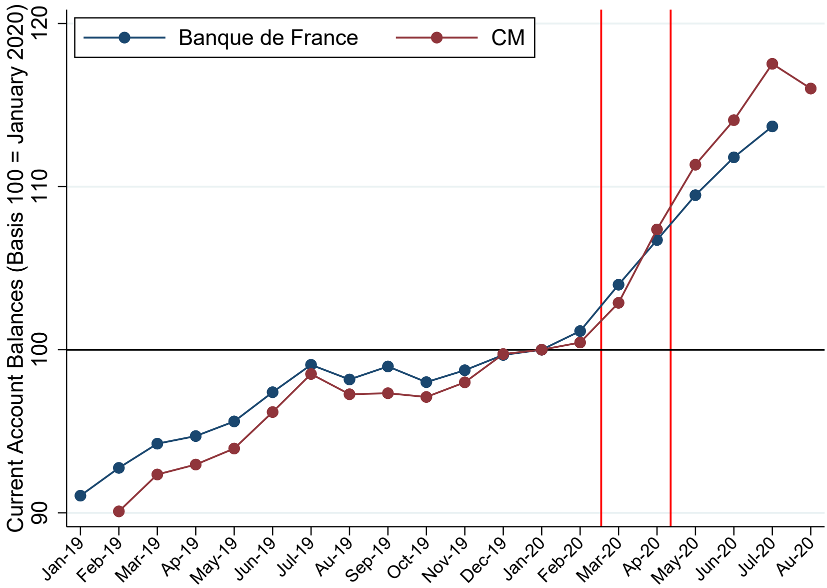
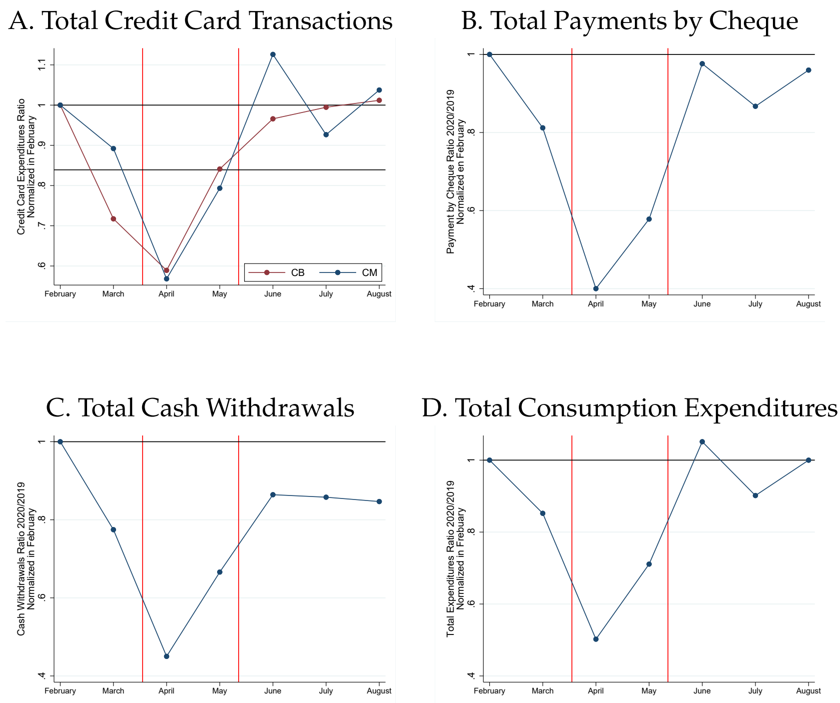


Figure 16: Evolution of Aggregate Balance of Liquid Bank Accounts: French Central Bank Data (Banque de France) vs CM Data



Substitution Across Payment Types

Figure 17: Evolution of Aggregate Monthly Expenditures in the CM Data For Different Payment Methods



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Is COVID-19 a consumption game changer? Evidence from a large-scale multi-country survey[1]

Alexander Hodbod,[2] Cars Hommes,[3] Stefanie J. Huber[4] and Isabelle Salle[5]

Date submitted: 19 November 2020; Date accepted: 19 November 2020

Covid Economics 59, 27 November 2020: 40-76

Prospective economic developments depend on the behavior of consumer spending. A key question is whether private expenditures recover once social distancing restrictions are lifted or whether the COVID-19 crisis has a sustained impact on consumer confidence, preferences, and, hence, spending. Changes in consumer behavior may not be temporary, as they may reflect long-term changes in attitudes arising from the COVID-19 experience. This paper uses data from a representative consumer survey in five European countries conducted in summer 2020, after the release of the first wave's lockdown restrictions. We document the underlying reasons for households' reduction in consumption in five key sectors: tourism, hospitality, services, retail, and public transports. We identify a large confidence shock in the Southern European countries and a permanent shift in consumer preferences in the Northern European countries. Our results suggest that horizontal fiscal support to all firms risks creating zombie firms and would hinder necessary structural changes to the economy.

1 We are indebted to the Amsterdam Centre for European Studies (ACES), Radboud Universiteit Nijmegen, and Gent University for funding this project. The views and opinions expressed in this article are those of the authors and do not necessarily reflect the view of the Bank of Canada or the European Central Bank.

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1 Introduction

"Recovery is sound only if it does come of itself. For any revival which is merely due to artificial stimulus leaves part of the work of depressions undone"
Schumpeter (1934)

In just a few months, the COVID-19 pandemic has driven a health crisis that has transformed life as we knew it and has plunged the world into the worst economic downturn since the 1930s (IMF, 2020). Following the onset of the COVID-19 crisis, governments have initially responded with massive fiscal stimulus to address the prevailing uncertainty, keep employers afloat and households solvent. However, as the extended duration of the crisis is becoming clear, governments are facing critical questions on how best to design their continuing support to the economy.

In particular, the longer the crisis lasts, the higher the likelihood that the post-COVID-19 economy will fundamentally differ from what preceded it. If consumer preferences have fundamentally shifted in response to the COVID-19 experience, many firms and sectors will become obsolete. Bailing out such firms is likely to create unsustainable so-called "zombies" and mismatch unemployment in the long run. A sector-specific approach is therefore critical to design appropriate support policies.

This paper is the first to document the drivers of the observed consumption changes during the first wave of the COVID-19 crisis. We do this by exploiting the two phases of the pandemic's first wave (i.e., March-September 2020). Most households worldwide have experienced a two-phase governmental strategy in response to the pandemic. Initially, governments responded with a strong lockdown (of different intensity and duration) by temporarily limiting economic activity to control the pandemic: this is the "hammer phase".[1] The second phase started when countries gradually lifted lockdown restrictions to restart economic activity, but before an effective treatment or vaccine was available: this is the "dance phase". Using a large-scale multi-country consumer survey, we identify how the "hammer phase" has impacted household consumption during the "dance phase".

We exploit the survey's cross-country dimension to vary the severity of the health crisis, the extent of lockdown restrictions, and fluctuations in economic fundamentals. We analyze their effects on households' reported changes in consumption behavior. A sample of 1,500 representative households per country was surveyed in France, Germany, Italy, The Netherlands, and Spain. These five countries represent most of the EU economy but have

[1] Pueyo (2020) describes this "hammer and dance" pandemic management from an epidemiological perspective.

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experienced differing health crisis severities and lockdown intensities.[2] We collected our data during the dance phase (July 2020) when the hammer phase's lockdown restrictions had been lifted.

The survey asks households how their consumption has changed during the dance phase compared to before the COVID-19 outbreak. Households are specifically asked to state the main reason for their consumption changes. The survey covers five sectors and activities: tourism (traveling abroad for private reasons), hospitality (restaurants, bars, and cafes), services (such as hairdressers), retail (shopping in malls and other stores), and public transport. This design allows us to reveal the underlying drivers for reported consumption changes and thereby to shed light on the nature of the COVID-19 shock. Are we merely experiencing a transitory income shock? Or a shock to consumer confidence? Or is the COVID-19 experience a game-changer, creating permanent changes in consumer preferences?

The survey is designed to focus on five self-reported drivers of consumption changes: (i) financial constraints, (ii) worry of infection risk, (iii) a lack of confidence in the future that induces a rise in precautionary savings, (iv) substitution to online alternatives, or (v) permanent shifts in taste and preferences arising from the lockdown experience. We focus on these key reasons, as each would imply a different optimal policy response.

Evidence on financial constraints as the driver for reduced consumption would merit direct fiscal transfers (or price cuts) to households to offset lost income. If health concerns are the key factor driving consumption, these financial transfers will not restore consumption and policy-makers cannot realistically hope to stimulate demand before controlling the virus's spread. Similarly, in case of a confidence shock, fiscal transfers to households will not help restore consumption; instead, targeted communication policies to reassure on the prospects for macroeconomic performance and employment may be preferable. By contrast, if households experienced permanent shifts in their consumption preferences due to the COVID-19 shock, this may have more profound long-term structural implications for the economy. Some businesses, perhaps whole sectors, will become obsolete. Policy-makers must avoid obstructing structural shifts of economic activity away from those old areas into new productive ones. In such a context, it is crucial to let the market function in bankrupting unviable businesses and reallocating resources into areas with more potential for the future.

Our paper contributes to the fast-emerging literature studying the effect of the COVID-

[2]In 2019, these five countries account for 70% the EU's GDP; 24.7% was generated by Germany, followed by France 17.4% and Italy 12.8%, ahead of Spain 8.9% and the Netherlands 5.8% (source: Eurostat).

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19 outbreak on households' consumption behavior.[3] To the best of our knowledge, this related literature is almost exclusively descriptive and mostly uses financial transaction data to document consumption patterns amid the first phase of the pandemic.[4] Using micro-simulations on UK data, Brewer and Gardiner (2020) discuss the economic and distributional effects of various fiscal interventions. The authors show that the COVID-19 crisis disproportionally impacts low-educated and low-income households. A handful of papers rely on large-scale survey data from households. For the US, Coibion et al. (2020a) document the impact of the lockdown measures on a wide range of household variables, including consumption patterns. Coibion et al. (2020b) show that public communication amid the COVID-19 crisis had little impact on households' beliefs and consumption decisions. Coibion et al. (2020c) use survey data and Karger and Rajan (2020) transaction data to document the impact of the fiscal stimulus payments "COVID-19 Economic Impact Payments" on US households' consumption. Using cross-country survey data, Adams-Prassl et al. (2020) document how the COVID-19 crisis exacerbates inequalities on the US labor market; see Piyapromdee and Spittal (2020) for the UK.

This paper adds to the literature in two crucial ways: First, the cross-country dimension allows us to link the survey outcomes to the economic fundamentals and the intensity of the COVID-19 experience. Second, and most importantly, the data on households' self-reported reasons for consumption changes allows us to go beyond the mere description of realized consumption changes. The results of this paper inform policy-makers regarding economic forecasts and the optimal design of fiscal policies throughout the crisis.[5]

Our analysis reveals six main findings, each of which has relevant policy implications. First, and compared to before the COVID-19 outbreak, a large proportion of households report to consume "less than before" or "not at all", ranging between a 38 and 66 percent reduction—depending on the consumption category. For the whole sample, we observe the largest decline for the tourism sector: sixty-six percent of households report that they will now travel less abroad for private reasons. The second-largest drop is found in the public transport sector, with 58 percent of households reporting to use public transport less

[3]We limit ourselves to the literature related to the COVID-19 pandemic. There are, of course, other large strands of related literature: on the determinants of households' consumption, the effects of recessions on households' behaviors, and the literature on survey and sampling methods.

[4]Chronopoulos et al. (2020) for the UK; Andersen et al. (2020) for Denmark; Baker et al. (2020) for the US; Bounie et al. (2020) for France; Carvalho et al. (2020) for Spain; Chen et al. (2020) for China.

[5]Fiscal transfers to households might lead to a V-shaped recovery if financial constraints are households' main reason for reducing consumption. These fiscal transfers might lead to an L-shaped recovery if the main reason for reducing consumption is a permanent change in consumer preferences. If the primary reason is a precautionary saving motive or heath concerns, fiscal transfers to households might not increase households' consumption expenditure, and a U-shaped recovery can be expected.

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following the COVID-19 outbreak. The third-largest drop concerns the hospitality sector, with 55 percent of households reporting a drop in their appetite to visit restaurants, bars, and cafes.[6] A similarly large impact in consumption demand is observed in the retail sector, with 46 percent of households reporting a drop in the frequency of their visits to shops, malls, and other physical retail outlets. Services such as hairdressers or beauty salons see the smallest decline, although substantial. Thirty-eight percent of households report using these services now less often. It is important to stress that these drops are not due to lockdown measures, as these restrictions (including travel-related ones) were lifted at the time of the survey.

Second, for almost all sectors and countries, the fraction of households that reduce their consumption correlates with the severity of the COVID-19 health crisis (measured by the number of confirmed deaths/1M population as of July 10, 2020). A personal experience with a COVID-19 infection explains a substantial part of households' consumption reduction, while standard socio-economic household characteristics such as income and education are not relevant. In contrast, behavioral factors such as personal experiences, macroeconomic expectations (pessimism), and psychological factors such as worry and fear matter for households' change in consumption.

Third, the largest fraction of households that report consuming now "less often than before" or "not at all" cite the infection risk as the main reason for changing their behavior. This result holds across all categories of consumption and all countries.

Fourth, the fraction of households reporting to consume less because the lockdown has permanently altered their preferences is substantial. Specifically, we observe high proportions of households reporting the realization that they have not missed consuming things. Such permanent preference shifts are particularly apparent in the services and hospitality sectors. For example, the fraction of households realizing that they do not miss services such as hairdressers amounts to 23 percent in France. Similarly, the fraction of households realizing they do not miss going to restaurants amounts to 21 percent in Germany. In France and Germany, households report that—across all sectors—"not missing it" is the second most powerful driver for households' reduced consumption. Similarly, in The Netherlands, the permanent preference shift is the second most frequent cited reason for reduced consumption in all but one sector. [7]

[6]This sector faces the second-largest decline in France, Germany, and Spain; and the third-largest decline in Italy and The Netherlands. The drop ranges from 66 percent of households visiting restaurants less often in Spain to 48 percent in France.

[7]The exception is the retail sector, where households' second primary reason is the substitution for online shopping.

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Fifth, precautionary saving is a substantial driver for changed consumption patterns in Spain and Italy. In these countries, increased saving appetite is cited as the second most important reason for reductions in consumption across almost all product categories. In contrast, only a small fraction of German households cite saving motives as the main reason for reducing consumption.

Sixth, the fraction of households reporting "financial constraints" as the main reason for reducing consumption is small. The fraction of households that cite either "precautionary saving motives" or "permanent changes in preferences" as the key reason for lower consumption is far greater than the fraction reporting "financial constraints". This observation is valid for all countries and sectors. This result shall be understood in light of the unprecedented size of the 2020 governmental financial support programs in all countries.

Given these behavioral changes, how can policy-makers boost economic recovery while containing the pandemic's adverse effects? We draw three policy conclusions.

First, our results suggest that policies such as VAT cuts and subsidies will not significantly increase households' consumption demand during the dance phase. Broad-based efforts to reduce the pricing of products and services would only be effective if a large proportion of households were to reduce consumption due to financial constraints, which is not the case according to our study.

Second, policies that support firms financially and support workers' wages under reduced-hour schemes might create a long-run risk of zombie firms and mismatch unemployment. Our results highlight that a large proportion of households experienced a permanent shift in their consumption preferences. During the lockdown, many households realized that they do not miss certain services, such as restaurants or hairdressers. As for the retail sector, a substantial fraction of respondents reported buying more online instead. Hence, successful management of the COVID-19 crisis may require a more sophisticated approach than simply horizontally supporting all firms in the task of surviving a temporary shock. Our results suggest that part of the consumption behavior changes are not temporary but instead reflect long-term changes in attitudes and tastes arising from the COVID-19 experience. Our results suggest therefore that it would be worthwhile for policy-makers to consider sectoral restructuring and targeted fiscal support to avoid an increase in mismatch unemployment in the long run.

Third, our results indicate that the objectives of protecting citizens from the virus risk and preserving economic prosperity may not lead to any trade-offs. During the time of the survey, lockdowns and travel restrictions were lifted in the countries under investigation.

However, the fraction of households reducing consumption during the dance phase highly correlates with the number of death per 1M population that mostly occurred during the hammer phase. Hence, governments should treat the control of the infection risk as a prerequisite to achieving their objectives of preserving economic prosperity.

The remainder of this paper is organized as follows. Section 2 describes the data and the survey design. Section 3 summarizes our main findings and Section 4 concludes.

2 Survey Design and Data

2.1 Data collection

To investigate households' consumption behavior during the COVID-19 dance phase, we conducted a representative survey in five countries: France, Germany, Italy, The Netherlands, and Spain. The company IPSOS collected the data on our behalf using their online panel of consumers. Samples are representative for the general population (aged 18 year-old and older) on gender, age, education and occupation (based on the one-digit ISCO-classification). The representativeness of the samples is ensured by setting a non-interlocking quota. The survey was conducted during the period from July 10th to July 28th, 2020. During this time, lockdowns and travel restrictions were lifted in all five countries. The sample size equals 7,501, see Table 1.

Sample Size		
France	1,500	20 %
Germany	1,500	20 %
Italy	1,500	20 %
The Netherlands	1,500	20 %
Spain	1,501	20 %
Total	7,501	100 %

Table 1: Number of observations by country

2.2 Descriptive Statistics

The survey first collected background information on the households. Data was collected on households' socio-economic situation, personal experience with a COVID-19 infection, concerns related to the COVID-19 crisis, macroeconomic expectations, and levels of trust and satisfaction with their government. Having answered these background questions, households were asked questions about their consumption behavior. This section provides descriptive statistics of the data.

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2.2.1 Households' socio-economic background

For each country, Appendix Tables A1-A2 report descriptive statistics of the socio-economic characteristics of the sample. Appendix Table A1 documents that the average respondent is 50 years old and shows the average household size and the distribution across three education categories (low, middle, high).

Financial Statistics: For each country, the distribution of households' income—yearly total income, after tax and compulsory deductions, from all sources (across ten income bins)—is reported in Appendix Table A2. Column 5 of Appendix Table A3 reports the fraction of households that have the ability to make an unexpected payment of one-month of income. More than two-thirds of the households have this ability. Interestingly, the variation across countries is negligible.

Column 6 of Appendix Table A3 reports households' perception of how they cope financially with their current income. The survey question is "Which of these descriptions comes closest to how you feel about your household's income nowadays?", with five answer categories, ranging from 1: "Very difficult on present income and insufficient to cover all the expenses" to 5= "Living comfortably on present income and able to save". The cross-country variation is small, ranging from 2.6 to 3.5. The average household is coping on current income in most countries. Spain is the country where households are facing the most financial difficulties, with an average value of 2.6.

Employment statistics: Appendix Table A3 reports the employment statistics for each country. Column 1 reports the fraction of households in paid work, Column 2 the fraction not being part of the labor force, and Column 3 the unemployment rate. Column 4 reports the fraction of households having experienced an unemployment spell for more than three months over the past five years. The fraction of households falling into this category varies between 13 percent in Germany to 39 percent in Spain.

2.2.2 Households' COVID-19 related concerns, exposure and expectations

Personal Experiences: Table 2 documents the number of confirmed COVID-19 death per 1M population (at the time of the survey July 10th, 2020) and the fraction of households that report having been personally exposed to a COVID-19 infection. Households were asked, "Did you or a person close to you suffer from severe COVID-19 infection?" Spain reports the highest fraction with 17 percent, followed by The Netherlands (9 percent), France (8 percent), Italy (7 percent), and Germany (3 percent).

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	Survey data			COVID-19 statistics	
Country	mean	st. dev.	N	deaths	deaths/ 1M pop
France	0.08	0.27	1478	29,979	459
Germany	0.03	0.17	1487	9,130	109
Italy	0.07	0.26	1474	35,092	580
The Netherlands	0.09	0.29	1487	6,135	358
Spain	0.17	0.38	1483	28,403	607
Total	0.09	0.29	7409	108,739	398

Notes: The first column documents the percentage of households having been personally exposed to a COVID-19 infection. The survey question is "Did you or a person close to you suffer from severe COVID-19 infection?" (1=yes; 0=no). The last two columns provide the number of confirmed COVID-19 deaths and the number of deaths/1M population for July 10th, 2020. Source: `https://www.worldometers.info/coronavirus/`.

Table 2: Direct exposure to COVID-19 infection

Financial and job-related concerns: Households report to be more worried about the broad negative effects that the coronavirus might have on their household's financial situation than about losing their job outright. Panel A in Table 3 reports how worried households are about losing their job in the near future. The median household in France, Germany, and The Netherlands is "not worried", while the median household in Spain and Italy are "somewhat worried". Panel B in Table 3 reports how concerned households' are about the effects that the coronavirus might have on the financial situation of their household. We observe a substantial cross-country heterogeneity. Households in Spain are most concerned, followed by Italy, France, the Netherlands, and Germany.

Macroeconomic expectations and pessimism: Table 4 documents households' expectations on when the COVID-19 crisis will end. Households were asked: "In your opinion, when will COVID-19 be totally under control such that it is safe to release all COVID-19 containment measures in your country?". The respondents could choose among five different time windows: July-September 2020, October-December 2020, January-June 2021, July-December 2021, and later. We observe considerable cross-country variation. Interestingly, Italy seems to be the most optimistic country in their predictions of the length of the crisis. Twenty-four percent believe that it is safe to release all COVID-19 containment measures by the end of 2020, while 41 percent think it will be later than July 2021. The second most optimistic country is The Netherlands, followed by Germany, then France. Spanish households have the most pessimistic outlook. Only 9 percent expect the crisis to be over by the end of 2020, while 64 percent expect the crisis to last later than July 2021.

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Panel A: Job Loss Concerns	mean	st. dev.	p10	p25	p50	p75	p90	N
France	1.63	0.74	1	1	1	2	3	859
Germany	1.49	0.66	1	1	1	2	2	897
Italy	1.87	0.77	1	1	2	2	3	886
The Netherlands	1.52	0.67	1	1	1	2	2	838
Spain	2.04	0.73	1	2	2	3	3	1017
Total	1.72	0.75	1	1	2	2	3	4497
Panel B: Financial Concerns	mean	st. dev.	p10	p25	p50	p75	p90	N
France	5.79	2.54	2	4	6	8	9	1460
Germany	4.44	2.98	1	2	5	7	8	1459
Italy	6.45	2.54	3	5	7	8	10	1457
The Netherlands	4.87	2.62	1	3	5	7	8	1463
Spain	7.42	2.20	5	6	8	9	10	1458
Total	5.79	2.80	1	4	6	8	9	7297

Panel A: The survey question is "How worried are you about losing your job in the near future?" Answer options: 1-3. 1= not worried; 2 = somewhat worried; 3 = very worried. Panel B: The survey question is "How concerned are you about the effects that the coronavirus might have for the financial situation your household?" Answer options: 0-10. 0 (= not at all concerned) to 10 (= extremely concerned).

Table 3: COVID-19 related financial concerns

	France	Germany	Italy	The Netherlands	Spain
	Percent	Percent	Percent	Percent	Percent
July-September-2020	3.33	4.27	7.47	6.93	2.73
October-December 2020	9.13	10.07	16.73	14.13	6.4
January-June 2021	28.73	28.67	35.20	34.80	26.98
July-December 2021	26.47	26.27	22.87	24.87	34.58
Later	32.33	30.73	17.73	19.27	29.31
Total	100	100	100	100	100

Notes: The survey question is "In your opinion, when will COVID-19 be totally under control such that it is safe to release all COVID-19 containment measures in your country?"

Table 4: Expectations about the duration of COVID-19 containment measures

Turning to our proxy for pessimism, Table 5 reports households' predictions about the unemployment rate before the crisis and their expectations about the current and future unemployment rates. In all countries, the average household overestimates the pre-crisis and current unemployment rates compared to the actual figures (source: OECD). This systematic expectation bias is common in household surveys and may not reflect pessimism but rather the misperception of macroeconomic variables. For this reason, in the sequel, we use the predicted *change* in the unemployment rate as a proxy for households' pessimism. This predicted change at one year ahead directly reflects the expected macroeconomic impact of the COVID-19 crisis and varies from 5 percentage points in Germany to 10 in Spain.

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	France	Germany	Italy	The Netherlands	Spain
Unemployment rate point prediction					
before the crisis	14.58	9.55	21.62	11.56	19.67
	(14.39)	(12.06)	(17.56)	(12.54)	(14.11)
now (July 2020)	20.89	14.21	31.39	19.68	20.30
	(18.57)	(15.66)	(22.91)	(18.28)	(20.30)
one-year-ahead	21.82	14.40	30.81	20.37	29.62
	(19.09)	(15.58)	(22.80)	(18.53)	(19.16)
in the next 2-3 years	19.49	13.10	26.48	16.25	24.08
	(19.37)	(15.66)	(22. 67)	(17.02)	(18.41)
Unemployment rate OECD data					
July 2019	8.5	3.0	9.7	3.4	14.3
July 2020	6.9	4.4	9.7	4.5	15.8

Notes: The first four rows report the (mean) point prediction, standard deviation in parentheses. The survey question is “Please indicate what you think the unemployment rate was or will be in your country at different points in time.” The last two rows show the realized unemployment rates, measured in numbers of unemployed as % of the labour force (seasonally adjusted). Source: OECD (2020), Unemployment rate (indicator). doi: 10.1787/52570002-en (Accessed on 2020-09-17).

Table 5: Macroeconomic Expectations

Panel A: Trust	mean	st. dev.	p10	p25	p50	p75	p90	N
France	3.30	1.24	2.00	2.00	3.00	4.00	5.00	1462
Germany	2.79	1.19	1.00	2.00	3.00	4.00	5.00	1451
Italy	3.22	1.27	2.00	2.00	3.00	4.00	5.00	1454
The Netherlands	2.68	1.28	1.00	2.00	2.00	4.00	5.00	1469
Spain	3.43	1.43	1.00	2.00	4.00	5.00	5.00	1469
Total	3.08	1.32	1.00	2.00	3.00	4.00	5.00	7305
Panel B: Satisfaction	mean	st. dev.	p10	p25	p50	p75	p90	N
France	3.51	1.23	2.00	2.00	4.00	5.00	5.00	1449
Germany	2.75	1.28	1.00	2.00	2.00	4.00	5.00	1458
Italy	2.96	1.34	1.00	2.00	3.00	4.00	5.00	1445
The Netherlands	2.59	1.34	1.00	2.00	2.00	4.00	5.00	1462
Spain	3.37	1.43	1.00	2.00	3.00	5.00	5.00	1464
Total	3.04	1.37	1.00	2.00	3.00	4.00	5.00	7278

Panel A: The survey question is “Please tell us how much you personally trust or distrust the (*country name*) government?”. Panel B: The survey question is “How satisfied are you with the way the (*country name*) government led by (*country leader name*) is doing its job?” Answer categories: 1= Very much trust, 2= Somewhat trust, 3= Neither trust nor distrust, 4= Somewhat distrust, 5= Very much distrust. Answer categories 6= I don’t know and 7= I prefer not to answer are dropped.

Table 6: Trust and Satisfaction with Government

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Trust and Satisfaction with the Government: Table 6 documents households' average reported trust and satisfaction level with the prospective government. Households were asked, "Please tell us how much you personally trust or distrust the (*country name*) government?". Table 7 shows in Panel A that governments are most trusted in The Netherlands, followed by Germany, Italy, France, and finally, Spain. Panel B of Table 7 shows that a similar pattern emerges for the satisfaction with governments. Households were asked, "How satisfied are you with the way the (*country name*) government led by (*country leader name*) is doing its job?". Households are most satisfied with their government in The Netherlands, followed by Germany, Italy, and Spain. The average French household is the most dissatisfied with its government.

	experience		**concerns**		**expectations**		**government**	
	deaths/ 1M pop	infection rate	job loss concern	financial concern	crisis end	unempl. rate	trust	satis-faction
Panel A:								
France	459	0.08	1.63	5.79	3.3	21.82	3.3	3.51
Germany	109	0.03	1.49	4.44	2.79	14.4	2.79	2.75
Italy	580	0.07	1.87	6.45	3.22	30.81	3.22	2.96
The Netherlands	358	0.09	1.52	4.87	2.68	20.37	2.68	2.59
Spain	607	0.17	2.04	7.42	3.43	29.62	3.43	3.37
Panel B: Cross-Country Correlation with COVID-19 experience								
deaths/1M pop	1	0.73	0.86	0.92	0.80	0.96	0.80	0.58
infection rate	0.73	1	0.77	0.81	0.60	0.65	0.60	0.50

Notes: The first column provides the number of confirmed COVID-19 deaths/1M population for July 10th, 2020. Source: `https://www.worldometers.info/coronavirus/`. Second column, survey question: "Did you or a person close to you suffer from severe COVID-19 infection?" (1=yes; 0=no). Third column, survey question: "How worried are you about losing your job in the near future?" Answer options: 1-3. 1= not worried; 2 = somewhat worried; 3 = very worried. Fourth column, survey question: "How concerned are you about the effects that the coronavirus might have for the financial situation your household?" Answer options: 0-10. 0 (= not at all concerned) to 10 (= extremely concerned). Fifth column, survey question: "In your opinion, when will COVID-19 be totally under control such that it is safe to release all COVID-19 containment measures in your country?". Sixth column, survey question: "Please indicate what you think the unemployment rate was or will be in your country in one year from now." Seventh column, survey question:"Please tell us how much you personally trust or distrust the (*country name*) government?". Eight column, survey question: "How satisfied are you with the way the (*country name*) government led by (*country leader name*) is doing its job?" Answer categories: 1= Very much trust, 2= Somewhat trust, 3= Neither trust nor distrust, 4= Somewhat distrust, 5= Very much distrust. Answer categories 6= I don't know and 7= I prefer not to answer are dropped.

Table 7: Cross-Country Correlations with COVID-19 infection and death experience

Next, we investigate the relationship between personal COVID-19 experiences and the variables discussed in this section (financial and job-related concerns, macroeconomic expectations, and the trust and satisfaction with the government). We measure personal COVID-19 experiences using the two variables presented in Table 2; that is, the reported average infection rate and the officially confirmed COVID-19 deaths per 1M population. Table 7 shows meaningful cross-country correlations. We find that the more severe the

COVID-19 experience in a country, the more concerned the average household about his financial situation and potential job loss. The severity of COVID-19 experience in a country also positively correlates with pessimism about the future. The more severe the COVID-19 experience in a country, the higher the expected one-year-ahead unemployment rate and the later the expected date when it will be safe to release all containment measures. Similarly, the severity of the COVID-19 experience in a country correlates negatively with households' average trust and satisfaction level with the government.

2.2.3 Households' consumption-specific questions

Households were surveyed about their consumption behavior in five sectors (*activities*): (i) public transports (*usage*), (ii) tourism (*traveling abroad for private reasons*), (iii) services (*use services such as hairdressers or beauty salons*), (iv) hospitality (*visiting restaurants, bars and cafes*), and (v) retail (*shopping in malls or other stores*). We chose these five sectors because they constitute a large part of total household consumption expenditure in normal times and because these sectors have been particularly affected by the lockdown (social-distancing) measures. We are particularly interested in quantifying the potentially long-lasting effects of the lockdown measures on households' consumption behavior during the dance phase.

For each sector, households are asked whether they are now consuming more, less, not at all, or the same compared to before the COVID-19 outbreak. We also screen for households who never consumed pre-pandemic.

If a household reports a change in consumption behavior, the household is asked to provide the main reason for the change. Households can select between six main reasons: (i) switch to online alternatives, (ii) realization that they do not miss it, (iii) desire to save more, (iv) non-affordability, (v) infection risk, or (vi) any other reason. We interpret alternatives (i) and (ii) as a durable if not a permanent shift in consumers' preferences, while alternative (iii) translates into a drop in consumer confidence where households build up precautionary savings. Alternative (iv) corresponds to financial constraints amid the recession. And alternative (v) purely relates to the temporary health risk.

Next, we analyzes for each country and consumption sector, the changes in household consumption behavior, and the reported primary reason for these changes.

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3 Survey results

This section first presents the households' reported consumption changes for each sector and country. The change refers to consumption during the dance phase (where restrictions were lifted) compared to before the COVID-19 outbreak. Second, this section analyzes the reported consumption changes in light of the demographic and other background information collected. Finally, this section documents the self-reported main reason for the change in consumption behavior.

3.1 Overview of consumption changes during dance phase

We find that a substantial fraction of households changed their consumption behavior during the dance phase in all sectors for all countries (compared to before the COVID-19 outbreak). For each country and sector, Appendix Figures A11-A15 provide the percentage of households reporting to consume "now more often than before", "same as before", "less often than before", "not at all", "never did this before". Two clear patterns emerge.

First, it is striking that the fraction of households consuming less is substantial, while the fraction reporting a consumption rise is negligible if not nonexistent. This confirms that the COVID-19 shock has heavily hit the sectors surveyed. Depending on the country and sector, the share of households reporting a consumption decrease ranges from 18% to 56.9%. The share of households reporting a complete consumption stop ranges from 3.9% to 30.6%. Compared to before the COVID-19 outbreak, Figures 1-5 show the fraction of households that reduced their consumption for each country and consumption sector—conditional of having consumed before the outbreak. Across all sectors, the largest proportion of households that reduce their consumption is found in Spain and Italy, which leads us to highlight the first observation:

Observation 1 (Overall consumption drop)**.** *Across all sectors, households substantially reduced their consumption during the dance phase, with the largest drop in Spain and Italy.*

These cross-country differences may reflect differences in the severity of the health crisis: At the time of the survey (July 10th, 2020), Spain had the highest number of confirmed COVID-19 death per 1M population, followed by Italy, France, The Netherlands, and Germany; see Table 2. In other words, a higher COVID-19 death rate in a given country (measured by the number of confirmed COVID-19 deaths per 1M population) seems to go hand-in-hand with a larger fraction of households that reduce their consumption. The only exception is France. It is striking to see that France is the country that displays the

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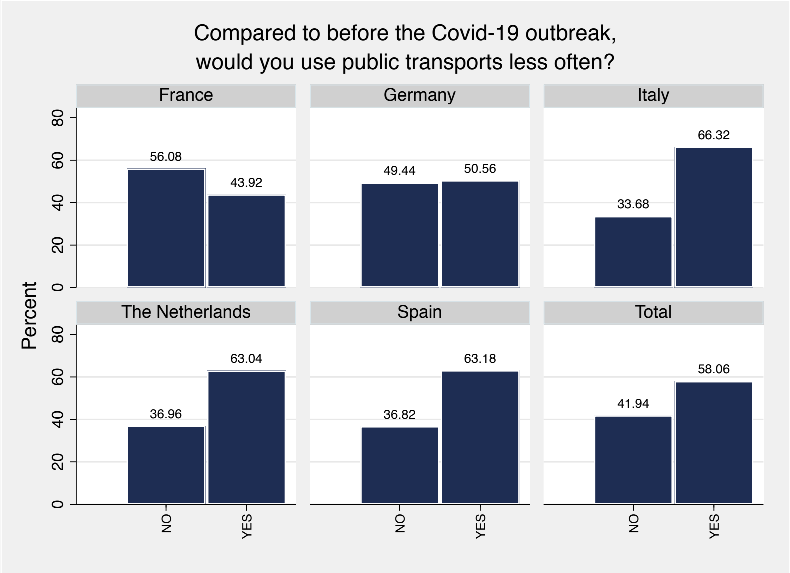
lowest fraction of households consuming less in each sector during the dance phase. In the remainder of this section, we analyze further the cross-country differences in households' consumption response. However, this finding provides anecdotal evidence for the view that governments might not face any trade-off in designing policies to rescue lives and the economy during a pandemic.



The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would use public transports: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before. Responses =5 are dropped and dummy created.

Figure 1: Lower usage of public transports (yes/no)

Observation 2 (Sectoral variation in the consumption drop)**.** *Across all countries, the tourism sector experienced the largest consumption drop and the services sector the smallest.*

The second pattern that stands out is the sectoral variation in the consumption drop. For the whole sample, we observe the largest decline for the tourism sector: 66 percent of households say that they will now travel less abroad for private reasons. The second-largest drop is found for the public transport sector, with 58 percent of households reporting to use this now less. For the whole sample, the third-largest drop concerns the hospitality sector: 55 percent of households report visiting restaurants, bars, and cafes less often. Then comes the retail sector: 46 percent of households shop less in malls and other stores physically. Services such as hairdressers see the smallest, albeit still substantial, decline

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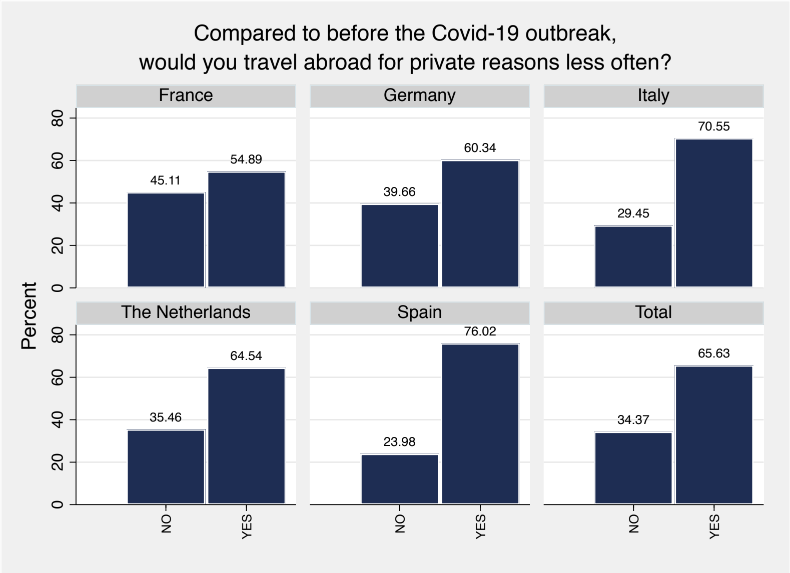
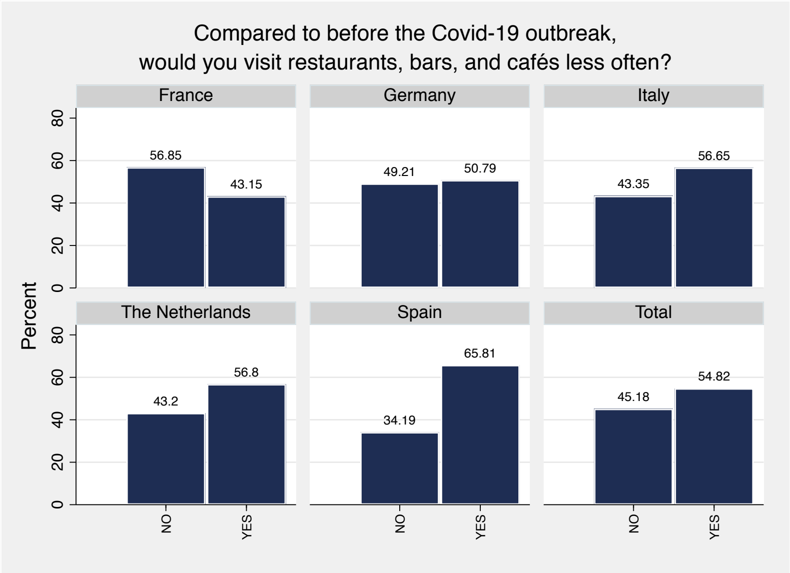


The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would travel abroad for private reasons: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before. Responses =5 are dropped and dummy created.

Figure 2: Less traveling abroad (yes/no)



The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would visit restaurants, bars, and cafes: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before. Responses =5 are dropped and dummy created.

Figure 3: Less visists to restaurants, bars, and cafes (yes/no)

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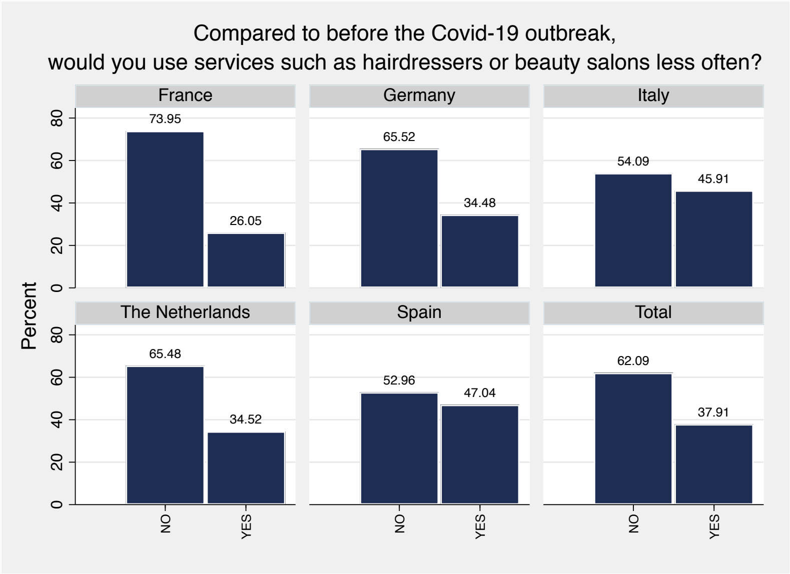
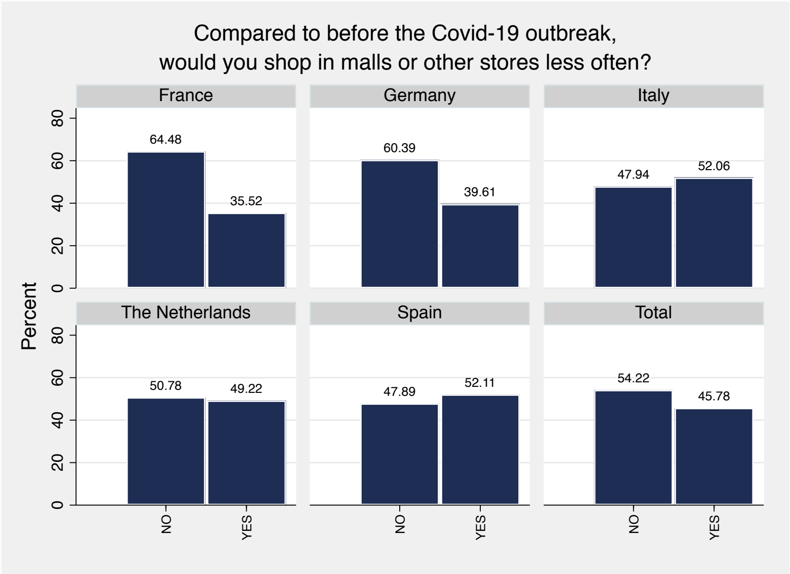


The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would use services such as hairdressers or beauty salons: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before. Responses =5 are dropped and dummy created.

Figure 4: Less usage of services such as hairdressers or beauty salons (yes/no)



The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would shop in malls or other stores: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before. Responses =5 are dropped and dummy created.

Figure 5: Less shopping in malls or other stores (yes/no)

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with 38 percent of households reporting to now use these services less.[8]

Next, we investigate factors that could explain the reported consumption changes during the dance phase.

3.2 Consumption changes and households' characteristics

Using the whole data set, we perform probit estimations of the following specification:

$$Less_{isc} = \beta_0 + \beta_1 X_i + \beta_2 \tilde{Z}_i + \varepsilon_{isc} \tag{3.1}$$

$Less_{isc}$ denotes the consumption behavior of the household i in sector s surveyed in July 2020, and who resides in the country c. This indicator is equal to one if household i reports to consume "less often than before" or "not at all" in sector s (compared to before the COVID-19 outbreak) and zero otherwise. X_i denotes a vector of standard controls for household i: we include age, gender, household size, income, employment status, and the education level. $\tilde{Z}_i$ denotes a vector of additional behavioral controls for household i, which vary depending on the specification considered: it includes households' personal experiences, households' macroeconomic expectations, and psychological factors such as worry and fear. The standard errors are clustered at the country level and denoted by ε_{isc}.

Socio-economic characteristics Table 8 presents the results of the baseline specification (3.1), where we only include the standard socio-economic characteristics X_i that are known to affect households' consumption behavior during a recession.

We find that gender is consistently significant: females are more likely to reduce consumption—this result holds across all sectors. We find that age does not drive changes in households' consumption behavior in the hospitality and public transport sectors. However, we find age to play a significant role in shifting consumption trends in the retail sector, services sector, and tourism sector. Compared to before the COVID-19 outbreak, older households are now more likely to travel less often abroad for private reasons than younger households. In contrast, younger households are more likely to cut their consumption in

[8] For each country, the tourism sector faces the largest decline, ranging from 76 percent of households traveling less abroad in Spain to 55 percent in France. The public transport sector faces the second-largest decline in Italy and in The Netherlands and the third-largest decline in Germany, France, and Spain. The drop ranges from 66 percent of households using less public transport in Italy to 44 percent in France. The hospitality sector faces the second-largest decline in France, Germany, and Spain. And the third-largest decline in Italy and The Netherlands. The drop ranges from 66 percent of households visiting less often restaurants in Spain to 48 percent in France. For each country, the retail sector faces the fourth-largest decline, ranging from 52 percent of households shopping less often in malls and other stores in Spain to 36 percent in France. For each country, the services sector faces the fifth-largest decline, ranging from 47 percent of households using these services less often in Spain to 26 percent in France.

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the hospitality and services sectors. As age is recognized as a major risk factor associated with more severe health consequences from COVID-19 infections, this finding is somewhat surprising. One could have expected the opposite effect: the older the household, the more likely the household will cut non-essential consumption to reduce social interactions and, hence, the infection risk. Our results do not support this narrative.

	tourism (travel abroad) (1)	hospitality (restaurants) (2)	services (hairdressers) (3)	retail (shopping) (4)	public transports (5)
age	0.00514***	0.00200	-0.00221**	-0.00236***	0.000583
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
male	-0.237***	-0.192***	-0.0978**	-0.275***	-0.167***
	(0.03)	(0.02)	(0.04)	(0.05)	(0.02)
household size	0.0705***	0.0562***	0.117***	0.0656***	0.0607**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
income	0.00923	-0.00763	-0.0345***	0.00525	0.0268***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employment Status					
unemployed	0.142**	0.107	0.115*	0.0224	0.118
	(0.07)	(0.08)	(0.06)	(0.05)	(0.09)
not in labor force	0.0865**	0.0588*	-0.0148	0.0203	0.0563***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.01)
Education Level					
middle education	0.0346	-0.0616***	-0.120***	-0.0576	-0.00149
	(0.04)	(0.02)	(0.03)	(0.06)	(0.03)
high education	0.0249	-0.000157	-0.105	0.0458	-0.0167
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
N	5570	6261	6007	6374	5583

Probit estimation. Marginal effects; Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is a dummy that is equal to one if individual i reports to consume "less often than before" or "not at all"—compared to before the COVID-19 outbreak; and zero otherwise. Income categories are: 1= Less than 12,700 euros; 2= Between 12,700 and 18,700 euros; 3= Between 18,700 and 25,000 euros; 4= Between 25,000 and 30,700 euros; 5= Between 30,700 and 36,400 euros; 6= Between 36,400 and 42,600 euros; 7= Between 42,600 and 49,700 euros; 8= Between 49,700 and 61,400 euros; 9= Between 61,40 and 84,200 euros; 10= More than 84,200 euros. Employment status categories are: has a paid job (omitted), unemployed, not in labor force (including education or training, permanently sick or disabled, retired, (unpaid) community or military service, housework, looking after children and/or other persons). Education categories are: low (omitted), middle, high.

Table 8: Socio-economic Factors

Turning to the role of income, we find that income is only significant for consumption changes in two sectors. Higher-income households are more likely to decrease the use of public transport compared to before the outbreak. For the services sector, we observe the opposite result. The higher the household income, the less likely that the household uses services like hairdressers less often. This result echoes those of Baker et al. (2020) and

Carvalho et al. (2020). While these authors find no correlation between income and changes in consumer behavior during lockdown (i.e., the hammer phase), we report a limited role of income for consumption changes during the dance phase. Yet, the unemployment status increases the probability of having reduced consumption during the dance phase in the tourism and services sectors, while not being in the labor force makes the household more likely to consume less in the tourism, hospitality, and public transport sector. Education does not play a large role in explaining changes in consumption behavior. We consider three education categories (low, middle, high) and find that high educational attainment does not affect the change in consumption behavior. Households with middle educational attainment are less likely to report consumption changes in the hospitality and service sectors (compared to the low-educated households). These insights are summarized by the first finding:

Finding 1 (Consumption drop and socio-economic profile)**.** *Gender is the only socio-economic household characteristic that is consistently and significantly associated with consumption changes during the dance phase, while income, age, employment status, and education play a minor role.*

Behavioral factors and expectations Next, we investigate whether households' change in consumption can be explained by households' personal experiences with a COVID-19 infection and previous unemployment spells, households' macroeconomic expectations, and psychological factors such as worry and fear.

First, we add personal experiences to the baseline specification. Table 9 reports the results. We find that a personal COVID-19 infection experience (i.e., exposure to a close person that suffered from a severe COVID-19 infection) makes households more likely to reduce consumption during the dance phase in the hospitality, services, and retail sectors. In contrast, this experience does not affect the tourism and public transport sectors. The same result holds for the experience of an unemployment spell of at least three months in the past five years. In terms of magnitude, the personal COVID-19 infection experience has roughly twice as large an impact than a personal unemployment spell experience.

Table 10 shows the regression results when adding households' macroeconomic expectations to the baseline regression. Households' expectations about the one-year-head change in the unemployment rate compared to the pre-crisis perception levels are significant for all sectors. The more pessimistic the household (i.e., the larger the expected Covid-19 induced increase in unemployment), the more likely the household reduces consumption in

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all sectors. Expectation about the pandemic's severity and length is the most significant variable for all sectors. The survey question is: "In your opinion, when will COVID-19 virus be totally under control such that it is safe to release all COVID-19 containment measures in your country?". The later the expected date, the more likely the household to reduce consumption during the dance phase compared to before the COVID-19 outbreak.

	tourism (travel abroad) (1)	hospitality (restaurants) (2)	services (hairdressers) (3)	retail (shopping) (4)	public transports (5)
past unemployment experience	0.0261	0.0783***	0.0880***	0.0786**	0.0450
	(0.07)	(0.02)	(0.03)	(0.03)	(0.07)
COVID-19 infection experience	0.102	0.161***	0.138*	0.208***	0.00414
	(0.07)	(0.06)	(0.08)	(0.08)	(0.06)
age	0.00536***	0.00259*	-0.00148	-0.00152**	0.000829
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
male	-0.239***	-0.196***	-0.0943**	-0.277***	-0.163***
	(0.03)	(0.02)	(0.05)	(0.05)	(0.02)
household size	0.0731***	0.0544***	0.117***	0.0641***	0.0642**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)
income	0.00993	-0.00462	-0.0322***	0.00820	0.0288***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employment Status					
unemployed	0.142***	0.0709	0.0662	0.00385	0.112*
	(0.04)	(0.08)	(0.05)	(0.04)	(0.06)
not in labor force	0.0978***	0.0650**	-0.00316	0.0208	0.0635***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Education Level					
middle education	0.0473	-0.0438*	-0.0985***	-0.0376	0.00700
	(0.03)	(0.02)	(0.03)	(0.06)	(0.04)
high education	0.0350	0.0164	-0.0887	0.0586	-0.00574
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
N	5495	6177	5928	6290	5504

Probit estimation. Marginal effects; Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is a dummy that is equal to one if individual i reports to consume "less often than before" or "not at all"—compared to before the COVID-19 outbreak; and zero otherwise. Income categories are: 1= Less than 12,700 euros; 2= Between 12,700 and 18,700 euros; 3= Between 18,700 and 25,000 euros; 4= Between 25,000 and 30,700 euros; 5= Between 30,700 and 36,400 euros; 6= Between 36,400 and 42,600 euros; 7= Between 42,600 and 49,700 euros; 8= Between 49,700 and 61,400 euros; 9= Between 61,40 and 84,200 euros; 10= More than 84,200 euros. Employment status categories are: has a paid job (omitted), unemployed, not in labor force (including education or training, permanently sick or disabled, retired, (unpaid) community or military service, housework, looking after children and/or other persons). Education categories are: low (omitted), middle, high. Past unemployment experience, the survey question is: "Have you been unemployed and seeking work for more than 3 months in the last 5 years?" (1=yes; 0=no). COVID-19 infection experience, the survey question is: "Did you or a person close to you suffer from severe COVID-19 infection?" (1=yes; 0=no).

Table 9: Personal Experiences

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	tourism (travel abroad) (1)	hospitality (restaurants) (2)	services (hairdressers) (3)	retail (shopping) (4)	public transports (5)
unemployment	0.00668***	0.00480***	0.00863***	0.00557***	0.00825***
(prediction)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
expectation pandemic	0.165***	0.162***	0.110***	0.113***	0.120***
severity and length	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)
age	0.00418***	0.00119	-0.00300***	-0.00301***	-0.000168
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
male	-0.198***	-0.156***	-0.0606	-0.246***	-0.133***
	(0.03)	(0.02)	(0.05)	(0.05)	(0.02)
household size	0.0746***	0.0608***	0.117***	0.0679***	0.0635**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)
income	0.0101	-0.00753	-0.0334***	0.00629	0.0288***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
unemployed	0.128*	0.0994	0.105*	0.00952	0.109
	(0.07)	(0.08)	(0.06)	(0.05)	(0.08)
not in labor force	0.110***	0.0791**	0.00754	0.0373	0.0792***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.01)
middle education	0.0391	-0.0595***	-0.110***	-0.0512	0.00557
	(0.04)	(0.02)	(0.04)	(0.06)	(0.03)
high education	0.0305	0.00234	-0.0903	0.0553	-0.00356
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)
N	5570	6261	6007	6374	5583

Probit estimation. Marginal effects; Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is a dummy that is equal to one if individual i reports to consume "less often than before" or "not at all"—compared to before the COVID-19 outbreak; and zero otherwise. Income categories are: 1= Less than 12,700 euros; 2= Between 12,700 and 18,700 euros; 3= Between 18,700 and 25,000 euros; 4= Between 25,000 and 30,700 euros; 5= Between 30,700 and 36,400 euros; 6= Between 36,400 and 42,600 euros; 7= Between 42,600 and 49,700 euros; 8= Between 49,700 and 61,400 euros; 9= Between 61,40 and 84,200 euros; 10= More than 84,200 euros. Employment status categories are: has a paid job (omitted), unemployed, not in labor force (including education or training, permanently sick or disabled, retired, (unpaid) community or military service, housework, looking after children and/or other persons). Education categories are: low (omitted), middle, high. Unemployment expectation, the two survey questions are: "Please indicate what you think the unemployment rate was before the crisis in your country" (point prediction) and "Please indicate what you think the unemployment rate will be in your country in one year from now" (point prediction). We use the difference of the two unemployment point predictions (one year from now – before the crisis). Expectation about COVID-19 pandemic severity and length, the survey question is: "In your opinion, when will COVID-19 be totally under control such that it is safe to release all COVID-19 containment measures in your country?". The households could choose among five different time windows: 1= July-September 2020, 2= October-December 2020, 3= January-June 2021, 4= July-December 2021, and 5= later.

Table 10: Macroeconomic Expectations

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Turning to psychological factors, Table 11 shows that worries about the future (financial and job insecurity) are important explanatory factors for households' decision to reduce consumption during the dance phase (compared to before the virus outbreak). The most considerable effects we observe for the hospitality, services, and retail sectors. Those insights lead us to the second finding.

	tourism (travel abroad) (1)	hospitality (restaurants) (2)	services (hairdressers) (3)	retail (shopping) (4)	public transports (5)
worry-finance	0.0637***	0.0553***	0.0529***	0.0389***	0.0331***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
worry-job	0.0514	0.118***	0.166***	0.128***	0.0939***
	(0.04)	(0.02)	(0.05)	(0.02)	(0.02)
age	0.00479***	0.00104	-0.00108	-0.00239	0.00209
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
male	-0.179***	-0.128***	-0.0510	-0.211***	-0.0762**
	(0.04)	(0.01)	(0.06)	(0.06)	(0.03)
household size	0.0166	0.00335	0.0568***	0.0299	0.0197
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
income	0.0175	0.00486	-0.0192*	0.0142	0.0307***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Employment Status					
unemployed	0.0571	0.0403	0.0169	-0.110	0.112
	(0.11)	(0.14)	(0.13)	(0.10)	(0.10)
not in labor force	0.0946	0.0963**	0.114***	0.0258	0.102***
	(0.09)	(0.05)	(0.04)	(0.05)	(0.03)
Education Level					
middle education	0.0758**	0.0258	-0.0751	-0.0116	0.0431
	(0.04)	(0.03)	(0.06)	(0.08)	(0.05)
high education	0.0585	0.108	-0.0415	0.117	0.0268
	(0.06)	(0.07)	(0.08)	(0.10)	(0.10)
N	3473	3809	3665	3834	3410
pseudo R^2	0.03	0.02	0.04	0.02	0.01

Probit estimation. Marginal effects; Clustered standard errors (at country level) are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is a dummy that is equal to one if individual i reports to consume "less often than before" or "not at all"—compared to before the COVID-19 outbreak; and zero otherwise. Income categories are: 1= Less than 12,700 euros; 2= Between 12,700 and 18,700 euros; 3= Between 18,700 and 25,000 euros; 4= Between 25,000 and 30,700 euros; 5= Between 30,700 and 36,400 euros; 6= Between 36,400 and 42,600 euros; 7= Between 42,600 and 49,700 euros; 8= Between 49,700 and 61,400 euros; 9= Between 61,40 and 84,200 euros; 10= More than 84,200 euros. Employment status categories are: has a paid job (omitted), unemployed, not in labor force (including education or training, permanently sick or disabled, retired, (unpaid) community or military service, housework, looking after children and/or other persons). Education categories are: low (omitted), middle, high. Worry-finance, the survey question is "How concerned are you about the effects that the coro- navirus might have for the financial situation your household?" Answer options: 0-10. 0 (= not at all concerned) to 10 (= extremely concerned). Worry-job, the survey question is "How worried are you about losing your job in the near future?" Answer options: 1-3. 1= not worried; 2 = somewhat worried; 3 = very worried.

Table 11: Psychological Factors—Worry and Fear

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Finding 2 (Consumption drop and behavioral factors)**.** *Personal COVID-19 experiences, pessimistic macroeconomic expectations, and concerns about the future are strongly and significantly associated with a drop in consumption during the dance phase.*

Using probit estimations, we find that most standard socio-economic household characteristics (expect gender) do not explain much of the large changes in household consumption behavior. Females (compared to men) are more likely to consume less in all sectors across all estimation specifications. Findings 1-2 indicate that financial hardship is not the primary driver for reducing consumption.[9] Instead, we find relevant behavioral factors explaining households' consumption changes such as personal experiences with a COVID-19 infection and previous unemployment spells, households' macroeconomic expectations, and psychological factors such as worry and fear. In light of this finding, the next section explores the self-reported reasons for changing (reducing) consumption and investigates to what extent the consumption shifts may be temporary or permanent. For policy, this analysis is essential to evaluate the overall impact of the COVID-19 shock, and hence for the optimal design of fiscal policies.

3.3 Self-reported reasons for changes in consumption behavior

Conditional on having reported consuming "less often than before" or "not at all", households were asked: "What is your main reason for doing now less of this activity?". Figures 6-10 show households' reported main reason for having reduced consumption for each sector and country. These Figures provide an overview of the percentage of households that reported (i) financial constraints, (ii) worry of infection risk, (iii) precautionary saving motives, (iv) lockdown has permanently altered preferences, and (v) substitution to online consumption.[10] Four main observations stand out, leading to four additional findings.

Finding 3 (Infection risk)**.** *The infection risk is the most reported reason for decreasing consumption (across countries and sectors).*

While the infection risk is the most reported reason for decreasing consumption (across countries and sectors), a non-negligible fraction of households reports what seems to be a shift in preferences, i.e. households report that they decreased their consumption because they realized that they do not miss it. It is striking that in France and in Germany, the

[9]This is consistent with households' reported perception of how they cope financially with their current income. We refer to Column 6 of Appendix Table A3.

[10]The answer options for the main reason are: "I buy more online instead'; "I realized I don't miss it"; "I want to save more"; "I cannot afford it anymore"; "I am worried to get infected with COVID-19"; "Other reason".

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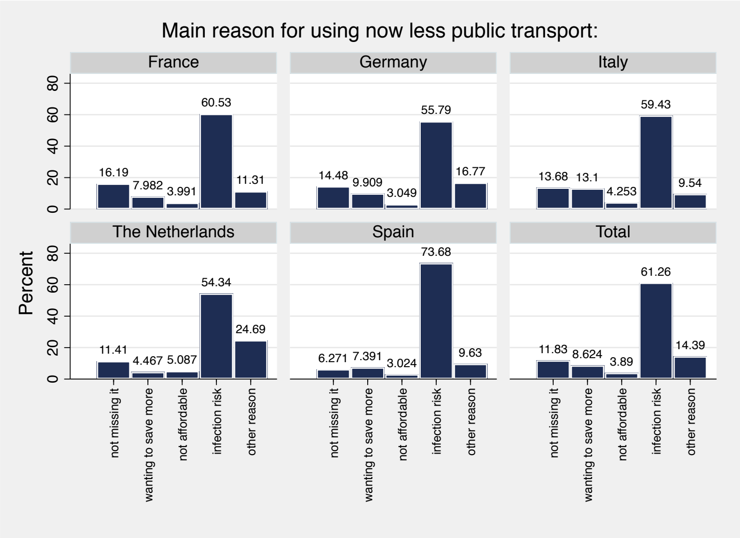

This survey question is only asked for people who reported "less often than before" or "not at all" in the previous question. The survey question is: "What is your main reason for doing now less of the following activity: Public transport?" 1= I realized I don't miss it; 2= I want to save more; 3= I cannot afford it anymore; 4= I am worried to get infected with COVID-19; 5= Other reason.

Figure 6: Reasons for lower usage of public transports during dance phase

reason "not missing it' is even the second main reason after the infection risk for all sectors. In the Netherlands, we observe the same pattern, except for the retail sector "shopping in malls or other stores'.[11] Households' permanent preference shifts are particularly observed in the services sector (such as hairdressers) and hospitality industry (i.e., restaurants). For example, the fraction of households that realized that they do not miss services such as hairdressers amounts to 23 percent in France, 19 percent in Germany and Italy, 14 percent in The Netherlands, and 10 percent in Spain. At the same time, the fraction of households that realized that they do not miss going to the restaurants amounts to 19 percent in France, 21 percent in Germany, 18 percent in Italy, 15 percent in The Netherlands, and 9 percent in Spain. These figures lead us to the next finding:

Finding 4 (Change in consumers' preferences)**.** *Across all sectors, the fraction of households that explain their reported consumption drop by a change in preferences is substantial (the realization of not missing it). It is even the second invoked reason behind the infection risk in France, Germany, and The Netherlands.*

[11]Dutch households report as the second main reason a subsitution to online shopping in the retail sector. The third main reason for reducing consumption in the retail sector is the realization of not missing it.

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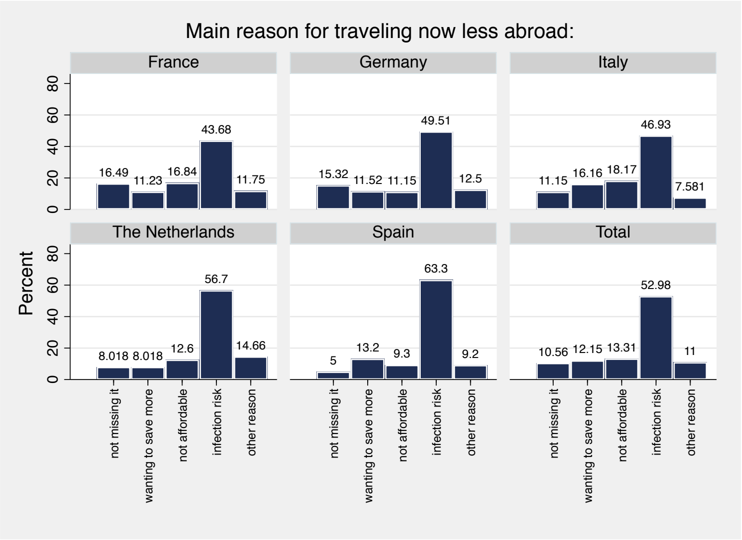
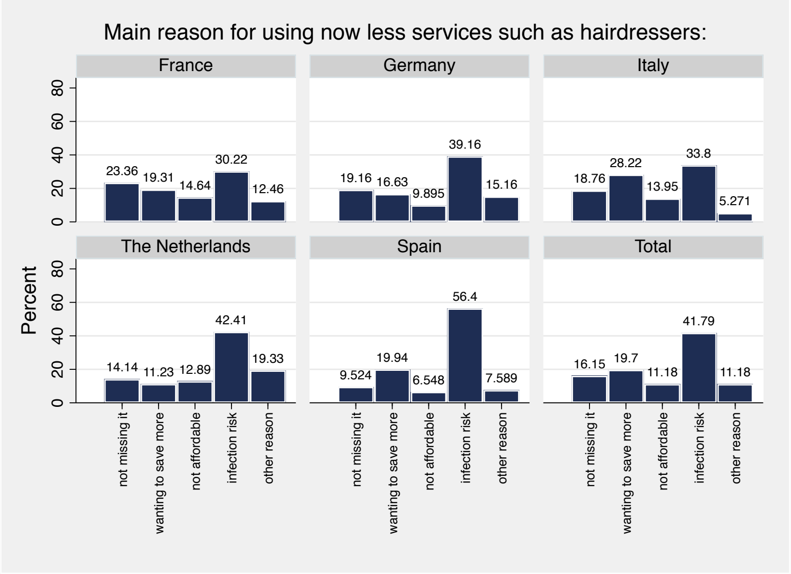


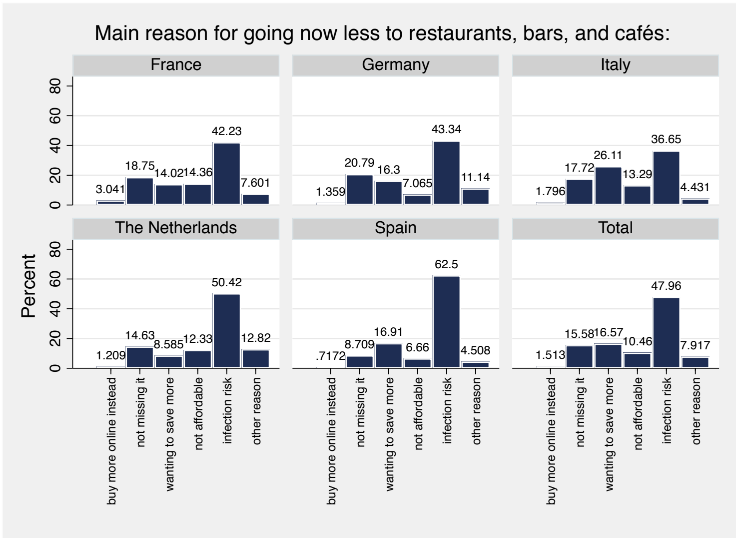
This survey question is only asked for people who reported "less often than before" or "not at all" in the previous question. The survey question is: "What is your main reason for doing now less of the following activity: Traveling abroad for private reasons?" 1= I realized I don't miss it; 2= I want to save more; 3= I cannot afford it anymore; 4= I am worried to get infected with COVID-19; 5= Other reason.

Figure 7: Reasons for fewer private travels abroad during dance phase



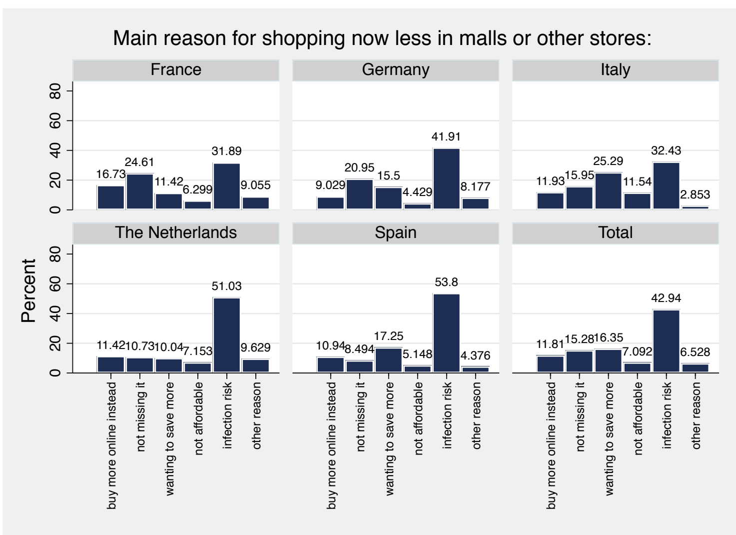
This survey question is only asked for people who reported "less often than before" or "not at all" in the previous question. The survey question is: "What is your main reason for doing now less of the following activity: use services such as hairdressers or beauty salons?" 1= I realized I don't miss it; 2= I want to save more; 3= I cannot afford it anymore; 4= I am worried to get infected with COVID-19; 5= Other reason.

Figure 8: Reasons for using less services during dance phase



This survey question is only asked for people who reported “less often than before” or “not at all” in the previous question. The survey question is: “What is your main reason for doing now less of the following activity: visiting restaurants, bars, and cafes?” 1= I plan to buy more online; 2= I realized I don’t miss it; 3= I want to save more; 4= I cannot afford it anymore; 5= I am worried to get infected with COVID-19; 6= Other reason.

Figure 9: Reasons for going less to restaurants, bars, and cafes during dance phase



This survey question is only asked for people who reported “less often than before” or “not at all” in the previous question. The survey question is: “What is your main reason for doing now less of the following activity: shopping in malls and other stores?” 1= I plan to buy more online; 2= I realized I don’t miss it; 3= I want to save more; 4= I cannot afford it anymore; 5= I am worried to get infected with COVID-19; 6= Other reason.

Figure 10: Reasons for shopping less in malls and other stores during dance phase

To the best of our knowledge, this paper is the first to provide evidence that the lockdown restrictions may have permanently altered households' consumption preferences. These altered preferences concern the nature of the consumption goods and services rather than the way of consuming. The reported drop in consumption is not necessarily compensated by a rise in online alternatives. In the survey, households could have chosen the reason "buy more online instead" to explain their consumption changes. For the hospitality sector, households rarely chose as the main reason "buy more online instead" to explain their reduction in visiting restaurants, bars, and cafes. The fraction of households reporting to compensate these visits by online orders and pick-up or delivery services is negligible, ranging from 3% in France to 0.7% in Spain. The substitution to online services is most prominent in the retail sector. The fraction of households reporting online substitution as the main reason for shopping less in malls and other stores is highest in France with 16% and lowest in Germany with 9%. This cross-country variation cannot be explained by cross-country differences in the importance of e-commerce in the retail sector.[12]

Aside from the main reasons "infection risk" and the "change in preferences", precautionary saving motives are substantial. A rise in savings is traditionally associated with pessimistic views about the future economic outlooks. This phenomenon reads as a confidence shock that may have a long-lasting impact on demand. For the whole sample, the fraction of households reporting as the main reason "wanting to save more" to explain their consumption reduction varies between 8.6% to 19.7%—depending on the sector. The hospitality and services sectors are the most impacted by precautionary savings, followed by the retail, tourism, and finally by the public transport sector. We observe important cross-country variations in the fraction of households reporting as a primary reason precautionary savings. In Spain and Italy, the desire to save more represents the second most often cited main reason for reducing consumption in almost all sectors. While in France and The Netherlands, precautionary saving motives are the third most often cited reason. In contrast, a higher saving behavior is relevant for only a very small fraction of German households. In this country, this is the second-least often reported reason. We highlight the following finding:

Finding 5 (Precautionary savings)**.** *The fraction of households explaining their consumption drop by a desire to save more is substantial for all sectors. In France, Germany, and The Netherlands, the saving motive is the third most often cited reason (after infection risk and change in preferences), and the second most popular reason in Italy and Spain.*

[12]In 2019, the percentage of online sales (of total retail sales) was 15.9% in Germany, 10.9% in France, 9.9% in The Netherlands, 5.4% in Spain, and 3.7% in Italy (sources: Center for Retail Research; Statistica).

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Financial constraints are the least reported reason for reducing consumption in most sectors and countries. This observation should be understood in light of the unprecedented size of governmental fiscal support before and at the time of the survey (July 2020).

Finding 6 (Financial constraints)**.** *Across all sectors and countries, the fraction of households that explain their reported consumption drop by financial constraints is small.*

For the public transport, retail, hospitality, and services sector, the fraction of households reporting as the main reason for reducing consumption "I cannot afford it anymore" is much smaller than the fraction reporting the infection risk, a permanent shift in preferences, or precautionary saving motives. The only sector that seems to lose demand because of households feeling financially constrained is the tourism sector. Adding-up the fraction of households that reported as the main reason for reducing consumption "precautionary saving motives" and "permanent change in preferences" leads to a substantially larger proportion of households than those that reported "financial constraints" as the main reason. This observation is valid for all countries and sectors. In the tourism sector, twice as many households report one of these two reasons to explain their reduced travels abroad (compared to those citing financial constraints). At the same time and compared to those citing financial constraints, four times as many households report one of these two reasons to explain their reduced public transportation use.

4 Conclusion

This paper provides novel survey-based evidence on the underlying reasons for household consumption changes after the experience of the COVID-19 lockdown restrictions. The representative survey was conducted in five European countries: France, Germany, Italy, The Netherlands, and Spain. During the time of the survey, July 2020, lockdowns and travel restrictions were lifted in all countries.

Unsurprisingly, we find that there has been a substantial reduction in household consumption to various sensitive sectors since the onset of COVID-19. Countries that have been heavier hit by the health consequences of COVID-19 are generally those that have seen bigger consumption reductions than those that have survived more unscathed.

While households cite "infection risk" as the main reason for their changed behaviour, "financial constraints" were not cited by respondents as a major driver of consumption changes. Permanent shifts in preferences and precautionary saving motives are far more substantial explanatory factors than financial constraints.

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We draw three policy conclusions from these results. First, policy-makers should reflect on the fact that reduced consumption is not primarily being driven by financial constraints. Broad-based efforts to reduce the pricing of products and services—e.g. via VAT cuts, or via subsidies—are unlikely to be effective.

Second, it is important for policy-makers to recognize that a large proportion of households report experiencing permanent shifts in their consumption preferences as a result of the COVID-19 experience. After the infection risk, the largest fraction of households reports "permanent preferences shifts" as the main reason for reduced consumption in France, Germany, and the Netherlands. In Italy and Spain, "permanent preferences shifts" are the third most powerful reason. This fraction is particularly large in the retail, hospitality, and services sectors. Broad-based and long-lasting schemes to support all sectors and firms—e.g. via guaranteeing their loans, or subsidizing the wages of employees—might therefore risk creating zombie firms and mismatch unemployment. As the crisis goes on, government support should become narrower and more targeted—allowing market forces to function on obsolete firms.

Third, our results indicate that the objectives of protecting citizens from virus risk and preserving economic prosperity may not lead to any real trade–offs. During the time of the survey, lockdowns and travel restrictions were lifted in the countries under investigation. However, the fraction of households reducing consumption during the dance phase is highly correlated with the number of deaths per 1M population and personal infection experience during the hammer phase. In addition, we find that standard socio-economic characteristics (except for gender) do not explain the drop in individual households' consumption. By contrast, behavioral factors such as macroeconomic expectations (pessimism) and psychological factors such as worries and fear are significant variables explaining individual households' drop in consumption. On an aggregate level, these behavioral factors highly correlate with the average households' personal experience with a COVID-19 infection and the country's severity of the health crisis. Hence, governments should see controlling infection risk as a prerequisite to achieving their objectives of preserving economic prosperity—at least until an effective vaccine arrives.

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5 Appendix

Country				household size			education		
		age	male	children	adults	total	low	middle	high
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
France	mean	50.85	0.48	1.43	1.06	2.4	0.25	0.44	0.31
	st. dev	17.90	0.50	0.78	0.88	1.16	0.43	0.5	0.46
	N	1500	1500	1176	1500	1500	1500	1500	1500
Germany	mean	50.97	0.49	1.37	0.94	2.21	0.2	0.55	0.25
	st. dev	17.04	0.50	0.76	0.86	1.13	0.40	0.50	0.43
	N	1500	1496	1106	1500	1500	1500	1500	1500
Italy	mean	50.44	0.49	1.44	1.56	2.96	0.41	0.43	0.17
	st. dev	16.91	0.50	0.75	0.99	1.14	0.49	0.49	0.37
	N	1500	1499	1380	1500	1500	1500	1500	1500
The Netherlands	mean	50.24	0.50	1.41	1.02	2.33	0.26	0.41	0.32
	st. dev	17.23	0.50	0.85	0.99	1.25	0.44	0.49	0.47
	N	1500	1500	1109	1500	1500	1500	1500	1500
Spain	mean	48.49	0.49	1.46	1.53	2.96	0.41	0.26	0.34
	st. dev	15.39	0.50	0.76	0.98	1.15	0.49	0.44	0.47
	N	1501	1500	1377	1501	1501	1501	1501	1501
Total	mean	50.2	0.49	1.42	1.22	2.57	0.31	0.42	0.28
	st. dev	16.93	0.50	0.78	0.98	1.21	0.46	0.49	0.45
	N	7501	7495	6148	7501	7501	7501	7501	7501

Notes: Column (1) reports the average age of the household, Column (2) the fraction of male households. Column (3)-(5) report the households' average number of children younger than 14 years, the average number of adults, and the average number of people within a household. Columns (6)-(8) report the fraction of households having attained low, middle, and high education levels, respectively.

Table A1: Descriptive socio-economic statistics by country I

Country	mean	st. dev	p10	p25	p50	p75	p90	N
France	5.44	2.79	1	3	6	8	9	1384
Germany	5.60	2.81	1	3	6	8	9	1329
Italy	5.83	2.62	2	4	6	8	9	1369
The Netherlands	6.08	2.70	2	4	6	8	10	1283
Spain	6.03	2.78	2	4	6	9	10	1323
Total	5.79	2.75	2	4	6	8	10	6688

Notes: The survey question is "Can you tell us which value describes your household's yearly total income, after tax and compulsory deductions, from all sources?" The variable is numeric, 10 categories: 1= Less than 12,700 euros; 2= Between 12,700 and 18,700 euros; 3= Between 18,700 and 25,000 euros; 4= Between 25,000 and 30,700 euros; 5= Between 30,700 and 36,400 euros; 6= Between 36,400 and 42,600 euros; 7= Between 42,600 and 49,700 euros; 8= Between 49,700 and 61,400 euros; 9= Between 61,40 and 84,200 euros; 10= More than 84,200 euros.

Table A2: Descriptive household income statistics by country II

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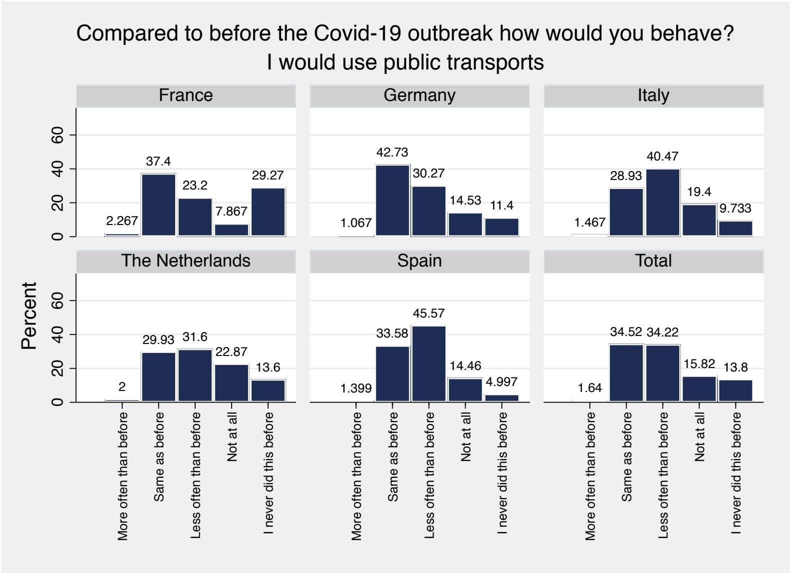
Country		employment statistics				financial statistics	
		employment	not in labor force	unemployment rate	past spell of unemployment	savings	income satisfaction
		(1)	(2)	(3)	(4)	(5)	(6)
France	mean	0.5	0.45	0.06	0.19	0.65	3.16
	st. dev	0.5	0.5	0.23	0.39	0.48	1.23
	N	1443	1443	1443	1481	1351	1469
Germany	mean	0.54	0.43	0.03	0.13	0.69	3.3
	st. dev	0.5	0.49	0.17	0.34	0.46	1.19
	N	1460	1460	1460	1470	1354	1454
Italy	mean	0.4	0.48	0.12	0.3	0.64	2.59
	st. dev	0.49	0.5	0.32	0.46	0.48	1.04
	N	1426	1426	1426	1468	1270	1451
The Netherlands	mean	0.47	0.47	0.05	0.19	0.67	3.51
	st. dev	0.5	0.5	0.22	0.4	0.47	1.19
	N	1454	1454	1454	1473	1268	1456
Spain	mean	0.55	0.32	0.13	0.39	0.64	3.03
	st. dev	0.5	0.47	0.34	0.49	0.48	1.16
	N	1464	1464	1464	1471	1295	1455
Total	mean	0.49	0.43	0.08	0.24	0.66	3.12
	st. dev	0.5	0.5	0.27	0.43	0.47	1.2
	N	7247	7247	7247	7363	6538	7285

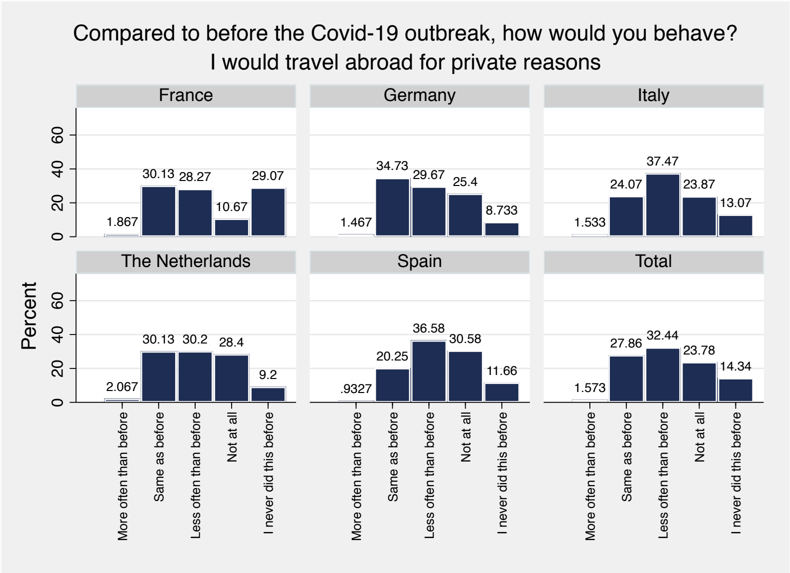
Notes: Column (1) reports the fraction of households in paid work, Column (2) the fraction not being part of the labor force, and Column (3) the fraction being unemployed. Column (4) reports the fraction of households having experienced an unemployment spell over the past 5 years. The survey question is "Have you been unemployed and seeking work for more than 3 months in the last 5 years?". Column (5) reports the fraction of households that have the ability to make an unexpected payment of one-month of income. The survey question is "Does your household have savings (excluding the value of your home) worth at least one month of the total net income of your household?" (1=yes, 0=no). Column (6) reports households' perception of how they cope financially with their income. The survey question is "Which of these descriptions comes closest to how you feel about your household's income nowadays?" The variable is numeric, 5 categories: 1= Very difficult on present income and insufficient to cover all the expenses; 2= Difficult on present income; 3= Coping on present income; 4= Living comfortably on present income, but unable to save; 5= Living comfortably on present income and able to save.

Table A3: Descriptive employment and financial statistics by country III



The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would use public transports: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before.

Figure A11: Usage of public transports



The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would travel abroad for private reasons: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before. .

Figure A12: Traveling abroad for private reasons

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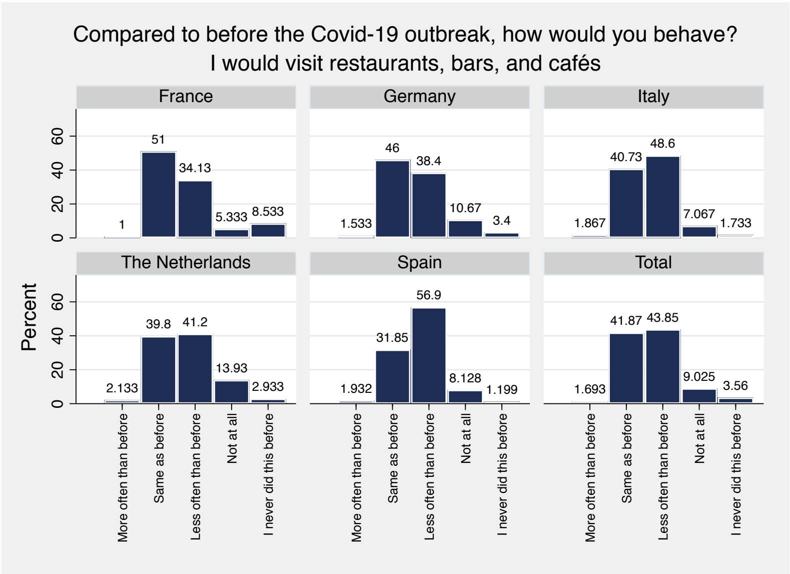
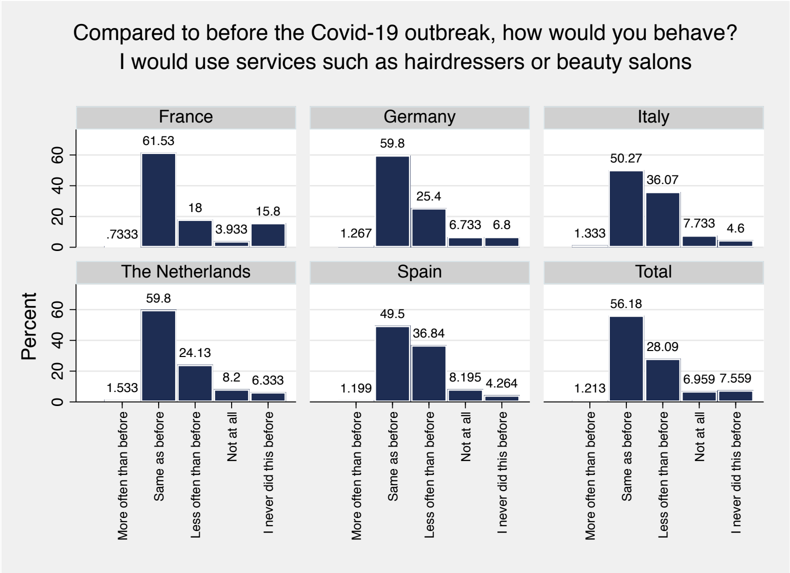


The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would visit restaurants, bars, and cafes: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before.

Figure A13: Visiting restaurants, bars, and cafes



The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would use services such as hairdressers or beauty salons: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before. Responses =5 are dropped and dummy created.

Figure A14: Usage of services such as hairdressers or beauty salons

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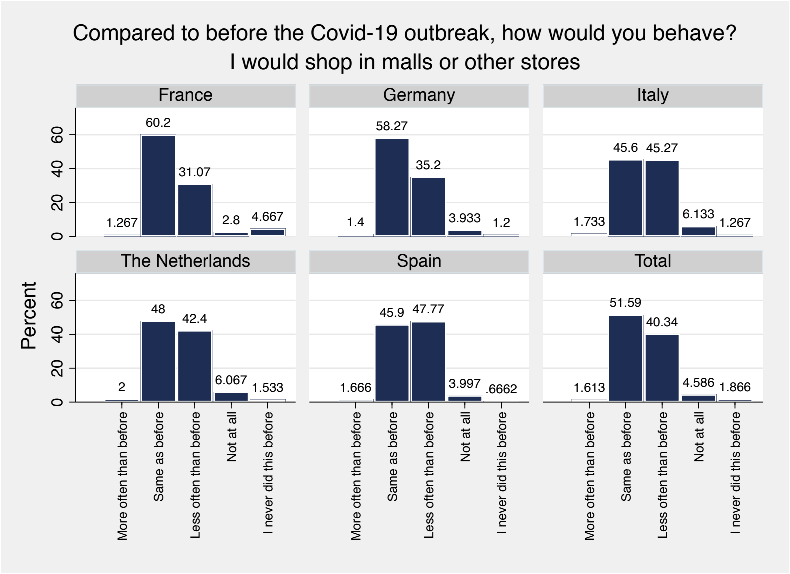

The survey question is: Compared to before the COVID-19 outbreak, how would you behave? I would shop in malls or other stores: 1= more often than before; 2= same as before; 3= less often than before; 4= not at all; 5= I never did this before.

Figure A15: Shopping in malls or other stores

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Concierge treatment from banks: Evidence from the Paycheck Protection Program

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Date submitted: 20 November 2020; Date accepted: 20 November 2020

We use the Paycheck Protection Program (PPP), a central piece of the 2020 CARES Act, as a laboratory to separate between favoritism and informational advantages in lending relationships. The PPP mutes information frictions because loans are fully guaranteed by the government and banks need not screen borrowers. We find that firms with prior lending relationships or personal connections to bank executives are more likely to obtain PPP loans. These effects lead to allocative distortions that force connected firms to return their loans. Consistent with favoritism, the role of connections is weaker when the likelihood of detection is higher.

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1. Introduction

A large body of research in economics and finance studies the role of agency frictions and information asymmetries in capital allocation. An important mechanism that can exacerbate or ameliorate these effects is the relationship between the involved parties. Despite the existing evidence on the role of relationships in exacerbating favoritism in various settings, such as preferential access to government resources (e.g., Sapienza (2004), Dinc (2005), Faccio, Masulis, and McConnell (2006), Duchin and Sosyura (2012)), the banking literature has focused primarily on the role of relationships in ameliorating information asymmetries (e.g., Lummer and McConnell (1989), Petersen and Rajan (1994), Berger and Udell (1995), Engelberg, Gao, and Parsons (2012)). In this paper, we seek to provide novel evidence on the role of relationships in preferential access to bank loans by exploiting the unique design of the Paycheck Protection Program.

The Paycheck Protection Program (PPP) is a central piece of the 2020 Coronavirus Aid, Relief, and Economic Security (CARES) Act, which extends government-guaranteed, forgivable bank loans to businesses to cover payroll, utilities, mortgage, and rent costs.[1] The PPP provides a unique setting to separate between favoritism and information asymmetries in relationship lending. First, PPP loans are forgivable and fully guaranteed by the Small Business Administration (SBA). Hence, participating banks are not exposed to credit risk due to these loans. Second, the PPP eligibility requirements only demand a good faith certification by the borrower, and the SBA does not require participating banks to collect soft information nor to screen borrowers. Consequently, the PPP generates a setting in which information frictions are muted, banks bear no default risk on the loans, and thus participating banks have no incentives (or requirements) to screen borrowers.

[1] See https://www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program.

On the other hand, the PPP setting is susceptible to favoritism. The Covid-19 crisis was an economy-wide shock, with millions of companies simultaneously applying for PPP loans, leading to credit rationing.[2] As such, banks played an important role in allocating loans and prioritizing borrowers, giving rise to possible favoritism in originating loans to borrowers with connections to the lender. Such behavior would arise because the incentives of banks likely differ from those of the government. At the margin, banks have an incentive to extend loans to firms with which they do business or have personal connections, even though these firms are less qualified for PPP loans. Under this scenario, the allocation of capital will deviate from the stated goals of the PPP, and the costs will be internalized by taxpayers and small businesses that fail to receive government aid.

Indeed, anecdotal evidence suggests that favoritism played a role in the origination of PPP loans. For example, an article in *Bloomberg* argued that "JPMorgan Chase & Co. provided loans to virtually all of its commercial banking customers that sought financing through the small business relief program, while the lender's smallest customers were almost entirely shut out."[3] Similarly, an article in the *Wall Street Journal* stated that "Companies with existing loans at big banks fared well in coronavirus-relief effort."[4] Following reports that the program "favored large, well-funded companies over struggling small businesses in underserved communities," the House Select Subcommittee on the Coronavirus crisis launched an investigation into the PPP. The preliminary analyses, published on September 1, 2020, "revealed significant potential fraud, waste, and abuse."[5]

[2] This observation is consistent with Li, Strahan and Zhang (2020), who show that during the last three weeks of March 2020, commercial banks witnessed the largest increase in credit demand ever observed. Similarly, Erel and Liebersohn (2020) argue that Covid-19 induced "tremendous stress on financial institutions, with an unprecedented demand for their services."
[3] See "JPMorgan's Small Business Loans Instead Went to Its Biggest Customers" by David McLaughlin and Michelle Davis, https://www.bloomberg.com/news/articles/2020-04-22/jpmorgan-commercial-clients-beat-out-smaller-ones-for-sba-loans.
[4] See "In Race for Small-Business Loans, Winning Hinged on Where Firms Bank" by Ruth Simon and Peter Rudegeair, https://www.wsj.com/articles/in-race-for-small-business-loans-winning-hinged-on-where-firms-bank-11587410421.
[5] See https://coronavirus.house.gov/sites/democrats.coronavirus.house.gov/files/2020-09-01.PPP%20Interim%20Report.pdf

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To investigate the role of favoritism in the allocation of PPP loans, we introduce two measures of connections between banks and firms. The first measure is based on lending relationships between borrowers and banks that predate the PPP. The role of such pre-existing business relationships in credit provision has been studied by several papers, including Peterson and Rajan (1994), Berger and Udell (1995), Degryse and Van Cayseele (2000), Schenone (2004), and Bharath, Dahiya, Saunders, and Srinivasan (2009). The second measure of connections is based on social connections between directors or executives from the borrowing firm and the lending financial institution. This measure includes shared education, previous employment, and nonprofit backgrounds of firms' and banks' executives and board members. The role of such personal relationships has been studied across a wide range of economic activities, including investments by mutual fund managers (Cohen, Frazzini, and Malloy (2008)), external finance (Engelberg, Gao, and Parsons (2012)), internal capital allocation (Duchin and Sosyura (2013)), and mergers and acquisitions (Schmidt (2015)).

The empirical analyses focus on public firms that obtained PPP funds. First, focusing on public firms allows us to obtain market and accounting data on PPP recipients. Second, it offers a natural sample to detect favoritism. In particular, public firms are less likely to qualify for a PPP loan than small private firms due to their size and their easier access to capital markets. We collect information on PPP loans from S&P Global Market Intelligence, FactSquared, corporate press releases, 8-K filings, 10-Q/K filings, and the SBA, and merge it with firm-level information from Compustat, data on syndicated loans from DealScan, and data on director/executive biographies and personal connections from BoardEx. In the sample, the average loan size is $3.5 million; 5.8% of PPP recipients have a past lending relationship with their PPP lender; and 36.0% of recipients have personal connections to top executives in the lending financial institution.

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In the first set of analyses, we investigate the effect of relationship lending and personal connections on the likelihood of obtaining a PPP loan. We match each public PPP borrower to several public nonborrowers based on industry, size, and the number of employees because PPP eligibility was determined based on industry-specific small business size standards, payroll size, and access to financing. The matched sample-based empirical design mitigates concerns that the estimates are driven by differences in eligibility criteria between PPP and non-PPP firms. We also include in the regressions lender fixed effects, industry fixed effects, location fixed effects, the local severity of the Covid-19 shock, and local government policies in response to Covid-19. Collectively, this design addresses selection concerns that the effects are driven by economic indicators correlated with credit demand and the severity of the Covid-19 crisis.

The estimates suggest that within a set of comparable firms, recent relationship lending in the syndicated loan market increases the likelihood of obtaining a PPP loan by a striking 57%. Likewise, a personal connection between the top management of the borrower and the lender increases this likelihood by 7.6%-7.8%. These effects are statistically significant and hold jointly after controlling for potential selection on borrowers' time-varying attributes, local exposures and policy responses to Covid-19, and the above fixed effects. Taken together, our results indicate that firms with personal or business connections to banks are more likely to obtain a PPP loan. Since the SBA's declared policy and participating banks' economic incentives do not require information gathering, the observed effects of connections on PPP allocation can be attributed to favoritism.

While the estimates show that favoritism played a role in loan allocation, it is possible that the connected PPP recipients were as eligible to receive the loans as their matched nonrecipients. Thus, while favoritism affected fairness, it did not necessarily deviate from the objectives of the PPP. To test this possibility, we investigate the effect of connections on the likelihood of returning

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PPP loans to avoid prosecution. We find that borrowers with past lending relationships are 24% more likely to return their PPP loan than their unconnected counterparts. Similarly, borrowers with personal connections are 10% more likely to return their loan. This evidence suggests that banks deviated from the stated objectives of the PPP program by favoring their connected borrowers.

In the second set of analyses, we investigate how the likelihood of detection affects the role of favoritism in PPP loans. Exploring the heterogeneous favoritism effect is both interesting from an institutional standpoint, and it can also provide suggestive evidence that our documented effect is not driven by other factors. First, we exploit the staggered implementation of the PPP. We conjecture that the public outcry that followed the initial stages of the PPP led to an increase in the scrutiny and public attention to the PPP in the second round, compared to the first round of the program.[6] Consequently, if the effect of connections on credit provision is driven by favoritism, we expect this effect to weaken in the second round. Consistent with this conjecture, the estimates show that relationship lending played a weaker role in the second round of the PPP. Interestingly, the effect of personal connections intensifies in the second round, possibly because personal connections are harder to monitor and detect.

Second, we exploit the variation in PPP eligibility criteria across industries. Unlike other industries, where parent firms with more than 500 employees do not qualify for PPP loans, the accommodation and food services (AF) industry is not subject to this constraint. Rather, each AF subsidiary/facility with fewer than 500 employees qualifies for a separate PPP loan. This criterion is harder to enforce since subsidiary/facility-level data are opaquer; hence, we conjecture that connections play a stronger role in the allocation of PPP loans to firms in the AF industry.

[6] See, for example, "Ruth's Chris to Repay Loan Amid Outcry Over Rescue Program" by Peter Rudegeair, Heather Haddon, and Ruth Simon, https://www.wsj.com/articles/public-companies-have-to-repay-small-business-rescue-loans-11587670442

Consistent with his conjecture, we find that the effect of favoritism on the likelihood of obtaining PPP loans is roughly 32% stronger in the AF industry, where monitoring is more difficult.

This paper is related to the literature on frictions in the allocation of government capital, a topic that has been examined primarily in the context of political connections. For example, Sapienza (2004) finds that the interest rates charged by government-owned banks in Italy reflect the power of the party that controls the bank, resulting in preferential access to capital for party-affiliated borrowers. Dinc (2005) finds that government-owned banks outside the United States increase their lending activity in election years to gain voter support. Faccio, Masulis, and McConnell (2006) find that politically connected firms are more likely to be bailed out in thirty-five countries, especially if these countries receive funding from the World Bank or the International Monetary Fund. Duchin and Sosyura (2012) find that politically connected banks are more likely to receive TARP capital in the aftermath of the 2008 financial crisis. We extend these prior studies by focusing on a different type of connections – those between firms and financial institutions rather than those between firms and politicians. These connections are particularly important in the PPP because it disbursed government capital through financial institutions rather than directly to firms, giving rise to an additional layer of business and social connections that can affect the allocation of government capital.

The paper also contributes to a growing empirical research that studies the role of connections between banks and various economic agents, including borrowers, depositors, investors, and government officials (e.g., Martinez and Schmukler (2001), Sapienza (2004), Engelberg et al. 2012). Since lending and personal relationships can simultaneously introduce favoritism and mitigate information asymmetries in credit provision, prior estimates capture the aggregate effect of these two non-mutually-exclusive forces. In contrast, we exploit the PPP to

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separate between the effects and provide novel disaggregated estimates of the effect of relationships on favoritism in credit provision.

This study is also related to the literature on regulatory arbitrage. Prior studies (e.g., Acharya, Schnabl and Suarez (2013) and Arteta, Carey, Correa, and Kotter (2008)) showed that banks exploit capital regulations by engaging in excessive risky lending. Along the same lines, we show that banks exploit the allocation of government-backed PPP loans to strengthen their business relationships with large, connected firms amid the Covid-19 crisis.

Finally, this paper is related to contemporaneous studies of the PPP. Autor et al. (2020) examine the impact of PPP on employment using administrative payroll data. Erel and Liebersohn (2020) focus on the role of FinTech in the provision of PPP loans. Most relevant to our study, Li and Strahan (2020) show that aggregate PPP supply at the bank-level decreases in bank size and increases in prior experience, commitment lending, and core deposits. Amiram and Rabetti (2020) show that, at the intensive margin, relationship-lending affected PPP loan size and the speed of obtaining PPP loans.

2. The Paycheck Protection Program (PPP)

The Coronavirus Aid, Relief, and Economic Security (CARES) Act was passed by Congress with overwhelming, bipartisan support and signed into law by President Trump on March 27th, 2020. In total, the CARES Act designated over $2 trillion dollars to combat the adverse economic impact of the Covid-19 pandemic, amounting to 10% of total U.S. gross domestic product (GDP), making it the largest economic relief package in the history of the United States.

The Paycheck Protection Program (PPP) is a centerpiece of $659 billion business loan program established by section 1102 of the CARES Act, which authorized the Small Business

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Administration (SBA) to distribute loans to support payroll and overhead expenses to eligible small businesses through its nationwide network of lenders. Lenders who already participated in the SBA's flagship 7(a) program were automatically eligible to disburse PPP loans, while other lenders had to obtain authorization from the SBA.

Each PPP loan was guaranteed by the SBA and loan applicants did not need to provide any collateral or personal guarantees to apply or be approved for a PPP loan. Participating lenders were not required to evaluate or screen borrowers and did not assume any credit risk by originating PPP loans. Thus, information frictions and adverse selection played no role in banks' approval process of PPP loans. Participating lenders earned an upfront origination fee proportional to the amount of the loan: 5% for loans under \$350k, 3% for loans between \$350k and \$2 million, and 1% for loans above \$2 million.[7]

The PPP focuses on small businesses, and, as such, eligibility for the PPP is based on the existing statutory and regulatory definition of a "small business concern" under section 3 of the Small Business Act, 15 U.S.C. 632. A business can qualify if it meets the SBA employee-based or revenue-based small business size standard corresponding to its primary industry. Alternatively, a business can qualify for the PPP if it meets the SBA's "alternative size standard," which requires a maximum tangible net worth of \$15 million and a maximum average net income for the two full fiscal years before the date of the application of \$5 million. Eligible applicants also include Sole proprietors, independent contractors, and self-employed persons, as well as non-profit organizations, veterans' organizations, and tribal business concerns that meet the criteria. A notable exception is the Accommodations and Food Services industry (businesses with a NAICS code that begins with 72). Such businesses were eligible even if the parent company exceeded the

[7] See: https://www.sba.gov/sites/default/files/2020-07/5000-20036-508.pdf

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above size standards, as long as they operated multiple physical locations with fewer than 500 employees per location. In these cases, each physical location was eligible for a separate PPP loan. In cross-sectional analyses, we exploit this exception to investigate whether the inclusion of larger AF firms, whose compliance with the PPP's criteria across multiple locations is harder to observe and monitor, fostered favoritism in the allocation of PPP loans.

The terms of PPP loans are highly attractive for borrowers. First, the principal of a PPP loan can be either partially or fully forgiven based on the usage of the loan proceeds. Second, even if not forgiven, PPP loans carry a low interest rate of one percent. Third, both the principal and interest payments are deferred until the loan is forgiven or, if the borrower does not apply for loan forgiveness, ten months after the end of the 24-week cover period.[8] Consequently, millions of businesses in the U.S immediately applied for PPP loans, which were accepted, approved, and disbursed on a first-come first-served basis, leading to credit rationing and generating a setting susceptible to favoritism.[9]

The first round of the PPP commenced on April 3, 2020 amidst government-mandated lockdowns in many states. Due to high demand, within 2 weeks, on April 16, 2020, the entire first round of $349 billion was depleted, and the SBA stopped accepting new applications from lenders.[10] A bill to add $310 billion of funding was passed by Congress and signed into law by President Trump on April 24, and the SBA began accepting new applications from lenders on April 27. The PPP was due to expire at midnight on June 30 with funds remaining, but just hours

[8] The SBA initially required that at least 75% of the loan be used for payroll, rent, mortgage interest, and utilities to be forgiven at the end of 8 weeks. On June 5, President Trump signed the PPP Flexibility Act, which reduced the proportion needed to be spent on payroll to 60% and extended the time period to use the funds from 8 to 24 weeks.
[9] While the SBA did not release information about the number of PPP applications or application approval rates, it reported a total of 4.67 million loans disbursed by June 20, 2020.
[10] See, for example, the article "Small business rescue loan program hits $349 billion limit and is now out of money," by Thomas Franck and Kate Rogers, published on CNBC on April 16: https://www.cnbc.com/2020/04/16/small-business-rescue-loan-program-hits-349-billion-limit-and-is-now-out-of-money.html

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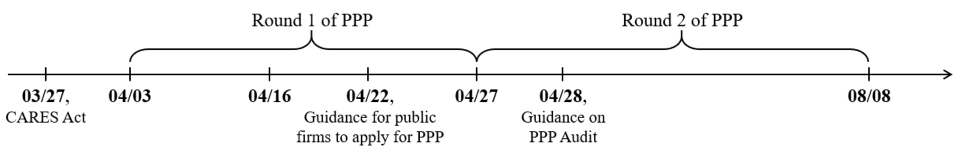
before the expiration of the program Congress authorized an extension through August 8. This date passed without a second extension to the program and the SBA stopped accepting applications. Figure 1 describes the timeline of the PPP. By the end of the program, the SBA has disbursed $525 billion of the $659 billion appropriated by Congress to this program. These numbers indicate stark differences in the demand for loans between the two rounds of the PPP: First-round PPP capital was quickly depleted, whereas second-round PPP capital exceeded aggregate demand. Hence, the differences between the two rounds provide a natural setting to study the relation between favoritism and credit rationing. [11]

Figure 1 Timeline of PPP

This figure describes the timeline of the two funding rounds of the Paycheck Protection Program and the accompanying guidance for public firms.



Moreover, we conjecture that in addition to lower demand, the second round of the PPP was also accompanied by more stringent oversight, potentially reducing the scope for favoritism in lending decisions. In particular, the first round was followed by public outcry surrounding the participation of large or public firms in the first round of the PPP.[12] Moreover, several lawsuits brought against J.P. Morgan Chase, Wells Fargo, Bank of America, and U.S. Bank by a range of California small businesses further alleged that the banks unfairly prioritized their large

[11] See "Tracker: Paycheck Protection Program Loans," by Thomas Wade: https://www.americanactionforum.org/research/tracker-paycheck-protection-program-loans/

[12] See, for example, the article "At Least 30 Public Companies Say They Will Keep PPP Loans," by Inti Pacheco, published by the Wall Street Journal on May 19, 2020: https://www.wsj.com/articles/at-least-30-public-companies-say-they-will-keep-ppp-loans-11589891223

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customers.[13] We therefore hypothesize that the apparent differences in both demand and oversight between the two rounds of the PPP provide a natural backdrop against which to examine the impact of favoritism on lending decisions amid changing oversight credit rationing conditions.

Furthermore, in a press briefing on April 22, 2020, Treasury Secretary Mnuchin warned of "severe consequences" for large businesses that received PPP funds.[14] Following Mnuchin's press briefing, the SBA instituted a "safe harbor" for the return of PPP funds by large businesses. On April 28, the Treasury and the SBA issued a joint statement that they would retroactively examine all loans over $2 million to certify that program qualifications were met.[15] Consequently, 69 PPP loans by public firms, totaling more than $436 million, were returned. Hence, we conjecture that favoritism played a particularly strong role in the subset of returned loans, and provide a comparative analysis of the role of connections in these loans relative to unreturned PPP loans. Moreover, the analysis of the role of connections in returned PPP loans helps shed light on whether favoritism led to deviations from the allocative goals of the program.

3. Data and Variables

3.1 Sample construction and variables

We begin our sample construction by identifying all public companies that received a PPP loan. We collect these data from S&P Global Market Intelligence, FactSquared, corporate press releases,

[13] See, for example, the article "Chase and other banks shuffled Paycheck Protection Program small business applications, lawsuit says," by Dalvin Brown, published in USA Today on April 20: https://www.usatoday.com/story/money/2020/04/20/small-businesses-sue-chase-bank-over-handling-stimulus/5163654002/. For further details on the lawsuits, please see: https://www.classaction.org/news/class-actions-say-wells-fargo-jpmorgan-chase-held-back-small-businesses-paycheck-protection-program-funds

[14] See https://www.businessinsider.com/treasury-mnuchin-consequences-big-companies-taking-ppp-small-business-loans-2020-4

[15] See https://factba.se/sba-loans for the list of public PPP borrowers, including those that subsequently returned the funds. The full PPP loan-level data can be found here: https://home.treasury.gov/policy-issues/cares-act/assistance-for-small-businesses/sba-paycheck-protection-program-loan-level-data.

8-K filings, 10-Q/K filings, and SBA. As shown in Appendix B, we start with 505 firms receiving PPP loans over the period of April 13, 2020 – June 30, 2020. We end the sample period on June 30, 2020 because no public firm received a loan between July 1, 2020 –August 8, 2020. The matching procedure and data availability lead to a final sample of 340 unique PPP borrowers, 121 unique lenders, and 343 unique PPP firm-lender pairs, corresponding to 347 PPP loans. As shown in Table 1, the mean and median loan sizes are \$3.2 million and \$1.9 million, respectively. We merge these data with firm-level financial information from Compustat, data on syndicated loans from the LPC Dealscan database, data on director/executive biographies and personal connections from BoardEx, data on Covid-19 from the New York Times, and county-level policy responses to Covid-19 from the National Association of Counties (NACo).

Table 1 also provides summary statistics on the variation in Covid-19 cases and government responses across states, MSAs, and counties where the sample firms are headquartered. The estimates show that the number of Covid-19 cases is right-skewed (the mean is considerably higher than the median), regardless of whether it is measured at the state, MSA or county level. Furthermore, there is considerable variation in counties' responses to Covid-19. While 80% of the counties declared a state of emergency, only 9% enacted business closure policies and 37% announced Safer-at-home policies.

To test the role of favoritism in the allocation of PPP loans, we introduce two measures of connections between banks and firms. The first measure is based on lending relationships between firms and banks prior to the PPP, because prior studies show that these pre-existing business relationships play an important role in credit allocation (e.g., Peterson and Rajan (1994), Berger and Udell (1995), Degryse and Van Cayseele (2000), Schenone (2004), and Bharath, Dahiya, Saunders, and Srinivasan (2011)). Specifically, we define an indicator variable, *Past lending*

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relationships, which equals 1 if the firm obtained a loan from the same PPP lender that matured in 2015 or later and 0 otherwise. If the loan is syndicated by a group of banks, we require the PPP lender to serve as a lead bank. We choose a five-year cutoff window because prior research commonly uses five years as the threshold to identify relationship lending (e.g., Gopalan, Nanda and Yerramilli (2011)). The intuition behind this cutoff is that borrowers are likely to still have an active relationship with the lender if their loan matured within the last five years.

The second measure of connections is based on social connections between executives or directors from the firm and executives or directors in the lending financial institution who are likely to influence the allocation of credit (*Personal connections*).[16] Personal connections may introduce favoritism by resulting in a bias known as homophile – an affection for similar others (McPherson, Smith-Lovin, and Cook (2001)). The conjecture that personal connections may affect credit allocation decisions is supported by earlier work, which shows that social networks influence corporate outcomes, such as executive compensation (Hwang and Kim (2009), Shue (2013), Engelberg, Gao, and Parsons (2011)), financial policy (Fracassi (2017)), governance (Fracassi and Tate (2012)), access to capital (Hochberg, Ljungqvist, and Lu (2007), Engelberg, Gao, and Parsons (2012)), incidence of fraud (Chidambaran, Kedia, and Prabhala (2011)), earnings management (Hwang and Kim (2011)), and acquisition activity (Ishii and Xuan (2014), Schmidt (2015), Shue (2013), Cai and Sevilir (2012)).

Consistent with prior literature, we define three types of personal connections: connections via education, connections via previous employment, and connections via nonprofit organizations. Educational connections foster a sense of belonging to a common group, which is evidenced by

[16] We consider directors and executives of financial institutions serving in the following roles: CEO, CFO, Deputy CFO, Independent director, Chief Corporate Banking Officer, Director-Corporate Banking, Vice President - Corporate Banking, Head of Corporate Banking, Senior VP - Corporate Business, and Executive VP- Corporate Banking.

alumni clubs, donations to the home school, and college sports. We define two executives or directors as connected via an *Educational* tie if they earned degrees from the same educational institutions no more than two years apart. Table 1 shows that 4.9% of the firms' executives or directors are connected to executives and directors in the financial institution via educational ties.

We define two executives or directors as connected via *Previous Employment* if they worked together or served on the same board of directors at a third-party firm in the past. Table 1 shows that 13% of the executives or directors share this connection with executives or directors in the financial institution. Lastly, two executives or directors are connected via *Nonprofit Organizations* if they share membership in the same nonprofit. These organizations typically include social clubs, religious organizations, philanthropic foundations, industry associations, and other nonprofit institutions defined in BoardEx as a manager's other activities. In our sample, 20% of the executives and directors share a nonprofit connection with executives and directors in the financial institution (Table 1).

Our empirical tests of personal connections focus on the aggregate measure that encompasses all three types of personal connections. The aggregation of personal connections formed via various networks into a summary measure is widely used in the social networks literature (e.g., Hwang and Kim (2009, 2011), Schmidt (2015), Fracassi (2017), Fracassi and Tate (2012)). In particular, if a firm has any of the three types of personal connections with executives and directors in the financial institution, it is considered connected to the lender. We set the indicator variable *Personal connections* equal to 1 if the firm is personally connected to the lender and 0 otherwise.[17] In our sample, 30% of the firms have personal connections with the lender.

[17] Our results (reported in Online Appendix 1) are robust to an alternative measure of personal connections based on *all* directors and executives of the lender albeit the economic magnitude of personal connections is smaller.

Lastly, to assess the overall effect of both *past lending relationships* and *personal connections*, we construct the *aggregate connections index*, defined as an indicator variable equal to 1 if the firm is connected to the lender through either *past lending relationships*, *personal connections*, or both, and 0 otherwise. Table 1 suggests that 33% of the firms have at least one of the connections with the financial institution in our sample.

Table 1 Summary Statistics

This table provides summary statistics for the sample of PPP loans, public firms that received PPP loans, and matched public firms that did not receive PPP loans. It summarizes loan characteristics, the connections between borrowers and lenders, firm-level attributes, and local exposures and responses to the Covid-19 crisis. All variables definitions are given in Appendix A.

Variable	**N**	**Mean**	**Std. Dev**	**p25**	**Median**	**p75**
PPP Loan Characteristics						
PPP-Loan Amount ($M)	347	3.24	5.19	0.81	1.87	4.42
PPP-Loan Amount/Total Assets	347	0.07	0.14	0.02	0.04	0.07
Firm-lender connections						
Past lending relationships	1,735	0.016	0.12	0	0	0
Personal connections	1,683	0.30	0.46	0	0	1
Educational	1,683	0.049	0.22	0	0	0
Previous employment	1,683	0.13	0.34	0	0	0
Nonprofit Organizations	1,683	0.20	0.40	0	0	0
Aggregate connections index	1,735	0.33	0.47	0	0	1
Loan outstanding	1,735	0.0173	0.1304	0	0	0
Firm Characteristics						
Total assets ($M)	1,735	144.77	502.85	14.96	43.19	113.05
Leverage	1,735	0.40	1.46	0.05	0.16	0.39
Market-to-book ratio	1,661	4.00	10.20	1.10	1.84	3.71
ROA	1,682	-0.10	0.38	-0.13	-0.02	0.02
Number of Employees	1,735	291.31	854.03	43	97	264
AF industry	1,735	0.0086	0.0926	0	0	0
Covid-19						
MSA Covid-19 Cases	1,735	17993.02	29420.10	4,182	10,260	12,569
State Covid-19 Cases	1,735	9188.93	19387.56	528	1,418	5,658
County Covid-19 Cases	1,735	1377.77	2184.34	280	711	1,216
County Emergency Declaration	1,735	0.80	0.40	1	1	1
County Business Closure Policy	1,735	0.09	0.29	0	0	0
County Safer-at-Home Policy	1,735	0.37	0.48	0	0	1

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3.2 Research Design

To test whether favoritism played a role in the allocation of PPP loans, we construct a matched sample by identifying a group of non-PPP firms (i.e., firms that did not receive a PPP loan) for each PPP borrower. Since only one PPP firm has a credit rating, we restrict the matched non-PPP firms US public firms that do not have a credit rating. To construct the matched sample, we employ the Mahalanobis distance approach (Rubin (1979) and Patton and Weller (2020)), with replacement, to find matching non-PPP firms in the same 2-digit NAICS or 1-digit NAICS industry group with the closest total assets and number of employees. We match on these attributes since they determine firms' eligibility for PPP loans.[18] For each treatment firm, we find four control firms. Total assets and number of employees are measured based on the most recent quarter available before the onset of the PPP. If the number of employees is missing, we linear-extrapolate it based on the firm's size. If we cannot find four matched control firms within the same 2-digit NAICS industry, we look for matching firms within the same 1-digit NAICS industry. If we still cannot find four control firms, we exclude the firm from our final sample. This procedure yields a total of 340 PPP firms and 1,360 matched non-PPP firms. Within the 1,360 control firms, 1,168 (85.88%) share the same 2-digit NAICS code with the treatment firm and 192 (14.12%) share the same 1-digit NAICS with the treatment firm.

Since a borrower can obtain multiple PPP loans in each of the two funding rounds, we collapse all loans obtained by the same borrower from the same lender in the same PPP funding round into a single observation. This procedure yields a matched sample comprising a total of 1,735 firm-lender-loan observations, of which 347 are in the treatment group (PPP firm-lender-loan) and 1,388 are in the control group (non-PPP firm-lender-loan).

[18] See: https://www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program.

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To assess the matching quality, Panel A of Table 2 reports difference-in-means estimates for several characteristics of PPP and non-PPP firms. Based on the point estimates, PPP firms are comparable in their asset size ($144 million vs. $141 million in total assets), leverage (0.44 vs. 0.39), market-to-book ratios (3.4 vs. 4.1), employees (299 vs. 288 employees), and profitability, as measured by ROA (-0.12 vs. -0.10). Importantly, the above differences between the two groups are statistically insignificant at conventional levels, as shown by the t-statistics of the difference-in-means estimates reported in Panel A. Moreover, we show that the two groups have essentially identical mean values by presenting the absolute standardized mean differences, which are small across all variables. Together, these estimates suggest that the Mahalanobis approach matches observationally similar PPP and non-PPP firms. Lastly, in Panel B of Table 2, we show that the composition of stock exchanges is similar across PPP and non-PPP firms.

Table 2 Covariate Balance

This table provides comparative statistics on the matched sample of public PPP loan recipients and nonrecipients. Panel A provides difference-in-means estimates of firm-level attributes across PPP recipients and their matched nonrecipients along with the corresponding p-values. In panel A, all variables are measured based on the most recent available quarterly report of 2019 except the number of employees, which is measured based on the most recent available annual report since 2018. Panel B compares between the stock exchanges where recipients and nonrecipients are listed. All variable definitions are given in Appendix A.

Panel A: Firm Characteristics

	PPP firms (N = 340)		Matched non-PPP firms (N = 1,360)		Difference between PPP firms and non-PPP firms	
	Mean	Std. dev.	Mean	Std. dev.	Absolute Standardized Mean Difference	P-value of Test of PPP firms = non-PPP firms
Total Assets ($SM)	144.1	526.6	141.2	498.7	[0.005]	*0.9243
Leverage	0.44	1.32	0.39	1.49	[0.035]	0.5760
Market-to-book ratio	3.41	11.51	4.15	9.66	[0.068]	0.2403
ROA	-0.12	0.59	-0.10	0.30	[0.049]	0.3148
Number of employees	299.2	880.4	288.4	857.1	[0.012]	**0.8369

*The p-value of testing the difference of log(Total Assets) between PPP firms and non-PPP firms is 0.6091.
**The p-value of testing the difference of log(Number of employees) between PPP firms and non-PPP firms is 0.5271.

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Table 2 (Continued)
Panel B: Stock Exchanges
Table 1 Panel B shows the comparison of listed exchanges between the PPP firms and their matched non-PPP firms. Data is collected from Compustat.

	PPP firms (N = 340)		Matched non-PPP firms (N = 1,360)	
Exchange	N	%	N	%
AMEX	30	8.82	111	8.16
NASDAQ	226	66.47	770	56.62
NYSE	16	4.71	81	5.96
OTC	68	20.00	398	29.26
Total	340	100	1,360	100

We investigate the effect of connections on the allocation of PPP loans by estimating the following linear probability model:

$$\text{Prob}\,(Treatment_{i,l,k} = 1) = \beta_0 + \beta_1 Connections_{i,l} + Controls_i + \alpha_{MSA} + \alpha_{lender} + \alpha_{industry} + \varepsilon_{i,l,k} \quad (1)$$

Where i indexes firms, l indexes lenders, and k indexes loans offered to firm i by lender l in either funding round. We include size and leverage as control variables, because they are likely to be correlated with credit demand and because Cororaton and Rosen (2020) find that PPP borrowers are smaller and more likely to have debt compared to eligible non-PPP firms. We also include Metropolitan Statistical Area (MSA) fixed effects based on the location of firm i's headquarters, as well as industry fixed effects. These fixed effects mitigate concerns that the effect of connections is driven by unobservable economic factors correlated with credit demand. We also control for the variation in the severity of the Covid-19 pandemic at the state, MSA, and county level, since the goal of the PPP was to help maintain employment for businesses hit by the pandemic. Lastly, we include lender fixed effects to control for any remaining cross-sectional variation in credit supply.

4. Results

4.1 The Role of Connections in the Allocation of PPP Loans

We begin by providing regression evidence on the role of connections in the allocation of PPP loans. The regressions follow the matched-sample specification in equation (1) and the results are

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reported in Table 3. The key variables of interest are *Past lending relationship*, *Personal connections*, and *Aggregate connections index*, which are discussed in the previous section, and capture the effect of connections on the likelihood of receiving a PPP loan.

In columns (1) and (2), we investigate the effect of *past lending relationships*. The estimates suggest that the existence of a past lending relationship increases the likelihood of receiving a PPP loan by 57%. This effect is statistically significant at the one percent level (t-statistic=5.7 or 5.6) and holds after controlling for MSA, industry, and lender fixed effects. In column (2), we include firm size and leverage as additional controls. The coefficients on both firm size and leverage are not statistically significant, suggesting that the matching procedure eliminates differences in firm characteristics associated with the likelihood of receiving a PPP loan.

In columns (3) and (4), we investigate the role of personal connections. The estimates suggest that the existence of personal connections increases the likelihood of receiving a PPP loan by 7.6% to 7.8%. This effect is also highly statistically significant (t-statistic=2.9 or 2.7) and holds after controlling for firm size, leverage, and the same set of fixed effects. In columns (5) and (6), we investigate the roles of past lending relationships and personal connections jointly. The coefficient estimates on both types of connections continue to be highly statistically significant at the one percent level and the economic magnitudes are very similar to those in columns (1)-(4). This evidence suggests that the two types of connections play a distinct role in the allocation of PPP loans.

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Table 3 The Role of Connections in the Allocation of PPP Loans

This table reports regression estimates from linear probability models explaining the likelihood of receiving a PPP loan. *Past lending relationships* is an indicator variable that equals 1 if the PPP lender served as a lead lender on a syndicated loan maturing on or after 2015, and 0 otherwise. *Personal connections* is an indicator variable that equals 1 if any the firm's directors or executives share an education, nonprofit, or employment connection with directors or executives at the lending financial institution, and 0 otherwise. *Aggregate connections index* is an indicator variable that equals 1 if the firm is connected to the lender either through *Past lending relationships, Personal connections*, or both, and 0 otherwise. The unit of observation is a firm-lender-loan triplet. The standard errors are clustered by PPP-borrower groups, where a group consists of a PPP firm-lender-loan and its four matched non-PPP firm-lender-loans. The t-statistics are given in parenthesis. *, **, *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables				Prob (treatment = 1)				
Past lending relationships	0.570***	0.568***			0.559***	0.565***		
	(5.741)	(5.551)			(5.734)	(5.655)		
Personal connections			0.0783***	0.0756***	0.0697**	0.0714**		
			(2.871)	(2.683)	(2.575)	(2.567)		
Aggregate connections index							0.0819***	0.0791***
							(3.144)	(2.931)
Log(total assets)		0.00271		0.00655		-0.00324		0.00690
		(0.398)		(0.931)		(-0.441)		(1.007)
Leverage		0.00619		0.00569		0.00509		0.00653
		(0.941)		(0.835)		(0.721)		(0.991)
Constant	0.180***	0.130	0.169***	0.0519	0.163***	0.217*	0.162***	0.0389
	(44.75)	(1.091)	(18.90)	(0.425)	(18.55)	(1.704)	(17.59)	(0.327)
Observations	1,681	1,681	1,630	1,630	1,630	1,630	1,681	1,681
R-squared	0.152	0.152	0.134	0.134	0.161	0.161	0.131	0.132
Std Error Clustered				PPP-borrower group				
Lender fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm NAICS2 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm MSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

We also estimate the relative importance of past lending relationships and personal connections. While both matter for the allocation of PPP loans, the economic magnitude of past lending relationships is roughly 7-8 times that of personal connections. A possible interpretation is that business relationships play a more important role in the PPP. Formally, an F-test for the difference between the coefficient estimates on *Past lending relationships* and *Personal connections* in column (5) yields a p-value of 0.000. In columns (7) and (8), we examine the overall role of connections. The coefficient on *Aggregate connections index* is again positive and highly significant at the one percent level.[19]

The above regression specifications include MSA fixed effects, which absorb demographic and economic differences across MSAs, as well as differences in the local severity of the Covid-19 pandemic and the government's response to it. To estimate the direct effects of the exposure to Covid-19 on the allocation of PPP loans, we drop the MSA fixed effects and augment equation (1) with the following four variables. The first variable, *Log (1+ # of Covid-19 Cases),* is defined as the logarithm of the number of positive Covid-19 cases as of April 3, 2020 (when the PPP was launched) in the state, MSA, or county where the firm is headquartered. The other three variables measure county-level policy responses to Covid-19, which likely had an effect on local businesses: (1) Declarations of a state of emergency, (2) Business closures, and (3) Safer-at-home policies.

We report these results in Table 4. Overall, the estimates provide two main takeaways. First, the effects of the variation in local exposures and responses to the COVID-19 pandemic are not robust, flip signs across specifications, and are often statistically insignificant at conventional levels, suggesting that the allocation of PPP loans was not systematically affected by differences in the impact of the Covid-19 pandemic across businesses and regions. These findings are

[19] We obtain similar results in bootstrapped regressions models (Santa-Clara and Valkanov (2003)) and in a more restrictive one-to-one matched sample within the same two-digit NAICS industry.

consistent with the evidence in Granja, Makridis, Yannelis, and Zwick (2020). Second, the effects of lending relationships and personal connections remain highly statistically significant and economically similar after controlling for these effects. This evidence mitigates concerns that correlated omitted variables related to local exposures and responses to the pandemic are driving our results.

Table 4 Local Exposures and Policy Responses to Covid-19

This table reports regression estimates from linear probability models explaining the likelihood of receiving a PPP loan. To estimate the direct effects of the exposure to Covid-19 on the allocation of PPP loans, we include the following four variables: (1) Log (1+ # of Covid-19 Cases), defined as the logarithm of the number of positive Covid-19 cases as of April 3, 2020 (when the PPP was launched) in the state, MSA, or county where the firm is headquartered; (2) Declarations of a state of emergency, (3) Business closures, and (4) Safer-at-home policies. *Past lending relationships* is an indicator variable that equals 1 if the PPP lender served as a lead lender on a syndicated loan maturing on or after 2015, and 0 otherwise. *Personal connections* is an indicator variable that equals 1 if any the firm's directors or executives share an education, nonprofit, or employment connection with directors or executives at the lending financial institution, and 0 otherwise. *Aggregate connections index* is an indicator variable that equals 1 if the firm is connected to the lender either through *Past lending relationships, Personal connections*, or both, and 0 otherwise. The unit of observation is a firm-lender-loan triplet. The standard errors are clustered by PPP-borrower groups, where a group consists of a PPP firm-lender-loan and its four matched non-PPP firm-lender-loans. The t-statistics are given in parenthesis. *, **, *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Prob (Treatment = 1)			
Variables	State-level # cases	MSA-level #cases	County-level #cases	County Emergence Declaration	County Business Closure policy	County Safer-at-home policy
Past lending relationships	0.581***	0.578***	0.578***	0.578***	0.578***	0.574***
	(6.546)	(6.457)	(6.450)	(6.418)	(6.501)	(6.440)
Personal connections	0.0711***	0.0717***	0.0712***	0.0722***	0.0720***	0.0727***
	(2.769)	(2.786)	(2.774)	(2.807)	(2.806)	(2.834)
log(1+ # Covid-19 Cases)	0.00841	0.000213	0.00419			
	(1.052)	(0.0564)	(0.821)			
County-level policy				-0.0210	-0.0264	0.0226
				(-0.762)	(-0.679)	(0.989)
Log (total assets)	-0.00774*	-0.00765*	-0.00755*	-0.00778*	-0.00812*	-0.00801*
	(-1.752)	(-1.711)	(-1.697)	(-1.727)	(-1.774)	(-1.775)
Leverage	0.00263	0.00282	0.00269	0.00297	0.00261	0.00219
	(0.375)	(0.404)	(0.386)	(0.424)	(0.369)	(0.315)
Constant	0.232**	0.304***	0.278***	0.324***	0.316***	0.303***
	(2.287)	(3.853)	(3.415)	(4.031)	(4.030)	(4.001)
Observations	1,682	1,682	1,682	1,682	1,682	1,682
R-squared	0.058	0.057	0.058	0.058	0.058	0.058
Std Error Clustered			PPP-borrower group			
Lender fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm NAICS2 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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4.2 Allocative Distortions

The estimates in the previous subsection show that favoritism played a role in the allocation of PPP loans. However, these estimates disentangle between the following two scenarios. On the one hand, it is possible that the connected PPP recipients were as eligible to receive PPP loans as their matched nonrecipients. Under this scenario, favoritism affected allocative fairness but did not lead to deviations from the objectives of the PPP. On the other hand, it could be that connected PPP recipients were less eligible to receive PPP loans. Under this view, favoritism led to distortions in the allocation of PPP loans.

To disentangle between these scenarios, we investigate the effect of connections on the likelihood of returning PPP loans to avoid prosecution. If connections led to allocative distortions, we would expect connected firms to be more likely to return their loans. These analyses focus solely on PPP borrowers (that is, they exclude matched non-PPP firms) and compare the likelihood of returning PPP loans across connected and unconnected firms.

The results are reported in Table 5. The dependent variable in the regressions is an indicator variable that equals one if the PPP borrower publicly announced returning its PPP loans and zero otherwise. The main variables of interest are *Past lending relationships* (column 1), *Personal connections* (column 2), and *Aggregate connections index* (column 4).

Across all the columns and measures of connections, we find that connected firms are considerably more likely to return their loans. These findings are economically large and statistically significant at conventional levels. Borrowers with *past lending relationships* are 37% more likely to return their PPP loans, whereas borrowers with *personal connections* 14% more likely to return their loans. Together, the results suggest that connected firms obtained PPP loans through preferential access to the program despite violating its stated goals and application criteria. Consequently, they were forced to return their loans to avoid prosecution as public pressure and scrutiny intensified. These findings further strengthen the role of connections in promoting favoritism in credit origination and indicate that favoritism not only affected the fairness, but also deviated from the objectives of the PPP.

Table 5 Allocative Distortions: Returning PPP Loans

This table reports regression estimates from linear probability models explaining the likelihood of returning a PPP loan. *Past lending relationships* is an indicator variable that equals 1 if the PPP lender served as a lead lender on a syndicated loan maturing on or after 2015, and 0 otherwise. *Personal connections* is an indicator variable that equals 1 if any the firm's directors or executives share an education, nonprofit, or employment connection with directors or executives at the lending financial institution, and 0 otherwise. *Aggregate connections index* is an indicator variable that equals 1 if the firm is connected to the lender either through *Past lending relationships, Personal connections*, or both, and 0 otherwise. The unit of observation is a firm-lender-loan triplet. The t-statistics are given in parenthesis. *, **, *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Variables	PPP-loan return dummy			
Past lending relationships	0.372***		0.338***	
	(4.645)		(4.221)	
Personal connections		0.143***	0.123***	
		(3.602)	(3.134)	
Aggregate connections index				0.153***
				(3.964)
Constant	0.128***	0.100***	0.0881***	0.0900***
	(6.688)	(4.206)	(3.750)	(3.736)
Observations	347	342	342	347
R-squared	0.059	0.037	0.085	0.044
Sample	Only PPP firm-lender-loan			
Std Error Clustered	No	No	No	No
Lender fixed effects	No	No	No	No
Firm NAICS2 fixed effects	No	No	No	No
Firm MSA fixed effects	No	No	No	No

4.3 Monitoring and Detection

In this section, we investigate how monitoring and the likelihood of detection affect the role of favoritism in the allocation of PPP loans. First, we exploit the staggered implementation of the PPP. The early stages of the PPP triggered significant public outcry about potential misallocations and preferential access to the loans, leading to increased monitoring and scrutiny, which could reduce the scope for favoritism.

To investigate this possibility, we begin by providing comparative analyses of the first and second rounds of the PPP. We classify PPP loans approved before April 27, 2020 as first-round loans and loans approved on or after April 27 as second-round loans. Overall, the sample includes 245 first-round loans, totaling roughly $885 million, and 102 second-round loans, totaling $240 million, that were extended to public firms.

In Table 6, we provide estimates from subsample regression analyses that separate between the first and second rounds of the PPP. Columns (1) to (4) focus on first-round PPP loans whereas columns (5) to (8) focus on second-round PPP loans. Based on columns (1) and (5), past lending relationships play a weaker role in the second round of the PPP (coefficient = 0.286; t-statistic = 1.08) compared to the first round of the PPP (coefficient = 0.650; t-statistic = 5.40). An F-test of the difference between the coefficients, however, suggests that the difference is not statistically significant at conventional levels.

Interestingly, based on columns (2) and (6), personal connections continue to play a role in loan originations in the second round of the PPP, and the magnitude of the effect is even larger in the second round (coefficient = 0.0631 in the first round vs. 0.118 in the second round). These effects are also illustrated in Panel A of Figure 2. A possible interpretation of these findings is that the opaquer nature of personal connections, which are considerably more difficult to detect and scrutinize than lending relationships, allows them to continue to play a role in the second-round of the PPP despite the increased levels of scrutiny and oversight.

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Table 6 The Role of Connections in the Allocation of First-Round Vs. Second-Round PPP Loans

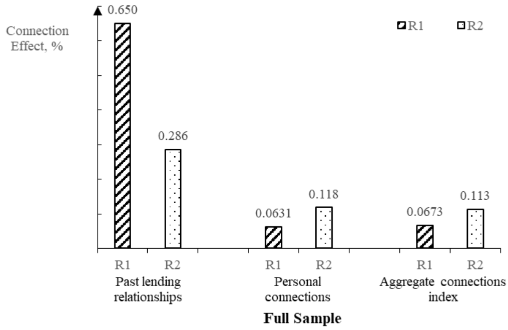
This table reports regression estimates from linear probability models explaining the likelihood of receiving a PPP loan. The regressions are estimated separately for first-round loans originated before April 27, 2020 (columns 1-4) and second round loans originated on or after April 27 (columns 5-8). *Past lending relationships* is an indicator variable that equals 1 if the PPP lender served as a lead lender on a syndicated loan maturing on or after 2015, and 0 otherwise. *Personal connections* is an indicator variable that equals 1 if any the firm's directors or executives share an education, nonprofit, or employment connection with directors or executives at the lending financial institution, and 0 otherwise. *Aggregate connections index* is an indicator variable that equals 1 if the firm is connected to the lender either through *Past lending relationships, Personal connections*, or both, and 0 otherwise. The unit of observation is a firm-lender-loan triplet. The standard errors are clustered by PPP-borrower groups, where a group consists of a PPP firm-lender-loan and its four matched non-PPP firm-lender-loans. The t-statistics are given in parenthesis. *, **, *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables				Prob (Treatment = 1)				
Past lending relationships	0.650***		0.648***		0.286		0.279	
	(5.398)		(5.576)		(1.081)		(1.051)	
Personal connections		0.0631*	0.0598*			0.118*	0.115*	
		(1.895)	(1.836)			(1.922)	(1.864)	
Aggregate connections index				0.0673**				0.113*
				(2.105)				(1.943)
Log(total assets)	0.0128	0.0223***	0.00847	0.0227***	0.0152	0.00688	0.00409	0.00803
	(1.501)	(2.622)	(0.929)	(2.784)	(1.057)	(0.426)	(0.253)	(0.508)
Leverage	0.0135	0.0159	0.0160	0.0149	0.00824	0.00719	0.00675	0.00768
	(0.782)	(0.978)	(0.966)	(0.897)	(1.247)	(1.054)	(1.003)	(1.139)
Constant	-0.0530	-0.229	0.00756	-0.242*	-0.0764	0.0414	0.0863	0.0175
	(-0.348)	(-1.515)	(0.0468)	(-1.675)	(-0.308)	(0.152)	(0.317)	(0.0655)
Observations	1,171	1,135	1,135	1,171	472	456	456	472
R-squared	0.178	0.151	0.186	0.148	0.225	0.237	0.242	0.230
Sample		PPP in Round 1				PPP in Round 2		
Std Error Clustered		PPP-borrower group				PPP-borrower group		
Lender fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm NAICS2 fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 2 Cross-Sectional Evidence

Panel A: First and Second Rounds of the PPP

This figure present cross-sectional evidence on the role of connections in the allocation of PPP loans. Panel A compares the effects of connections the allocation of PPP loans across first-round loans originated before April 27, 2020 and second round loans originated on or after April 27.



Second, we exploit the variation in PPP eligibility criteria across industries. In particular, the eligibility terms of the program restrict parent companies with 500 employees or more from obtaining PPP loans. A notable exception, however, applies to firms in the Accommodation and Food (AF) Industry, which have access to the program as long as their subsidiaries have fewer than 500 employees. Subsidiary-level information, however, is considerably opaquer. It is therefore harder to enforce compliance with the program's criteria in the AF industry. Consequently, this exception provides an opportunity for lenders to provide preferential access to large firms in the AF industry. As such, the favoritism hypothesis implies that lending relationships and personal connections should play a stronger role in the AF industry. On the other hand, if connections ameliorate information frictions, there is no reason to expect that connections will play a stronger role in the AF industry.

In Table 7, we investigate whether the role of connections is stronger in the AF industry. The key variables of interest are the interaction terms *Lending relationships x AF industry*, *Personal connections x AF industry*, and *Aggregate connections index x AF industry*, where *AF industry* is an indicator variable that equals one if the PPP firms are from the Accommodation and

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Food industry (2-digit NAICS = 72) and zero otherwise. The estimates in Table 7 show that the coefficients on the interaction terms *Lending relationships x AF industry*, *Personal connections x AF industry*, and *Aggregate connections index x AF industry* are significantly positive, suggesting that connections played a stronger role in the AF industry, as predicted by the favoritism hypothesis. These findings are also illustrated in Panel B of in Figure 2.

Table 7 The Accommodation and Food Services Industry

This table reports regression estimates from linear probability models explaining the likelihood of receiving a PPP loan. *AF Industry* is an indicator variable that equals 1 if the borrowing firm is in the Accommodation and Food Services Industry (NAICS2=72). *Past lending relationships* is an indicator variable that equals 1 if the PPP lender served as a lead lender on a syndicated loan maturing on or after 2015, and 0 otherwise. *Personal connections* is an indicator variable that equals 1 if any the firm's directors or executives share an education, nonprofit, or employment connection with directors or executives at the lending financial institution, and 0 otherwise. *Aggregate connections index* is an indicator variable that equals 1 if the firm is connected to the lender either through *Past lending relationships, Personal connections*, or both, and 0 otherwise. The unit of observation is a firm-lender-loan triplet. The standard errors are clustered by PPP-borrower groups, where a group consists of a PPP firm-lender-loan and its four matched non-PPP firm-lender-loans. The t-statistics are given in parenthesis. *, **, *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
		Prob (Treatment = 1)	
Variables	Connection = Past Lending relationships	Connection = Personal connections	Connection = Aggregate connections index
Connection	0.540***	0.0708**	0.0746***
	(4.958)	(2.481)	(2.730)
AF Industry	0.0138	-0.136	-0.132
	(0.163)	(-1.627)	(-1.600)
Connection * AF industry	**0.353****	**0.322*****	**0.316*****
	(2.399)	**(5.760)**	**(5.817)**
Log (Total Assets)	0.00319	0.00701	0.00736
	(0.466)	(0.996)	(1.074)
Leverage	0.00621	0.00571	0.00654
	(0.941)	(0.838)	(0.993)
Constant	0.121	0.0449	0.0319
	(1.011)	(0.368)	(0.269)
Observations	1,681	1,630	1,681
R-squared	0.153	0.136	0.133
Sample		All	
Std Error Clustered		PPP-borrower group	
Lender fixed effects	Yes	Yes	Yes
Firm NAICS2 fixed effects	Yes	//Yes	Yes
Firm MSA fixed effects	Yes	Yes	Yes

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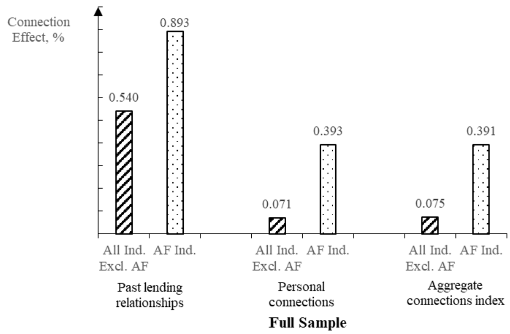
Figure 2 Cross-Sectional Evidence (continued)
Panel B: The Accommodation and Food Services Industry

This figure present cross-sectional evidence on the role of connections in the allocation of PPP loans. Panel B compares the across the Accommodation and Food Services Industry (NAICS2=72) and non-AF industries.



Taken together, the evidence in this section indicate that the monitoring and the likelihood of detection affected the role of connections in the allocation of PPP loans. This evidence is consistent with the view that connections foster favoritism and inconsistent with the alternative view that connections ameliorate information frictions.

4.4 Existing Loans

In the final set of analyses, we exploit the heterogeneity of lending relationships by separating between connected firms that have a current outstanding loan with their PPP lender and connected firms without a current outstanding loan. We conjecture that the effect of a current outstanding loan is twofold. First, a concurrent lending relationship likely represents a stronger connection between the lender and borrower compared to past lending relationships. We therefore expect that the effect of connections on the allocation of PPP loans would be stronger when the firm has a loan from its PPP lender maturing after the disbursement of the PPP loan. Second, banks might have an incentive to prioritize loans to their existing customers with outstanding loans because the provision of PPP government funds will increase their customers' credit worthiness and reduce

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their rollover risk and probability of default.[20] Borrowers' credit risk could play an important role during the Covid-19 crisis. This is evident from the poor operating performance of our sample firms, as captured by the average negative ROA in Table 1 Panel B, and from ample anecdotal evidence. This scenario also predicts that connections play a stronger role in the allocation of PPP loans to firms with an existing loan from their PPP lenders.

To investigate this hypothesis, we distinguish between connected PPP borrowers that had an outstanding loan from their PPP lender when they obtained PPP funds and connected PPP borrowers that did not have an outstanding loan from their PPP lender. This analysis focuses on connected PPP borrowers and identifies the incremental effect of an existing loan from the PPP lender.

The estimates in Table 8 show that an existing loan played a significant role in the allocation of PPP loans to connected borrowers. In column (1), the coefficient on *Past lending relationships, loan outstanding* is larger than the coefficient on *Past lending relationships, without loan outstanding* (0.767 vs. 0.494), suggesting that lending relationships were particularly important in the allocation of PPP loans to existing borrowers. An F-test of the difference between the two coefficients yields a p-value of 0.0497, implying that the effect of *Past lending relationships, loan outstanding* is significantly stronger. These results are also shown in Panel C of Figure 2, which depicts a considerable increase in the likelihood of obtaining a PPP loan by connected borrowers with outstanding loans from their PPP lender.

[20] See, for example, the article by S&P Global Intelligence on May 12, 2020 titled "Billions of dollars to flow to bank coffers from COVID-19 small business program." According to the article, Houston-based Cadence Bancorp disclosed that borrowers representing about half of its restaurant portfolio applied for PPP loans from the bank. Its Chairman and CEO Paul Murphy Jr. said on an April 29 call that the bank sees the PPP loans as immediate credit support to the bank in the near term.

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Table 8 Existing Loans

This table reports regression estimates from linear probability models explaining the likelihood of receiving a PPP loan. *Connection, loan outstanding* is an indicator variable that equals 1 if the PPP lender and the borrower are connected and the borrower had an outstanding loan with its PPP lender when the PPP loan was originated, and 0 otherwise. *Connection, without loan outstanding* is an indicator variable that equals 1 if the PPP lender and the borrower are connected and the borrower did not have an outstanding loan with its PPP lender when the PPP loan was originated, and 0 otherwise. The unit of observation is a firm-lender-loan triplet. The standard errors are clustered by PPP-borrower groups, where a group consists of a PPP firm-lender-loan and its four matched non-PPP firm-lender-loans. The t-statistics are given in parenthesis. *, **, *** represent significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
Variables	Prob (Treatment = 1)		
Past lending relationships, loan outstanding	0.767***		
	(10.71)		
Past lending relationships, without loan outstanding	0.494***		
	(3.852)		
Personal connections, loan outstanding		0.0793	
		(0.700)	
Personal connections, without loan outstanding		0.0755***	
		(2.662)	
Aggregate connections index, loan outstanding			0.246**
			(2.492)
Aggregate connections index, without loan outstanding			0.0746***
			(2.754)
Log(total assets)	0.00451	0.00652	0.00549
	(0.655)	(0.908)	(0.784)
Leverage	0.00629	0.00569	0.00641
	(0.960)	(0.835)	(0.974)
Constant	0.0996	0.0525	0.0649
	(0.824)	(0.421)	(0.536)
Observations	1,681	1,630	1,681
R-squared	0.141	0.134	0.132
Std Error Clustered	PPP-borrower group		
Lender fixed effects	Yes	Yes	Yes
Firm NAICS2 fixed effects	Yes	Yes	Yes
Firm MSA fixed effects	Yes	Yes	Yes

In column (2), however, we find that the coefficients on *Personal connections, loan outstanding*, and *Personal connections, without loan outstanding* are similar in magnitude (0.0793 vs. 0.0755). These estimates suggest that unlike past lending relationships, the role of personal

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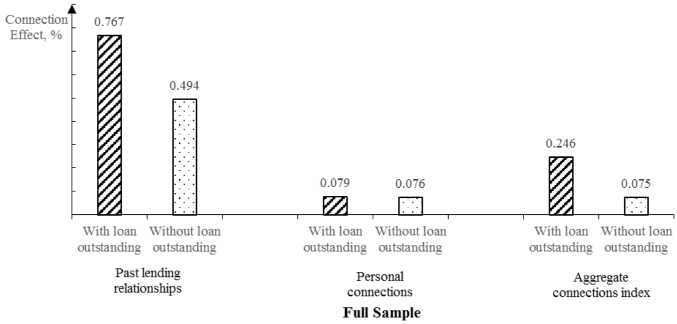
connections in the allocation of PPP loans is unaffected by current outstanding loans. Interpreted broadly, these estimates suggest that the existence of an outstanding loan strengthens the business connections between borrowers and lenders, but does not affect the role of their personal connections.

Figure 2 Cross-Sectional Evidence (continued)
Panel C: Existing Loans
This figure present cross-sectional evidence on the role of connections in the allocation of PPP loans. Panel C compares the effects across connected borrowers with and without current outstanding loans from their PPP lenders.



5. Concluding Remarks

This paper exploits the unique features of the Paycheck Protection Program (PPP) to provide novel estimates of the role of connections in preferential access to credit. Unlike other government aid programs that allocated capital directly to their end-users, PPP capital was disbursed by banks that were not required to screen borrowers and were not exposed to borrowers' credit risk. Consequently, the PPP provides an ideal setting to isolate the role of favoritism from information frictions in bank lending.

The main findings suggest that both past lending relationships and personal connections between borrowers and financial institutions play important, distinct roles in the allocation of PPP loans: Connected firms are considerably more likely to obtain PPP loans. Using a matched sample,

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these effects hold in regression specifications that control for local exposures and government responses to the Covid-19 crisis as well as increasingly restrictive systems of fixed effects. They also remain statistically robust with bootstrapped coefficient estimates and standard errors, and in alternative matched samples.

We provide several analyses that further isolate the role of favoritism in the provision of PPP loans. First, we show that connected PPP borrowers were more likely to return their PPP loans. These estimates suggest that lending relationships and personal connections not only affected the allocative fairness of the PPP, but also led to distortions that were undone by forcing connected firms to return the capital they obtained through the program. Second, we show that monitoring and the likelihood of detection mediated the role of connections in the allocation of PPP loans. In the analysis of the staggered implementation of the PPP, we find that that connections played a weaker role in the second round of the PPP, which was more heavily scrutinized and monitored. These effects hold particularly for lending relationships which are easily observable. In contrast, we find no difference in the role of opaquer personal connections between the two PPP rounds. In the cross-industry analysis, we show that the role of connections was stronger in the AF industry, for which the size cap on access to the PPP was laxer, consequently increasing the scope for prioritizing loans to large connected companies. Lastly, we show that the role of connections was stronger for borrowers with existing outstanding loans from their PPP lender. A possible interpretation is that the existence of an outstanding loan generates a stronger business relationship between the lender and the borrower. Alternatively, banks may have a particularly strong incentive to prioritize loans to such borrowers because they lower their credit risk exposure by doing so.

Collectively, these findings provide some of the cleanest estimates, to-date, of the role of connections in fostering favoritism in loan provision by financial institutions. Furthermore, they

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highlight the conflicts of interest resulting from the design of the Paycheck Protection Program, emphasizing the importance of oversight and aligned incentives in financial intermediation.

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Appendix A: Variable definition

Variable	Description	Data Source
Treatment	An indicator variable equal to 1 if the firm receives a PPP-loan after April 3, 2020, and 0 otherwise.	8-K, 10-Q/K, S&P Market Intelligence, FactSquared, SBA website
Connections		
Past lending relationships	An indicator variable equal to 1 if the firm borrows at least a loan that ends on and after 2015 from the PPP-lender that acts as lead lender of the loan, and 0 otherwise.	DealScan
Personal connections	An indicator variable equal to 1 if any directors or executives of the firm has educational, previous employment, or non-profit organization connection with any directors or executives who have influence on credit allocation of the PPP-lender, and 0 otherwise.	BoardEx
Aggregate connections index	An indicator variable equal to 1 if the firm is connected to the PPP-lender through at least one of the past lending relationships or personal connections, and 0 otherwise	DealScan, BoardEx
Educational connection	An indicator variable equal to 1 if any directors or executives of the firm and any directors or executives who has influence on credit allocation of the PPP-lender graduated from the same educational institution on the same year or within 2 adjacent years, and 0 otherwise.	BoardEx
Previous employment connection	An indicator variable equal to 1 if any directors or executives of the firm and any directors or executives who has influence on credit allocation of the PPP-lender worked in the same place or served on the same board at the same time before, and 0 otherwise.	BoardEx
Nonprofit organizations connection	An indicator variable equal to 1 if any directors or executives of the firm and any directors or executives who has influence on credit allocation of the PPP-lender participated in the same social organizations on and after Jan 01, 2019, and 0 otherwise.	BoardEx
Firm Characteristics		
Total Assets	Book value of total assets, from the most recent available observation of 2019.	Quarterly Compustat
Leverage	Current liabilities plus total long-term debt scaled by book value of total assets, from the most recent available observation of 2019.	Quarterly Compustat
Market-to-Book	Quarterly close price times common shares outstanding minus total common equity, scaled by total assets, from the most recent available observation of 2019	Quarterly Compustat
ROA	Operating Income Before Depreciation scaled by total assets, from the most recent available observation of 2019	Quarterly Compustat

Variable	Description	Data Source
Number of employees	Number of Employees, from the most recent available observation after 2018	Annual Compustat Footnote
Covid-19		
State Covid-19 Cases	The number of Covid-19 positive cases in the state of the firm headquarter, as of April 03, 2020	New York Times
MSA Covid-19 Cases	The number of Covid-19 positive cases in the MSA are of the firm headquarter, as of April 03, 2020	New York Times
County Covid-19 Cases	The number of Covid-19 positive cases in the county of the firm headquarter, as of April 03, 2020	New York Times
County Emergency Declaration	An indicator variable equal to 1 headquarter county of the firm has the Emergency Declaration, and 0 otherwise	National Association of Counties
County Business Closure Policy	An indicator variable equal to 1 headquarter county of the firm has the Business Closure policy, and 0 otherwise	National Association of Counties
County Safer-at-Home Policy	An indicator variable equal to 1 headquarter county of the firm has the Safer-at-home policy, and 0 otherwise	National Association of Counties
Other		
AF industry	An indicator variable equal to 1 if the PPP firm has 2-digit NAICS = 72, and 0 otherwise. For the control firms, we assign the value of AF industry equal to their corresponding treatment pairs.	Compustat
Loan outstanding	An indicator variable equal to 1 if the PPP firm took out at least a syndicate from the PPP-lender who acted as a lead lender and the loan matures after the awarding date of the PPP-loan. For the control firms, we assign the value of Loan outstanding equal to their corresponding treatment pairs.	DealScan
Number of the PPP-loans	Total number of PPP-loans the borrower, or any subsidiary of the borrower, receives from each lender.	8-K, 10-Q/K, S&P Market Intelligence, FactSquared
Total amount of PPP-loans	The sum of the amount of PPP-loans the borrower, or any subsidiary of the borrower, receives from the same lender.	8-K, 10-Q/K, S&P Market Intelligence, FactSquared
PPP loan return dummy	An indicator variable equal to 1 if the PPP firm announce to return or have returned the PPP-loan to the lender, and 0 otherwise	8-K, 10-Q/K, S&P Market Intelligence, FactSquared

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Appendix B: Sample Construction

		Number of PPP firms	Number of PPP firm-lender	Number of PPP firm-lender-loan
	All firms disclose approvals of PPP loans	505		
Require 1	With Ticker available	493		
Require 2	Matched to 2019 quarterly Compustat with total assets and leverage	417		
Require 3	Headquarter and listed in the US	406		
Require 4	With identified lender	393	398	
Require 5	Matched to 4 non-PPP firms in the same 2-digit NAICS or 1-digit NAICS industry, with difference in total assets and leverage less than 50%	340	343	347
	Final	340	343	347

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Covid Economics **Issue 59, 27 November 2020**

How effective is social distancing?[1]

Difang Huang[2]

Date submitted: 25 November 2020; Date accepted: 26 November 2020

We identify the effects of social distancing policy on reducing the transmission of the COVID-19 spread. We build a model that measures the relative frequency and geographic distribution of COVID-19 infections and provides hypothetical infection distribution in the counties that enacted social distancing policy. We apply the model to a panel of daily COVID-19 infection cases of all counties in the United States and find social distancing lowered the average daily infection cases by 12%. We further provide evidence that the effects are heterogeneous in an individual's income, race, education, and political belief.

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1 I am grateful to the seminar participants in FEES 2020 virtual conference, Monash University, Placekey Community virtual conference, Victor Couture, Xiaodong Fan, John Friedman, Jiti Gao, Yi He, Gael Martin, Yan Meng, Bin Peng, Donald Poskitt, Wei Wei, Joakim Weill for helpful discussions. We thank the Joakim Weill, David Van Dijcke, Google Mobility, MIT Election Lab, The New York Times, Nielsen NLTV, PlaceIQ, and SafeGraph for sharing the data. Difang gratefully acknowledges financial support by the Australian Government Research Training Program (RTP). Any mistakes, errors, or misinterpretations are my alone.

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1 Introduction

In response to the outbreak of the highly contagious COVID-19 disease, the governments worldwide have issued unprecedented restrictive policies. China enacted the total lockdown of Wuhan city on January 23th, 2020, and subsequently adopted a national shutdown (see Chinazzi et al., 2020; Fang et al., 2020; Tian et al., 2020). In other countries, the policies are more decentralized. For example, in the United States, the federal government issued social distancing recommendations and delegated health authority within states and counties to determine the mitigation procedures, leading to spatial and temporal variation in the implementation of restrictive policies.

In this paper, we identify whether and to what extent the social distancing policy reduces the spread of virus. We also investigate the possible heterogeneous effects for individuals with distinct incomes, races, education levels, and political beliefs. These questions have profound implications for policy-making. Individuals with lower income have worse health outcomes before the pandemic and are less capable of handling the economic and health shocks after the COVID-19 outbreak (Aizer and Currie, 2014; Weill et al., 2020). If there is substantial heterogeneity, health authority needs to implement the policy that is most suitable for individuals who belong to each group to achieve a more significant decline in the incidence of cases and fatalities.

We model the infection transmission using the factor model with interactive fixed effects to capture both observed and unobserved time-varying individual heterogeneity. We use the population mobility measures as covariates to measure the observed daily individual's social distancing response. We also use the interactive fixed effects to measure the unobserved common factors that drive the infection distribution to change over time. These factors include the individual's awareness that influenced by daily media reports and day-to-day changes in public expectations (Fowler et al., 2020; Kucharski et al., 2020). Based on our model, we derive the econometric specifications for both average and individual treatment effects to study the effectiveness of social distancing policy. Our approach alleviates the endogeneity concern and provides the explicit identification for the relationship between social distancing policy and the reductions in daily infection cases.

We document that our model measures the cross-sectional and time-series variation of COVID-19 infections across all United States counties. We further present evidence on the treatment effects of social distancing at the county level. The average treatment effects across

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counties are effective in reducing the log level of daily infection cases by 12.38%. The effects are disparate: counties with higher income, higher education, more Asian/White people, and more democratic voters experience a larger reduction in the daily infection that is causally related to social distancing.

This paper contributes to several strands of the literature. A growing strand of research in biostatistics, epidemiology, and economics are engaged in the modeling of the COVID-19 pandemic. Liu et al. (2020) focus on the Bayesian estimation in dynamic panel data models to forecast the daily infections for a panel of countries. Fernández-Villaverde and Jones (2020) investigate the forecasts based on the SIR model. Murray (2020) study the estimates for COVID-19 using the data from hospital demands and deaths. Our model complements this strand of literature by combining observed daily population movement and unobserved interactive fixed effects to explain the relative frequency and geographical distribution of the infection cases accurately.

Another strand of literature focus on the effectiveness of social distancing on COVID-19 infection. Recent works adopt difference-in-difference approach or instrument variable approach to reduce the endogeneity concern as social distancing are endogenously implemented by health authority (see Dave et al., 2020b; Fang et al., 2020; Fan et al., 2020; Friedson et al., 2020; Gupta et al., 2020; Lauer et al., 2020; Qiu et al., 2020; Simonov et al., 2020, among others). We contribute to this strand of literature by adopting the factor approach which accounts for the observed and unobserved factors that could affect the infection distribution over time and cross-sectional and consistently estimates the treatment effects of social distancing across counties in the United States (see Bai and Ng, 2020).

Our paper provides useful guidance on policy-making. Some papers show that the compliance with social distancing in the United States is dependent on political partisanship and media viewership (see Baker et al., 2020; Barrios and Hochberg, 2020; Gupta et al., 2020; Painter and Qiu, 2020; Simonov et al., 2020, for example). We further contribute to this strand of literature by showing that the individual attributes, including income, race, education, and political beliefs, are related to the variation in social distancing effectiveness and highlighting the importance for the policymakers to take this heterogeneity into account in future policy-making.

The remainder of the paper is structured as follows. Section 2 introduces our model. Section 3 describes the data. Section 4 presents the empirical results. Section 5 discusses the policy implication. Section 6 concludes. We show the proofs in the Appendix and additional results in the Online Appendix.

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2 The Model

Let $Y_{it}(1)$ and $Y_{it}(0)$ denote the county i's daily infection case in day t with and without social distancing policy, respectively. The policy intervention effect to county i at time t is

$$\theta_{it} = Y_{it}(1) - Y_{it}(0)$$

As we do not simultaneously observe $Y_{it}(1)$ and $Y_{it}(0)$, the observed data can be shown as

$$Y_{it} = D_{it}Y_{it}(1) + (1 - D_{it})Y_{it}(0) \tag{1}$$

where D_{it} is the dummy variable that equals to one if the county i is under social distancing (treatment) at time t and zero otherwise.

We assume that a vector of common latent factors F_t drives the infection distribution of all counties to change over time. In our case, these factors can be the daily availability of testing, the change in government policies, and individual beliefs influenced by the social media (Fowler et al., 2020; Kucharski et al., 2020). We also include a vector of observed covariates X_{it} of population mobility measures that are epidemiologically informative to characterize the distribution of infection cases both nation-wide and state-wide (see Baud et al., 2020; Chinazzi et al., 2020; Fang et al., 2020; Kraemer et al., 2020, for examples).

We denote the treated group with $\mathcal{T}$ and the control group with $\mathcal{C}$ and index the variable for treatment group by 1 and for the control group by 0. The group size for treated group and control group are N_1 and N_0 with the total group size $N = N_1 + N_0$. The pre-treatment period for unit i in treated group $\mathcal{T}$ is $T_{0,i}$. As the $T_{0,i}$ is differnt across i, we denote $T_0 = \min_{i \in \mathcal{T}} T_{0,i}$ and $T_1 = T - T_0$ where T is the total time observations.

For county i in treatment group $\mathcal{T}$, social distancing policy is adopted starting from period $T_{0,i} + 1$. We model the daily infection cases as

$$Y_{it} = \begin{cases} X_{it}'\beta + \Lambda_i' F_t + e_{it}, & i \in \mathcal{T}, \quad t = 1, \ldots, T_{0,i} \\ \theta_{it} + X_{it}'\beta + \Lambda_i' F_t + e_{it}, & i \in \mathcal{T}, \quad t = T_{0,i} + 1, \ldots, T \end{cases} \tag{2}$$

where θ_{it} is the treatment effects that capture the impact of social distancing on daily infection cases for county i at day t, β is the vector of coefficient for observed covariates X_{it}, F_t is the latent common factor, Λ_i is the factor loading vector, $C_{it} = \Lambda_i' F_t$ is interactive fixed effect, and

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e_{it} is the error term.

For county i in control group $\mathcal{C}$, as the social distancing is not enacted, all such counties do not have such policy intervention and we model the daily infection cases as

$$Y_{it} = X_{it}'\beta + \Lambda_i' F_t + e_{it}, \quad i \in \mathcal{C}, \quad t = 1, \dots, T \tag{3}$$

Combine (1) to (3), we have the model for observed Y_{it}:

$$Y_{it} = \theta_{it} D_{it} + X_{it}'\beta + \Lambda_i' F_t + e_{it}. \tag{4}$$

We can represent the observed data of Y as

$$Y = \begin{bmatrix} Y(0)_{T_0 \times N_0} & Y(0)_{T_0 \times N_1} \\ Y(0)_{T_1 \times N_0} & Y(1)_{T_1 \times N_1} \end{bmatrix}$$

As $Y_{it}(0)$ is not observable for county $i \in \mathcal{T}$ and $t \geq T_{0,i} + 1$, we can represent the observed data of $Y(0)$ as

$$Y(0) = \begin{bmatrix} Y(0)_{T_0 \times N_0} & Y(0)_{T_0 \times N_1} \\ Y(0)_{T_1 \times N_0} & \textsc{Miss} \end{bmatrix}$$

Following the terminlogy in Bai and Ng (2020), we denote the block matrix $Y(0)_{T_0 \times N_0}$ with Bal, the block matrix $[Y(0)_{T_0 \times N_0}\ Y(0)_{T_1 \times N_0}]'$ with Tall, the block matrix $[Y(0)_{T_0 \times N_0}\ Y(0)_{T_0 \times N_1}]$ with Wide, and block matrix Miss. Therefore, we need to estimate the counterfactual distribution for Miss block.[1] We build the following algorithm to estimate both average treatment effects and individual treatment effects that allow the pre-treatment period $T_{0,i}$ for each county $i \in \mathcal{T}$ to be different.

Algorithm 1. *We introduce the following algorithm to calculate the average treatment effects and individual treatment effects:*

1. *We estimate the coefficient of β using the observations in the* Tall *block matrix with ordinary least square method. We then estimate the residual R_{it} for the whole observations where $R_{it} \equiv Y_{it} - X_{it}'\widehat{\beta}$.*

2. *We estimate the latent factor F using the observations in the* Tall *block matrix of residual R_{Tall} with asymptotic principal components method.*

[1] Bai and Ng (2020) pioneer the factor imputation procedure that estimates the factors from a Tall block and the factor loading from a Wide block to impute counterfactual values in a panel data framework under the assumption of strong factor structure.

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3. *We estimate the factor loadings Λ using two step approach:*

   (a) *For $i = 1, \ldots, N$, create the new matrix $\widetilde{F}_i = [\mathbb{I}_i \ F_i]$, where F_i is the submatrix of F with the row from $1 : T_{0,i}$ and $\mathbb{I}_i$ is $T_{0,i} \times 1$ matrix of one.*

   (b) *For $i = 1, \ldots, N$, estimate the $\widetilde{\Lambda}_i = (\widetilde{F}_i' \widetilde{F}_i)^{-1} \widetilde{F}_i' R_{it}$.*

4. *We estimate the missing value with $\widehat{Y}_{it}(0) = X_{it}'\widehat{\beta} + \widetilde{C}_{it}$, where $\widetilde{C} = [\mathbb{I}_T \ \widetilde{F}] \times \widetilde{\Lambda}'$, $\mathbb{I}_T$ is $T \times 1$ matrix of one.*

5. *We compute the individual treatment effects $\widehat{\theta}_{it} = Y_{it}(1) - \widehat{Y}_{it}(0)$, $i \in \mathcal{T}$, $t = T_{0,i}+1, \ldots, T$.*

6. *We compute the average treatment effects on treated $\widehat{\theta}_t = \frac{1}{N_1} \sum_{i \in \mathcal{T}} \widehat{\theta}_{it}$.*

7. *We compute the average treatment effects on treated for the individuals in group j, $\widehat{\theta}_{j,t} = \frac{1}{N_j} \sum_{i \in \mathcal{J}} \widehat{\theta}_{it}$, where $i \in \mathcal{J}$, and N_j is the sample size of group j.*

Under the notations and regular conditions in Appendix, we establish the distribution results for the average treatment effects $\widehat{\theta}_t$.

Proposition 1. *Let the Assumption 1–3 hold. As $N_0, T_0, N_1 \to \infty$, we have:*

1. *The average treatment effects on treated $\widehat{\theta}_t$ is asymptotically normal:*

$$\delta_{N_0,N_1} \left(\frac{\widehat{\theta}_t - \theta_t}{\sqrt{\mathbb{V}_{\theta,t}}} \right) \xrightarrow{d} N(0,1).$$

2. *The asymptotic variance $\widehat{\sigma}_{e,t}^2$ can be consistently estimated by:*

$$\widehat{\sigma}_{e,t}^2 = \widehat{\mathbb{V}}_{\theta,t} / \delta_{N_0,N_1}.$$

We further consider the treatment effects $\widehat{\theta}_{j,t}$ for a group of j that belongs to the treated group $\mathcal{T}$.

Proposition 2. *Let the Assumption 1–4 hold. As $N_0, T_0, N_1 \to \infty$, we have:*

1. *The heterogenous treatment effects on group j, $\widehat{\theta}_{j,t}$ is asymptotically normal:*

$$\delta_{N_0,N_1} \left(\frac{\widehat{\theta}_{j,t} - \theta_{j,t}}{\sqrt{\mathbb{V}_{\theta,j,t}}} \right) \xrightarrow{d} N(0,1).$$

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2. The asymptotic variance $\widehat{\sigma}^2_{j,t}$ can be consistently estimated by:

$$\widehat{\sigma}^2_{j,t} = \widehat{\mathbb{V}}_{\theta,j,t}/\delta_{N_0,N_1}.$$

Social distancing are endogenously enacted by health authority, and recent works on the causal effects of social distancing policy adopted difference-in-difference approach (see Dave et al., 2020b; Fang et al., 2020; Fan et al., 2020; Friedson et al., 2020; Gupta et al., 2020; Lauer et al., 2020) or instrument variable approach (Qiu et al., 2020; Simonov et al., 2020, among others) to alleviate the concern of reverse causality, voluntary precautions, anticipation effects, and spillover effects (see Goodman-Bacon and Marcus, 2020, for detailed explanation).

Although these studies confirm the effectiveness of social distancing, some observed and unobserved factors may confound this relationship. For example, the enaction of social distancing policy in local counties is closely related to the national recommendations including travel restriction and gathering restrictions. There might also exist a spurious correlation between local factors (such as the date of onset of the disease or the health system) and the timing of stay-at-home orders. We provide an alternative approach that is flexible in taking into account the factors that could influence the virus transmission over time and cross counties and is also robust in the possible endogeneity issue (Athey et al., 2017; Bai and Ng, 2020). Our factor model approach consistently estimates the average and heterogeneous treatment effects and identifies the causal relationship between social distancing and the reductions in COVID-19 infection.

3 Data

3.1 Social Distancing Policies

There are five social distancing policies including the gathering restrictions, restaurant restrictions, school closures, non-essential business closures, and stay-at-home orders. Local governments typically apply several measures cumulatively to fight against the pandemic. To avoid the complication in these packaged policies and the variation in policy timing (Goodman-Bacon and Marcus, 2020), we focus on the most restrictive one: stay-at-home orders.[2]

Throughout our analysis, we restrict our sample period to begin from January 20 to April 20, 2020, as many states reopened the economy starting from April 20. We collect the date

[2] As shown in Adolph et al. (2020), among all five social distancing policies, only the stay-at-home orders have significant effects on individual's response (measured by daily movement), we confirm this with the event study in Online Appendix.

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and time of the county-level social distance policies from local newspapers. During our sample period, California was the first state to enact the stay-at-home order on March 19, 2020, and 42 out of 55 states adopted stay-at-home orders by April 20. For each county, we recorded the earliest date that social distance policies were enacted. We create social distancing policy index $D_{i,t}$ that equals to one if the stay-at-home order is in effect at county i at day t and zero otherwise.[3]

3.2 Variables

Our sample covers all 3,148 counties across all of the United States. We obtain data on the county-level daily new infection cases from The New York Times as dependent variable. Social distancing is likely to decrease population interaction and increase virus awareness after the introduction of social distancing intervention in mid-March (Cui et al., 2020; Jia et al., 2020). Therefore we use the daily change of population mobility data as explanatory variables from SafeGraph and PlaceIQ.[4] Following Weill et al. (2020), we use the data from SafeGraph to calculate the "completely home ratio" and "median distance traveled", and the data from PlaceIQ to show the "device exposure index".[5]

4 Empirical Results

As documented by the Susceptible-Infectious-Recovered model (see Acemoglu et al., 2020; Fan et al., 2020), social distancing influences the infection distribution both directly and indirectly. On the one hand, it can decrease the physical interaction between infected and susceptible people. On the other hand, it can affect virus transmission indirectly by increasing the mental awareness of the virus for all populations. Our model takes both mechanisms into account and provides a useful tool to infer the incidence of new infections for various counties and help

[3]There is one notable exception of Texas, which is widely exploited as a large scale nature experiment (Dave et al., 2020a). In Texas, about two-thirds of densely populated counties adopted the stay-at-home orders in mid-March while the state-wide stay-at-home orders are enacted until April 2, 2020. We studythe treatment effects for the early and late adopting counties in Online Appendix.

[4]We use the change of population mobility data as explanatory variables for two reasons, the first one is level data contain too much noise, the second one is level data is nonstationary, by taking the first order difference, the variable is stationary and more informative (We thank Victor Couture and Bin Peng for pointing this out).

[5]The SafeGraph data are available at the census block group level and provide the best spatial coverage with almost all counties represented. The PlaceIQ data are complied by Couture et al. (2020) and offer the distinct device exposure indices in both the state-level and country-level, including income, education, and race details device owners. The index calculates how many different smartphones visited any of the places that this device visited today for a given state/county. The Google Mobility data are available at the county level and not consistently available for all days and counties due to anonymity constraints. Therefore we exclude the data in our analysis as there are missing values in January and February.

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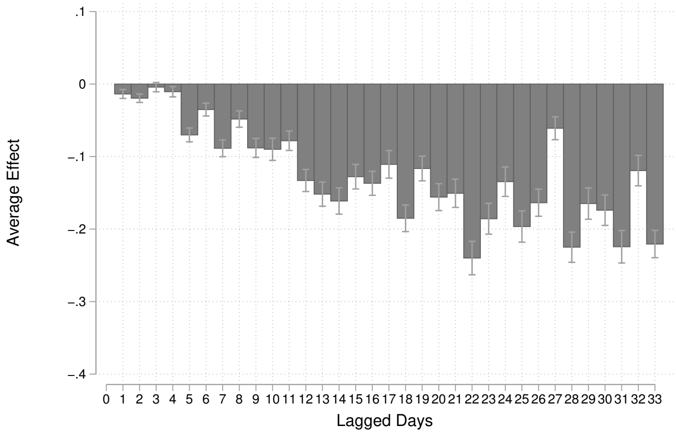

Figure 1: Average treatment effects of social distancing (in percentage) . This figure presents the effects of the day-lagged county-level social distancing on the number of daily infection cases in log level. The error bars plot the 95% confidence interval.

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policy-makers make statistically accurate assessments for the future growth and spread pattern of COVID-19.

4.1 Average Treatment Effects of Social Distancing

We study the average treatment effects of social distancing using county-level data. The average treatment effects for log level of daily infection cases are 12.38% (95% CI: 11.07% to 13.69%) during our data sample period from January 21th to April 20th.

Figure 1 presents the effect of the day-lagged county-level social distancing policy on the number of daily infection cases with 95% confidence intervals. Social distancing policy starts to reduce daily infection cases from the fourth day since its enactment, consistent with the virus' incubation period of averages 4-5 days (Lai et al., 2020). It is associated with 8.85% (95% CI: 7.70% to 10.01%) reduction in daily cases after seven days, 16.12% (95% CI: 14.31% to 17.94%) reduction in daily cases after fourteen days, 15.06% (95% CI: 13.11% to 17.01%) reduction in daily cases after twenty-one days, and 22.49% (95% CI: 20.41% to 24.58%) reduction in daily cases after twenty-eight days.

4.2 Heterogeneous Treatment Effects of Social Distancing

In this section, we investigate the possible heterogeneity in social distancing effectiveness based on the individual's character including income, race, education, and political beliefs. The policy-makers need to identify whether and to what degree different individuals benefit from the social distancing policy and to determine future policy equal beneficial to all lives.

4.2.1 Income heterogeneity

We study the social distancing treatment effects for the counties with different income levels. As the high-income households have a better pre-existing health condition and are less affected by the economic and health shocks (Aizer and Currie, 2014), the household's social distancing response to the emergency declaration is very heterogeneous in income (Weill et al., 2020). Therefore, we hypothesis that there exist income heterogeneity in the treatment effects of social distancing.

We use the data from SafeGraph to identify the income level for the household in our sample and aggregate the county-level income and divide all counties into four income quartiles. We show the results in Figure 2. There is a clear pattern differentiated by income group. For the bottom quartile, the social distancing policy is associated with 3.29% (95% CI: 1.19% to 5.39%) reduction in daily cases after seven days, 7.41% (95% CI: 5.08% to 9.74%) reduction in daily cases after fourteen days, 14.27% (95% CI: 11.52% to 17.01%) reduction in daily cases after twenty-one days, and 16.27% (95% CI: 13.37% to 19.17%) reduction in daily cases after twenty-eight days. For the top quartile, it is associated with 17.62% (95% CI: 15.53% to 19.72%) reduction in daily cases after seven days, 32.4% (95% CI: 30.01% to 34.75%) reduction in daily cases after fourteen days, 33.09% (95% CI: 30.35% to 35.84%) reduction in daily cases after twenty-one days, and 48.63% (95% CI: 45.73% to 51.53%) reduction in daily cases after twenty-eight days. Overall, the effects range from the weakest for the bottom quartile to the strongest for the top quartile and the difference is persistent for the all lagged days we considered.

4.2.2 Race heterogeneity

In this section, we study the social distancing treatment effects for individuals with different races including the Asian, Black, Hispanic, White. Using the data from Census of Population, we define a county with certain race majority if more than 30% of the county population belong to this race.

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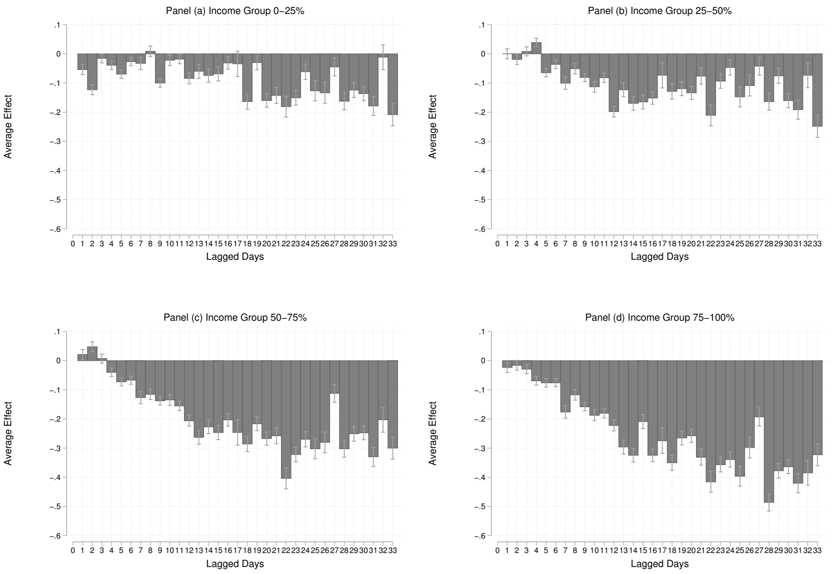

Figure 2: Average treatment effects of social distancing (in percentage) by income group. These figures present the effects of the day-lagged county-level social distancing on the number of daily infection cases in log level. Panel (a) is the results for counties in 0-25% income group, Panel (b) is the results for counties in 25%–50% income group, Panel (c) is the results for counties in 50%–75% income group, and Panel (d) is the results for counties in 75%–100% income group. The error bars plot the 95% confidence interval.

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We present the results in Figure 3. There is a large and persistent difference in the policy effects for counties with difference race majority. The effects on both White and Asian majority counties are significantly larger than those on Black and Hispanic, raising the concern for more support on these communities. For the Black majority counties, the social distancing policy is associated with 7.47% (95% CI: 5.38% to 9.57%) reduction in daily cases after seven days, 10.26% (95% CI: 7.94% to 12.59%) reduction in daily cases after fourteen days, 9.78% (95% CI: 7.03% to 12.53%) reduction in daily cases after twenty-one days, and 13.46% (95% CI: 10.55% to 16.36%) reduction in daily cases after twenty-eight days. For the White majority counties, it is associated with 13.72% (95% CI: 11.63% to 15.82%) reduction in daily cases after seven days, 28.50% (95% CI: 26.18% to 30.83%) reduction in daily cases after fourteen days, 27.75% (95% CI: 25.00% to 30.50%) reduction in daily cases after twenty-one days, and 32.13% (95% CI: 29.23% to 35.03%) reduction in daily cases after twenty-eight days.

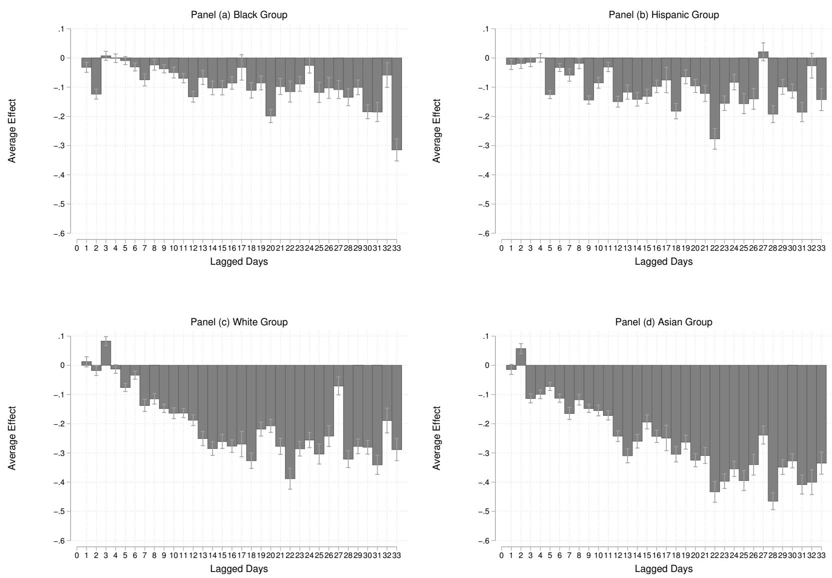

Figure 3: Average treatment effects of social distancing (in percentage) by race. These figures present the effects of the day-lagged county-level social distancing on the number of daily infection cases in log level. Panel (a) is the results for counties with Black group, Panel (b) is the results for counties with Hispanic group, Panel (c) is the results for counties with White group, and Panel (d) is the results for counties with Asian group. The definition of race group is defined in the main context. The error bars plot the 95% confidence interval.

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4.2.3 Education heterogeneity

We study the social distancing treatment effects for individuals with various education level. Following Couture et al. (2020), we calculate the education level based on the college share within each county and partition all counties into four education quartiles.

We present the results in Figure 4. We find that the difference in the effects of social distancing by education quartiles is large. For an individual in the lowest education quartile, the average reduction in daily infection is about one-third of that for an individual with the highest education. For the bottom education quartile, the social distancing policy is associated with 7.55% (95% CI: 5.45% to 9.65%) reduction in daily cases after seven days, 9.98 (95% CI: 7.66% to 12.31%) reduction in daily cases after fourteen days, 8.90% (95% CI: 6.15% to 11.65%) reduction in daily cases after twenty-one days, and 12.53 (95% CI: 9.63% to 15.43%) reduction in daily cases after twenty-eight days. For the top education quartile, it is associated with 17.63% (95% CI: 15.53% to 19.72%) reduction in daily cases after seven days, 32.42% (95% CI: 30.10% to 34.75%) reduction in daily cases after fourteen days, 33.09% (95% CI: 30.35% to 35.84%) reduction in daily cases after twenty-one days, and 48.63% (95% CI: 45.73% to 51.54%) reduction in daily cases after twenty-eight days.

4.2.4 Political heterogeneity

Empirical evidence documents that counties with more Trump voters are less likely to enact social distancing policies (Painter and Qiu, 2020) and the political beliefs have a substantial impact on the effectiveness of county-level social distancing response (Adolph et al., 2020; Fowler et al., 2020). In this section, we investigate the political heterogeneity in the social distancing treatment effects.

We use the county-level presidential election returns in 2016 from MIT Election Lab as the measure for political heterogeneity of each county and present the results in Figure 5. The social distancing policy is larger in reducing the daily infection for democratic counties than republican ones. For the democratic counties, the social distancing policy is associated with 15.57% (95% CI: 13.48% to 17.67%) reduction in daily cases after seven days, 22.85% (95% CI: 20.52% to 25.18%) reduction in daily cases after fourteen days, 22.67% (95% CI: 19.93% to 25.42%) reduction in daily cases after twenty-one days, and 30.97% (95% CI: 28.07% to 33.87%) reduction in daily cases after twenty-eight days. For the republican counties, it is associated with 2.56% (95% CI: 0.46% to 4.66%) reduction in daily cases after seven days, 10.76% (95%

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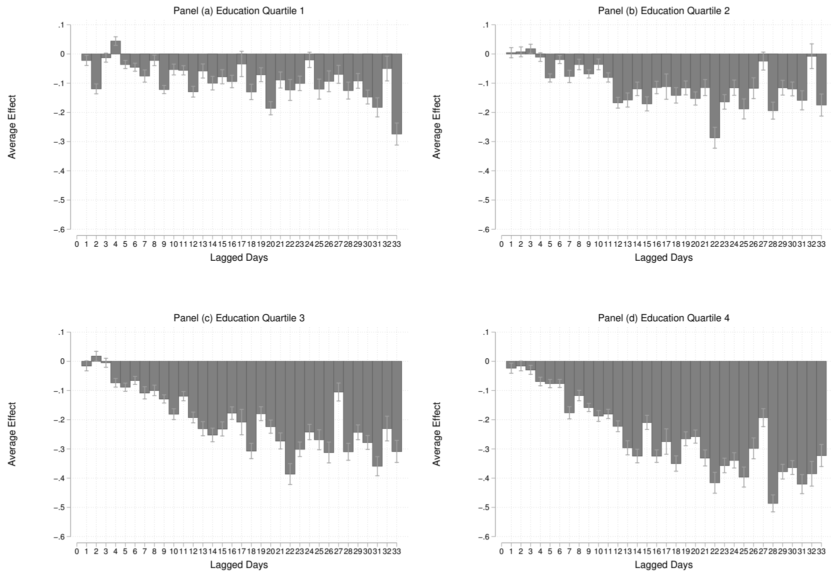

Figure 4: Average treatment effects of social distancing (in percentage) by education group. These figures present the effects of the day-lagged county-level social distancing on the number of daily infection cases in log level. Panel (a) is the results for counties in 0-25% education group, Panel (b) is the results for counties in 25%–50% education group, Panel (c) is the results for counties in 50%–75% education group, and Panel (d) is the results for counties in 75%–100% education group. The definition of education group is defined in the main context. The error bars plot the 95% confidence interval.

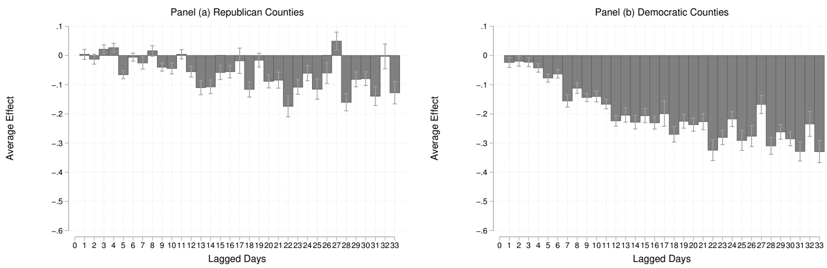

Figure 5: Average treatment effects of social distancing (in percentage) by political beliefs. These figures present the effects of the day-lagged county-level social distancing on the number of daily infection cases in log level. Panel (a) is the results for counties with more Republican voters, Panel (b) is the results for counties with more Democratic voters. The error bars plot the 95% confidence interval.

CI: 8.43% to 13.08%) reduction in daily cases after fourteen days, 8.46% (95% CI: 11.20% to 19.92%) reduction in daily cases after twenty-one days, and 16.05% (95% CI: 13.15% to 18.95%) reduction in daily cases after twenty-eight days.

5 Discussion

The COVID-19 disease triggered unprecedented social distancing worldwide to reduce the spread of these diseases, but the effectiveness of such policy is unclear. Our paper's results provide strong statistical support on its efficacy as the policy reduced the spread of COVID-19 by 12.38% in average daily infection and suggest that efforts to flatten the curve indeed reduced the virus growth rate both in spatial and temporal.

We also find evidence of social distancing policy heterogeneity on the reduction of virus infection. In particular, counties with more republican supporters experience a significantly more substantial reduction in infection than those with more democratic supporters. Moreover, individuals with less education and income appear to benefit less from the policy than more education and income counterparts. Our results also highlight the immediate attention on the social distancing policy for Black and Hispanic communities to archive a similar effect for White and Asian. However, it is also a theoretical and empirical challenge to unpack the specific mechanisms through which communities' characteristics are associated with the effectiveness of social distancing policy. These mechanisms involve various ingredients in decision-making under uncertainty, including the availability of information, how information affects the individual's risk preferences and behavior, and the impact of personal constraints on decision-making (Feld-

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man and Johnston, 2013; Deschênes et al., 2017). While establishing the causality relationship between an individual's characteristics and mechanisms is largely constrained by data availability, we take the first step by documenting the heterogeneity in the treatment effects of social distancing policy at the county-level of the United States and call for special care from health authority to different communities to mitigate the spread of the virus in greater magnitude.

6 Conclusion

In this paper, we study the effectiveness of social distancing. We use the factor imputation methodology to identify the treatment effects of social distancing policy across counties on reducing the daily infection cases of COVID-19 in the United States.

We apply our model to the daily infection across all counties in the United States and find that social distancing reduced the average daily infection cases by 12%. Furthermore, we find considerable heterogeneous effects of the social distancing policies for individuals with different income, race, education, and political beliefs. Given the sizable difference in the impact of the policies on reducing the spread of the virus, there is a significant benefit for the local government to consider a case-by-case social distancing policy with particular attention to lower-income, lower education, and Black and Hispanic communities. Our results also highlight the need for bipartisan support in social distancing policy to flatten the curve.

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A Assumptions

We denote some quantities before our assumption and proofs. For $i = 1, \dots, N$, $t = 1, \dots, T$, $\delta_{N_0,N_1} = \min\{\sqrt{N_0}, \sqrt{N_1}\}$, and $K = \dim(\beta)$,

$$\mathbb{V}_{\theta,t} = \frac{\delta^2_{N_0,N_1}}{N_0}\bar{\Lambda}'_{\mathcal{T}}\left(\frac{\Lambda'\Lambda}{N}\right)^{-1}\Gamma_t\left(\frac{\Lambda'\Lambda}{N}\right)^{-1}\bar{\Lambda}_{\mathcal{T}} + \frac{\delta^2_{N_0,N_1}}{N_1}\sigma^2_e.$$

$$\widehat{\mathbb{V}}_{\theta,t} = \frac{\delta^2_{N_0,N_1}}{N_0}\bar{\Lambda}'_{\mathcal{T}}\left(\frac{\widehat{\Lambda}'\widehat{\Lambda}}{N}\right)^{-1}\Gamma_t\left(\frac{\widehat{\Lambda}'\widehat{\Lambda}}{N}\right)^{-1}\bar{\Lambda}_{\mathcal{T}} + \frac{\delta^2_{N_0,N_1}}{N_1}\widehat{\sigma}^2_e.$$

$$\mathbb{V}_{\theta,j,t} = \frac{\delta^2_{N_0,N_1}}{T_0}F'_t\left(\frac{F'F}{T}\right)^{-1}\Phi_j\left(\frac{F'F}{T}\right)^{-1}F_t + \frac{\delta^2_{N_0,N_1}}{N_0}\bar{\Lambda}'_j\left(\frac{\Lambda'\Lambda}{N}\right)^{-1}\Gamma_t\left(\frac{\Lambda'\Lambda}{N}\right)^{-1}\bar{\Lambda}_j + \delta^2_{N_0,N_1}\sigma^2_{e,t}.$$

$$\widehat{\mathbb{V}}_{\theta,j,t} = \frac{\delta^2_{N_0,N_1}}{T_0}F'_t\left(\frac{F'F}{T}\right)^{-1}\Phi_j\left(\frac{F'F}{T}\right)^{-1}F_t + \frac{\delta^2_{N_0,N_1}}{N_0}\bar{\Lambda}'_j\left(\frac{\widehat{\Lambda}'\widehat{\Lambda}}{N}\right)^{-1}\Gamma_t\left(\frac{\widehat{\Lambda}'\widehat{\Lambda}}{N}\right)^{-1}\bar{\Lambda}_j + \delta^2_{N_0,N_1}\widehat{\sigma}^2_{e,t}.$$

$$\widehat{\sigma}^2_e = \frac{1}{TN_0 - r\,(T+N_0) + r^2 - K}\sum_{i\le N_0}\sum_{t=1}^{T}\widehat{e}^2_{it}.$$

$$\widehat{\sigma}^2_{e,t} = \frac{1}{N-1}\sum_{i\ne j}^{N-1}\widehat{e}^2_{it}.$$

Assumption 1. *There exists a constant M such that*

1. *(Factors)*
   - *(a)* $E\left\|F^0_t\right\|^4 \le M \le \infty$,
   - *(b)* $T^{-1}\sum_{t=1}^{T}F^0_tF^{0\prime}_t \xrightarrow{p} \Sigma_F$, *where Σ_F is a positive definite matrix.*
2. *(Factor Loadings)*
   - *(a)* $\left\|\Lambda^0_i\right\| \le M$,
   - *(b)* $N^{-1}\sum_{i=1}^{N}\Lambda^{0\prime}_i\Lambda^0_i \xrightarrow{p} \Sigma_\Lambda$, *where Σ_Λ is a positive definite matrix,*
   - *(c) The eigenvalues of $\Sigma_F\Sigma_\Lambda$ are distinct.*
3. *(Error terms):*
   - *(a)* $E\left(e_{it}\right) = 0, E\left|e_{it}\right|^8 \le M$;
   - *(b)* $E\left(N^{-1}\sum_{i=1}^{N}e_{it}e_{is}\right) = \gamma_N(s,t)$, *where* $\sum_{t=1}^{T}\left|\gamma_N(s,t)\right| \le M, \forall s$;
   - *(c)* $E\left(e_{it}e_{jt}\right) = \tau_{ij,t}$, *where* $\left|\tau_{ij,t}\right| \le \left|\tau_{ij}\right|$ *for some* τ_{ij}, *and* $\sum_{j=1}^{N}\left|\tau_{ij}\right| \le M, \forall i$;
   - *(d)* $E\left(e_{it}e_{js}\right) = \tau_{ij,st}$ *and* $(NT)^{-1}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{t=1}^{T}\sum_{s=1}^{T}\left|\tau_{ij,ts}\right| < M$,

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(e) *For every* (t,s), $E\left(N^{-1/2}\sum_{i=1}^{N}\left[e_{is}e_{it}-E\left(e_{is}e_{it}\right)\right]^4\right)\leq M$,

(f) $E\left(N^{-1}\sum_{i=1}^{N}\left\|\frac{1}{\sqrt{T}}\sum_{t=1}^{T}F_t^0 e_{it}\right\|^2\right)\leq M$.

4. *(Central Limit Theorems)*

   (a) *For each* i, *as* $N\to\infty$, $N^{-1/2}\sum_{i=1}^{N}\Lambda_i^0 e_{it}\xrightarrow{d}N\left(0,\Gamma_t\right)$,

   (b) *For each* t, *as* $T\to\infty$, $T^{-1/2}\sum_{t=1}^{T}F_t^0 e_{it}\xrightarrow{d}N\left(0,\Phi_i\right)$.

Assumption 2. *Order conditions:*

1. *The conditions* $T\times N_0>r(T+N_0)$ *and* $N\times T_0>r(N+T_0)$ *are satisfied for any* N,T,N_0,T_0,
2. $\frac{\sqrt{N}}{\min\{N_0,T_0\}}\to 0$ *as* $N_0,N\to\infty$ *and* $T_0,T\to\infty$,
3. $\frac{\sqrt{T}}{\min\{N_0,T_0\}}\to 0$ *as* $N_0,N\to\infty$ *and* $T_0,T\to\infty$.

Assumption 3. *Factors and factor loadings:*

1. $\frac{\Lambda_0^{0\prime}\Lambda_0^0}{N_0}\xrightarrow{p}\Sigma_{\Lambda,0}>0$, $\frac{\Lambda_m^{0\prime}\Lambda_m^0}{N_m}\xrightarrow{p}\Sigma_{\Lambda,m}>0$, $\frac{1}{\sqrt{N_0}}\sum_{i=1}^{N_0}\Lambda_i^0 e_{it}\xrightarrow{d}N\left(0,\Gamma_{0t}\right)$;
2. $\frac{F_0^{0\prime}F_0^0}{T_0}\xrightarrow{p}\Sigma_{F,0}>0$, $\frac{F_m^{0\prime}F_m^0}{T_m}\xrightarrow{p}\Sigma_{F,m}>0$, $\frac{1}{\sqrt{T_0}}\sum_{s=1}^{T_0}F_s^0 e_{is}\xrightarrow{d}N\left(0,\Phi_{0i}\right)$.

Assumption 4. *Error terms:* $e_{jt}\sim\mathcal{N}(0,\sigma_{e,t}^2)$.

B Proofs

B.1 Proofs of Proposition 1

The average treatment effects on treated is defined as:

$$\theta_t=\frac{1}{N_1}\left[\sum_{i\in\mathcal{T}}Y_{it}(1)-Y_{it}(0)\right], \tag{5}$$

It follows that

$$\begin{aligned} Y_{it}(1)-\widehat{Y}_{it}(0)&=\theta_{it}+X_{it}'(\beta-\widehat{\beta})+C_{it}-\widehat{C}_{it}+e_{it},\\ Y_{it}(0)-\widehat{Y}_{it}(0)&=X_{it}'(\beta-\widehat{\beta})+C_{it}-\widehat{C}_{it}+e_{it}. \end{aligned} \tag{6}$$

Combine (5) and (6), we have

$$\widehat{\theta}_t-\theta_t=\frac{1}{N_1}\sum_{i\in\mathcal{T}}X_{it}'(\beta-\widehat{\beta})+\frac{1}{N_1}\sum_{i\in\mathcal{T}}\left(C_{it}-\widehat{C}_{it}\right)+\frac{1}{N_1}\sum_{i\in\mathcal{T}}e_{it}=A_1+A_2+A_3.$$

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By Assumption 1, we have

$$A_3 = \frac{1}{\sqrt{N_1}} \sum_{i \in \mathcal{T}} e_{it} = O_p(1).$$

By Assumption 2, β is homogeneous across i and t, we apply the Theorem 1 in Bai (2009),

$$A_1 = \widehat{\beta} - \beta = O_p\left(\frac{1}{\sqrt{T_0 N_0}}\right).$$

Based on our algorithm, we have

$$\begin{aligned}
A_2 =& \frac{1}{N_1} \sum_{i \in \mathcal{T}} \left(\widehat{C}_{it} - C_{it}\right) \\
=& F_t' \left(\frac{F'F}{T}\right)^{-1} \mathbf{B}_F \frac{1}{T_0 N_1} \left(\sum_{i \in \mathcal{T}} \sum_{s=1}^{T_{0,i}} F_s e_{is}\right) + \bar{\Lambda}_{\mathcal{T}} \left(\frac{\Lambda'\Lambda}{N}\right)^{-1} \mathbf{B}_\Lambda \frac{1}{N_0} \sum_{k=1}^{N_0} \Lambda_k e_{kt} + O_p\left(\delta_{N_0,T_0}^{-2}\right) \\
=& A_{21} + A_{22} + A_{23},
\end{aligned}$$

By Assumption 1,

$$A_{21} = O_p\left(\frac{1}{\sqrt{T_0 N_1}}\right).$$

We have:

$$\begin{aligned}
\widehat{\theta}_t - \theta_t =& - \bar{\Lambda}_{\mathcal{T}}' \left(\frac{\Lambda'\Lambda}{N}\right)^{-1} \mathbf{B}_\Lambda \frac{1}{N_0} \sum_{k=1}^{N_0} \Lambda_k e_{kt} + \frac{1}{N_1} \sum_{i \in \mathcal{T}} e_{it} \\
&+ O_p\left(\frac{1}{\sqrt{T_0 N_0}}\right) + O_p\left(\frac{1}{\sqrt{T_0 N_1}}\right) + O_p\left(\delta_{N_0,T_0}^{-2}\right).
\end{aligned}$$

$\square$

B.2 Proofs of Proposition 2

The individual treatment effects on treated for group j is defined as:

$$\begin{aligned}
\widehat{\theta}_{j,t} - \theta_{j,t} =& X_{jt}'(\beta - \widehat{\beta}) - F_t' \left(\frac{F'F}{T}\right)^{-1} \mathbf{B}_F \frac{1}{T_0} \left(\sum_{s=1}^{T_0} F_s e_{js}\right) \\
&- \Lambda_j' \left(\frac{\Lambda'\Lambda}{N}\right)^{-1} \mathbf{B}_\Lambda \frac{1}{N_0} \sum_{k=1}^{N_0} \Lambda_k e_{kt} + O_p\left(\delta_{N_0,T_0}^{-2}\right) + e_{jt} \\
=& B_1 + B_2 + B_3 + B_4 + B_5.
\end{aligned}$$

By Assumption 2,

$$B_1 = X_{jt}'(\beta - \widehat{\beta}) = O_p\left(\frac{1}{\sqrt{T_0 N_0}}\right).$$

Similar to the Proofs in Proposition 1,

$$B_2 = O(1/\sqrt{T_0}).$$

$$B_3 = O(1/\sqrt{N_0}).$$

By the Assumption 4, the distribution of $\widehat{\theta}_{jt} - \theta_{jt}$ is identically normal distribution and can be estimated by the residuals $\widehat{e}_{it} = Y_{it}(0) - \widehat{Y}_{it}(0)$.

We have:

$$\widehat{\theta}_{jt} - \theta_{jt} = O_p\left(\frac{1}{\sqrt{T_0 N_0}}\right) + O_p\left(\frac{1}{\sqrt{T_0}}\right) + O_p\left(\frac{1}{\sqrt{N_0}}\right) + O_p\left(\delta_{N_0,T_0}^{-2}\right) + e_{jt}.$$

$\square$

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Internet Appendix for

How Effective Is Social Distancing?

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(not for publication)

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IA.A. Additional Results

IA.A.1. News coverage heterogeneity

We study the effects of social distancing for individuals with different cable news viewership. The persuasive effect of media viewership during the COVID-19 can cause important economic and health implications (Ferguson et al., 2020). As documented by Simonov et al. (2020), the increase in Fox News cable viewership for households can lead to decrease in the propensity to stay at home. We, therefore, anticipate that a higher viewership of Fox News would lead to a lower treatment effects of social distancing. We use the data of Nielsen's monthly NLTV in 2015, which covered 30,517 zip codes across the United States and recorded the geographic details and channel positions for households. We calculate the Fox new coverage heterogeneity for each county and show the results in Figure IA.1. Consistent with the Simonov et al. (2020), the effects are relative smaller for residents with more FOX news exposure than those for residents with more CNN news exposure.

IA.A.2. The treatment effects for early and late adoption counties in Texas

We exploit treatment effects heterogeneity for Texas, in which about two-thirds of the state's counties adopted stay-at-home orders before March 26th, while the state-wide orders is adopted until April 2nd (See Figure IA.2 for details). We show the results in Figure IA.3. The early enacted counties experience sustainably more reduction in infection cases than the late enacted counties and this difference is persistent for all the lagged days we considered, showing a possible long-term treatment effect.

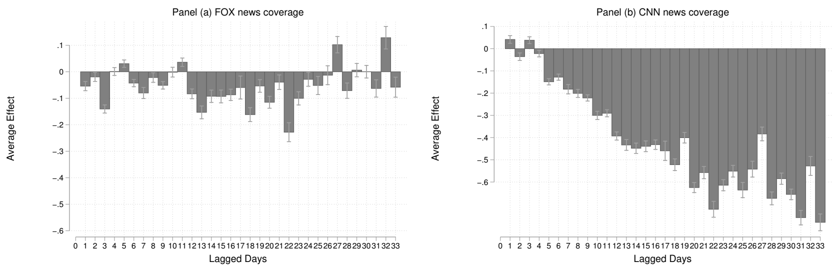

Fig. IA.1. Average treatment effects of social distancing (log level) by news coverage. These figures present the effects of the day-lagged county-level social distancing on the number of daily infection cases in log level. Panel (a) is the results for counties with more FOX news exposure, Panel (b) is the results for counties with more CNN news exposure. The definition of news exposure is given in the Appendix. The error bars plot the 95% confidence interval.

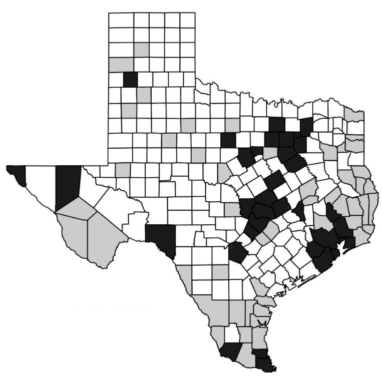

Fig. IA.2. Early and Late Adoption of Stay at Home Orders in Texas. The black shade are early enacted counties (before March 26th), the gray shade are late enacted counties (between March 27th and April 1st), and the others are with no enaction by April 2nd.

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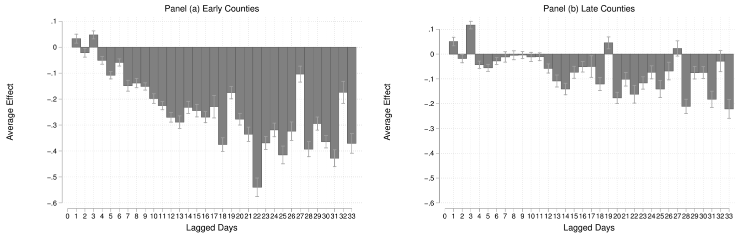

Fig. IA.3. Average treatment effects of social distancing (log level) by early and late adoption of social distancing. These figures present the effects of the day-lagged county-level social distancing on the number of daily infection cases in log level. Panel (a) is the results for counties with early enaction of social distancing, Panel (b) is the results for counties with late enaction of social distancing. The definition of enaction time is given in the Appendix. The error bars plot the 95% confidence interval.

IA.A.3. Augmented Dickey–Fuller tests of unit roots

We test for the existence of unit roots in the daily new cases. Figure IA.4 reports the Mackinnon approximated p-values from the augmented Dickey-Fuller tests on the county-level time series. As we can see from Figure IA.4, for the log levels of infection cases in most counties, we can reject the unit-root hypothesis with or without drift for the majority of counties time series. We interpret these results as follows: daily growths in infection cases are mostly stationary while the cumulative infection cases in log levels are mostly nonstationary series, although for some counties, the time series render stationary after controlling for a time trend. Based on such findings, we conduct our estimation with daily infection cases measured in log levels, consistent with the our assumption.

IA.A.4. Event study analysis

In this section, we study the impact of social distancing on the daily population mobility measures X_{it} using a simple event study framework:

$$X_{it} = \sum_{k=-21}^{k=21} D_{ik} + \boldsymbol{\theta} Z_{it} + \Lambda_i' F_t + e_{it}$$

where X_{it} is the mobility measure ("devious exposure") in county i on calendar day t. D_{ik} is a dummy variable that equals to one if the county i is k days away from the social distancing orders and zero otherwise, Z_{it} is the daily cumulative infection

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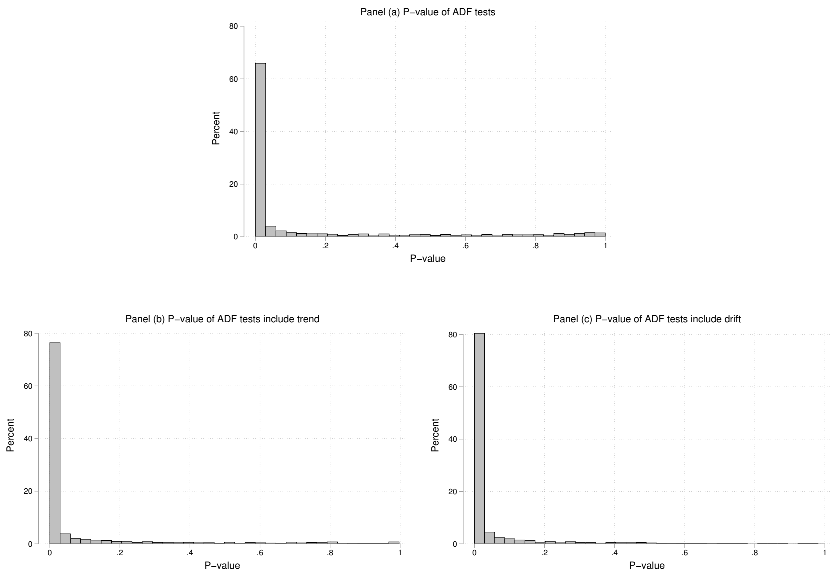

Fig. IA.4. Augmented Dickey–Fuller tests of unit roots for log new cases. These figures report the Mackinnon approximated p values of the ADF tests on new infection cases of all counties in United States in log level under various specifications. Panel (a) reports the test specification with no drift or trend, Panel (b) reports the test specification allows for a trend, Panel (c) reports the test specification allows for a drift. All tests employ one lags and the results are robust to various lag lengths. The sample size of each test is 93.

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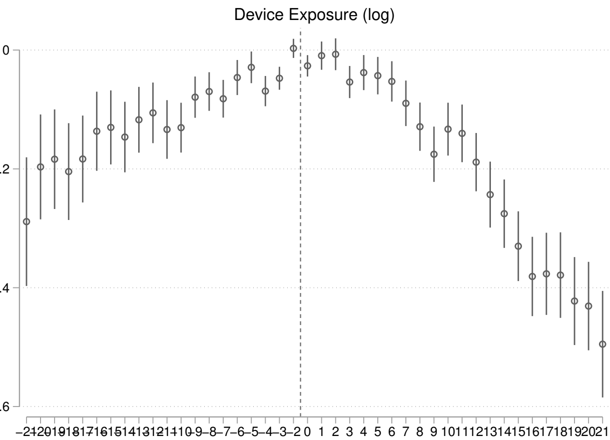

Fig. IA.5. Event study coefficient estimates of the change in population mobility measure (device exposure) relative to social distancing orders. Error bars represent 95% CIs. State declaration occurs at day $t = 0$.

cases, and $\Lambda_i' F_t$ is the interactive fixed effects (Bai, 2009). Since the enaction of social distancing orders, the daily population measure decline significantly and there is the strong correlation between the infection transmission and device exposure, confirming the observed covariates X_{it} as explanatory variable.

IA.B. Supplementary Details

We show the detailed statewide stay-at-home orders timeline in Table IA.1.

IA.B.1. Statewide Stay-at-Home Orders Timeline

Table IA.1
Statewide Stay-at-Home Orders Timeline. The data is collected from state government websites and is updated at April 20, 2020. The Governor of Pennsylvania began the stay-at-home orders for some counties on March 23, while applied the orders state-wide at April 1.

Statewide Stay-at-Home Orders Timeline		
State	Date Announced	Effective Date

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Alabama	April 3	April 4
Alaska	March 27	March 28
Arizona	March 30	March 31
Arkansas	-	-
California	March 19	March 19
Colorado	March 26	March 26
Connecticut	March 20	March 23
Delaware	March 22	March 24
District of Columbia	March 30	April 1
Florida	April 1	April 3
Georgia	April 2	April 3
Hawaii	March 23	March 25
Idaho	March 25	March 25
Illinois	March 20	March 21
Indiana	March 23	March 24
Iowa	-	-
Kansas	March 28	March 30
Kentucky	March 22	March 26
Louisiana	March 22	March 23
Maine	March 31	April 2
Maryland	March 30	March 30
Massachusetts	March 23	March 24
Michigan	March 23	March 24
Minnesota	March 25	March 27
Mississippi	March 31	April 3
Missouri	April 3	April 6
Montana	March 26	March 28
Nebraska	-	-
Nevada	April 1	April 1
New Hampshire	March 26	March 27

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New Jersey	March 20	March 21
New Mexico	March 23	March 24
New York	March 20	March 22
North Carolina	March 27	March 30
North Dakota	-	-
Ohio	March 22	March 23
Oklahoma	-	-
Oregon	March 23	March 23
Pennsylvania	March 23	April 1
Rhode Island	March 28	March 28
South Carolina	-	-
South Dakota	-	-
Tennessee	March 30	March 31
Texas	March 31	April 2
Utah	-	-
Vermont	March 24	March 24
Virginia	March 30	March 30
Washington	March 23	March 23
West Virginia	March 23	March 24
Wisconsin	March 24	March 25
Wyoming	-	-
Guam	-	-
Northern Mariana Islands	-	-
Puerto Rico	-	-
Virgin Islands	-	-

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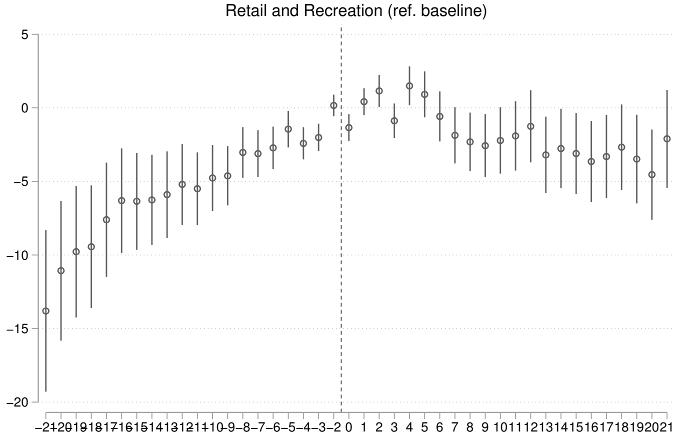

Fig. IA.6. Event study coefficient estimates of the change in population mobility measure (retail and recreation) relative to social distancing orders. Error bars represent 95% CIs. State declaration occurs at day $t = 0$.

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