COVID ECONOMICS
VETTED AND REAL-TIME PAPERS

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.

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Ethics

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

Economic Journal

Economics of Disasters and Climate Change

International Economic Review

Journal of Development Economics

Journal of Econometrics*

Journal of Economic Growth

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Journal of the European Economic Association*

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 Political Economy

Journal of Population Economics

Quarterly Journal of Economics*

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*.

Covid Economics
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Contents

Preserving job matches during the COVID-19 pandemic: Firm-level evidence on the role of government aid[1]

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We analyze the impact of the COVID-19 pandemic and government policies on firms' aid take-up, layoff and furlough decisions using newly collected survey data for 10,642 small, medium and large Danish firms. This is the first representative sample of firms reporting the pandemic's impact on their revenue and labor choices, showing a steep decline in revenue and a strong reported effect of labor aid take-up on lower job separations. First, we document that relative to a normal year, a quarter more firms have experienced revenue declines exceeding 35 percent. Second, we characterize the firms that took up aid and the type of aid package they chose – labor-based aid, fixed cost support or fiscal-based tax delays. Third, we compare their actual layoff and furlough decisions with reported counterfactual decisions in the absence of aid.

1   Introduction

A large part of the economic impact of the COVID-19 pandemic happens through firms and the labor-based decisions they make. Social distancing requires all but the most essential employees to either work from home or not go to work at all. Approximately 40% of workers in Denmark have jobs that allow them to work from home (Dingel and Neiman; 2020), a figure that is similar to other high-income European countries and the United States. Governments across the world have adopted emergency policies that focus on employment subsidy, cost subsidies and tax (VAT) delays. In particular, government support for furloughing employees of private firms has been a popular policy, as it facilitates public health by enabling social distancing and helps reduce firm costs.

We analyze the potential impact of three types of government aid on how firms manage their workforce in response to the pandemic collecting new survey data from 10,642 firms in Denmark. The Danish government has offered aid packages that share many similarities with the policy response in other countries, providing a lens to help understand the potential impact of government aid programs elsewhere. Our representative sample covers small, medium and large firms with 3 to 20,000 employees across all industries. We ask firms about pandemic-related disruptions to their normal operations, with a focus on alternative labour arrangements and government aid take-up. We also collect data on baseline firm employment, costs, and liquidity, as well as perceptions on the crisis and the recovery period.

We report three main findings. First, firms in Denmark, as elsewhere, were hit hard by the pandemic but there is significant heterogeneity of the impact. Second, we show that government programs in Denmark are likely to have had a strong and positive effect on labor retention. Third, we focus on the different types of aid policies and find that employment subsidies have the strongest correlation with the targeted labor choices, while we find a weaker correlation with cost subsidies. We find mixed evidence for tax subsidies with no clear impact on labor choices. Taken together, we interpret our results as strong evidence that targeted government policy can be successful in helping firms stay afloat and creating incentives for firms to retain their employees, thereby reducing the country's aggregate level of unemployment during the pandemic. Our estimates suggest that the aid policies in this context helped to reduce layoffs by approximately 81,000 jobs, and increased furloughs by 285,000.

To consider the impact of the COVID-19 pandemic on revenues, we compare reported changes in revenues with the distribution of changes in revenues in a normal year. We show that a quarter more firms in early 2020 are experiencing a negative revenue shock larger

than 35 percent (the threshold for aid eligibility), relative to 2016. We document that the impact was felt similarly across the firm size distribution, with the bulk of the variation attributed to industry differences. While at least half of the firms in almost all industries report decreases in revenue, some were hit much harder than others. As elsewhere in the world, industries in accommodation and food services were severely affected with an average of 73 percent decrease in revenues, as were arts/entertainment (69 percent decrease) and education (50 percent decrease). Retail and manufacturing were also badly affected, with nearly 70 percent of firms reporting decreases.[1] About 34 percent of firms report no impact or a positive impact on revenue. We find that firms that have taken up government support, however, tend to be those firms that report being in the highest levels of distress.

Our second main result is that there is a strong relationship between government aid and how firms manage their employment relationships. While we find that firms' primary response to the crisis has been to furlough a large share of their workforce, they report that without government support they would have expected to instead enact layoffs. The average firm taking aid furloughed 30 percent and laid off only 2 percent of workers. Without aid, they predict that they would have furloughed closer to 17 percent and laid off 25 percent of workers. We find a strong correlation between the magnitude of the revenue decrease and the share of workers that are furloughed and laid off, suggesting the policy was effective.

Our third main result focuses on the relative relationship between each of the three types of aid and firm choices. We find labor subsidies to have a strong and consistent relationship with more furloughs and fewer layoffs across specifications. Firms receiving cost aid tend to report fewer layoffs, though they only furlough more workers if the firm also takes labor aid. Firms taking on fiscal aid tend to be less worse-off, and the impact on labor outcomes is not as clear. We take this as evidence that firms taking on labor aid are primarily doing so for the intended reason of keeping workers on the payroll, though impact of other types of aid is less clear.

Related literature

Our study adds to the emerging rapid-response literature documenting the economic toll on firms and workers around the world. Bartik et al. (2020) surveyed approximately 5,800 small firms in the USA and found that almost half of the businesses temporarily closed with many cutting their labour forces by nearly half. Looking at start-ups, Sterk and Sedláček (2020) estimate a substantial loss in employment that is likely to extend beyond a decade, even under a "short slump" scenario. However, some firms are also doing better. For

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[1]The average decrease in revenue in manufacturing and retail was 22 percent and 25 percent, respectively

example, Albuquerque et al. (2020) show that firms with high social ratings and advertising expenditure outperform others with higher returns and lower volatility. Similarly, Amore et al. (2020) show that firms with controlling family shareholders are more resilient and have fared better during the pandemic. Our data is the first representative sample including the full firm size distribution and industry composition, allowing for an economy-wide evaluation of the impact of aid programs on labor decisions.

Another strand of the literature focuses on the labor market effects of the pandemic. Barrero et al. (2020) estimate 42 percent of recent layoffs will become permanent job losses. Del Rio-Chanona et al. (2020) estimate that the shocks could cause a 22 percent drop in GDP, 24 percent job losses and 17 percent reduction in total wage income. Coibion et al. (2020) use a household survey from Nielsen in the US to document job losses as large as 20 million by early April, far surpassing official unemployment numbers. Alstadsæter et al. (2020) use real-time register data to report that close to 90 percent of layoffs in Norway are temporary, though suggest that some smaller, less productive firms may be enacting permanent layoffs. Some studies have started to document the characteristics of workers most affected. Montenovo et al. (2020) show that communication-related workers and female Hispanics with large families aging from 20 to 24 are more prone to lose jobs. Hensvik et al. (2020) use data on vacancy postings to document that the pandemic is shifting job-seekers' search behavior, moving their searches towards "less hit" jobs. While administrative datasets can provide evidence on actual outcomes, our survey elicits predictions for the counterfactual labor outcomes in the absence of government aid, allowing for a new type of evaluation.

Finally, our work also relates to the literature on the impact of government policy on real economic outcomes, though work on the microeconomic implications of government policy has not yet been prolific. Cororaton and Rosen (2020) look at the impact of US Paycheck Protection Program, reporting that while half of public firms were eligible to apply, only 13% ultimately became borrowers. They suggest additional eligibility requirements may help in targeting most financially constrained firms. There have also been notable contributions on the macroeconomic literature, including Faria-e Castro (2020); Caballero and Simsek (2020); Balajee et al. (2020) and Elgin et al. (2020). We evaluate firms responses to a set of popular government policies.

2 Institutional setting

The government policy packages in Denmark are similar to packages offered by other countries in Europe and around the world. They have focused on providing subsidies for retaining

employees, propping up businesses with fixed cost grants and allowing for deferral in tax obligations. We briefly describe each in turn, and provide a summary table of government programs in selected countries in the Appendix. The costs of the aid programs in Denmark are estimated to be close to 100 billion Danish kroner (14.7 billion US$, 13.4 billion Euro) and are expected to allow 100,000 jobs to be retained (Finansministerium; 2020).[2] This figure is within the margin of error of our estimates.

Labor-related support: furlough support and sick leave

The Danish government is subsidizing 75 percent of salary costs, subject to a cap, for employees that otherwise would have been fired as a result of financial stress caused by COVID-19.[3] The requirement for a company to be eligible is that it otherwise would have fired a minimum of 30 percent of its employees and that employees spend five days of holiday before becoming eligible.[4] Furloughed employees are not allowed to work, such that those working from home are not eligible for this policy.

Other countries have enacted similar policies. In Germany, Italy and the UK the government subsidizes up to 80 percent of the salary costs for furloughed workers. The Dutch government subsidizes 90 percent of wages if firm revenue is expected to decrease by 20 percent, and in France the compensation level is 70 percent subject to a cap. Sweden does not subsidize furloughs, but subsidizes a reduction in hours worked to 80 percent of capacity with workers receiving 90 percent of their salary. The United States has an additional direct payment to citizens, beyond unemployment insurance.

Cost-related support: fixed costs and cancelled events

To help firms survive and cover their immediate costs, governments have offered various non-salary cost subsidies, including 25 to 80 percent of fixed costs if the firm experiences between 35 to 100 percent reduced turnover. Firms facing lock-down are compensated for 100 percent of fixed costs. In Sweden, the government compensates up to 75 percent of costs for firms experiencing at least 30 percent reduction in turnover. In the Netherlands, firms in distress

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[2]As of 18 May 2020, the government had committed around 1.5 billion US$ in employment subsidies for firms. As of 22 May, the government had received 31,000 applications of which 28,000 had been approved. These covered 211,000 jobs — equivalent to 161,000 full time jobs (Andersen et al.; 2020).

[3]In Denmark, social-security benefits are paid through general taxes. European countries have a minimum number of days for sick leave, which has to be covered by the firm. In Denmark, the government is covering the first month of sick leave that would have normally been the responsibility of the firm.

[4]Our survey elicits predictions of the share of employees that would be laid off, and we do not observe a discontinuity at 30 percent.

can apply for a EUR 4,000 lump-sum payment while in Germany firms with fewer than 10 employees can expect a direct payment of up to EUR 15,000. The French government also offers a lump sum transfer of up to EUR 1,500 for the self-employed or small businesses with a drop of 70 percent or more in revenue. The UK has a similar cash grant based on the prior three years profit, with a cap at GBP 2,500 per month and the Italian government has a regional fund set up to help small firms with redundancy payments. The Danish government is also offering compensation for cancelled events.

Fiscal-related support: tax deferral and loans

A number of countries are also delaying tax payments, such as value added tax (VAT) payments and payroll taxes. Denmark, Germany, Sweden, UK and the Netherlands all have corporate tax deferral schemes, and the United States has a 50 percent payroll tax reduction for affected firms that do not carry out layoffs and delayed corporate tax filings. France, similarly, has instituted early corporate tax repayments and postponed employers' social security contribution. In Italy, there is a six month suspension of loan repayment for small and medium sized firms.

To help firms cope with short term liquidity problems, many governments are offering loans or loan guarantees. The Danish government is offering a loan guarantee of 70% of new corporate loans if a firm's operating loses exceed a set threshold.[5] The Swedish government has instituted a similar policy, but without distinctions in firm size and cap. In Germany and Italy the loan guarantee is 100%, though Germany has a cap at 25 percent of firm revenue. France has a loan guarantee of 70-90 percent, with the maximum depending on firm size, while the UK has a guarantee with a cap for small and medium sized firms and 80 percent for large firms. The Netherlands offers a loan guarantee of 50 percent, while the United States is instead offering low-interest federal loans to affected small businesses.

3 Data and methodology

We developed a self-respondent survey that was sent out on 23 April 2020 to 44,374 firms; effectively the entire population of firms with more than 3 employees in Denmark. The survey is sent to a special email inbox for government mail, which yields a substantially higher response rate than regular email surveys. Participation was voluntary, and no financial

[5]For small and medium-sized firms, the threshold is 50 percent. For large firms, the threshold is 30percent.

compensation was offered to respondents.[6] We received 10,642 responses by 1 June 2020 yielding a response rate of 24 percent. The responses were fairly balanced across firm size and industry, though there was a relatively stronger response rate from larger firms. We estimate that the survey respondents represent between 20 and 40 pct of the private labor market in Denmark.[7] Our industry mix is similar to the industry mix in the total population, highlighting that our final sample is representative at a firm size as well as industry level.[8]

The survey included a total of 23 questions, including basic firm characteristics (such as employment in January, revenue change between January and April, closure status, costs and liquidity) and a series of questions on government aid take-up and labor choices. The survey included a list of available aid packages and asked respondents to mark the packages they used. All firms were asked to report the number of employees they furloughed and laid off as a result of the pandemic, and firms that reported taking aid were also asked to report the number of furloughs and layoffs that they would have expected to enact if they had not taken aid. Over 90 percent of the survey respondents were primarily owner-managers or non-owner CEOs.[9] Thus, almost all respondents are likely to be familiar with the financial and labor choices made in the firm. All firms have a unique firm identifier allowing for links to accounting register data up to 2019, and Danish Statistics data up to 2016.

4 Results

The majority of firms — 66 percent — reported a negative impact of COVID-19 on their revenue, while about 26 percent report no change and about 8 percent report an increase in revenue. The median firm in our sample expects to face a 20 percent revenue decrease, while the median firm reporting a decrease expects a 35 percent decrease.

4.1 The reported impact of COVID-19 on firm revenue

Figure 1 plots the distribution of the reported revenue change in the shaded bars, and overlays the distribution of revenue change for the population of similar firms between 2015

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[6]The survey was carried out by Epinion, a private survey firm in Denmark. The respondent managers will receive a special advance report with our findings after the completion of the survey. The report also provides a benchmarking of the individual firms' answers against a relevant group of other firms.

[7]See the Data Appendix for a thorough description of the data and response rates. Our firms self-reported 700,000 employees covering both part-time and full time employees. For some large firms, the response may also cover subsidiaries within and outside Denmark.

[8]We provide an online Data Appendix with details on the survey and its representative nature relative to the population.

[9]The remainder of the respondents were non-managing owners or other administrative staff.

Figure 1: Density Distribution of Actual and Expected Changes in Revenue
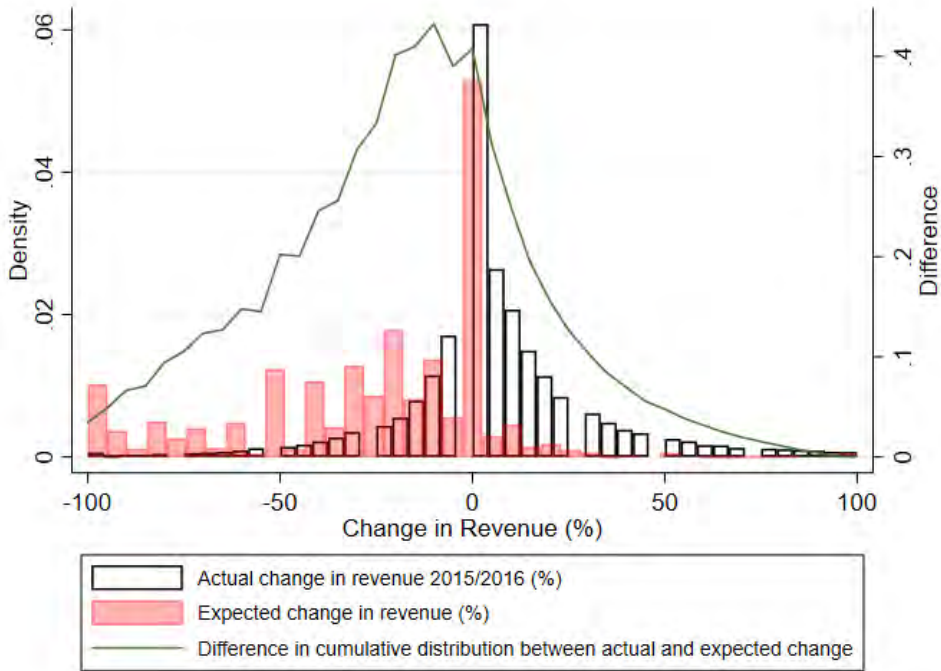
Notes: The outlined bars plot the distribution of the value of the actual change in revenue between 2015 and 2016, using Danish register data for the universe of firms with more than 3 employees (N = 73,498). The shaded bars plot the distribution of the reported revenue change from the authors' survey of firm managers responding to the effect of COVID-19 on their firms (N = 10,642). The COVID-19 survey was sent to over 44,000 firms with more than 3 employees, had a 24 percent response rate and yielded a representative sample along firm size and industry categories.

and 2016 in the outlined bars.[10] While in any given year many firms experience decreases in revenue, including substantial decreases beyond 35 percent, the decline reported in April 2020 is unprecedented. In total, 40 percent more firms face declines in revenue relative to firms in 2016. The overlaid line plots the difference between the cumulative distribution functions of both distributions at each bin interval. It shows that 7 percent more firms face revenue declines of more than 90 percent, while 20 percent more firms have declines of more than 50 percent, and over a quarter of firms face declines in revenue of more than 35 percent. This pattern is similar across firm size bands, though the magnitude of the reported impact is heterogeneous across industries. While nearly all industries have over half of the firms reporting expected decreases in revenue, some industries are particularly hard hit — such as accommodation and food services, arts and entertainment, education, manufacturing and retail.[11]

4.2 Government aid take-up

Our data suggest that the bulk of firms taking up government aid in Denmark are, in fact, those in the most need. The majority of firms reporting no expected change in revenues also report not being aid recipients.[12] Approximately 56 percent of firms in our survey reported taking advantage of one or more government aid programs, with nearly all firms experiencing revenue decreases beyond 50 percent taking some form of aid. Out of the remaining 44 percent that did not take aid, about half chose not to do so despite being eligible.

Figure 2 summarizes the aid take-up relationship with revenue change impact at the industry level. Each circle represents an industry at the 1-digit NACE level, and the size of the circle shows the relative share of firms accounted for by each industry. Firms in accommodation and food — the hardest-hit industry — are the firms most likely to take on aid. Retail and manufacturing report revenue declines that are at the median, and have approximately 60 percent of firms taking on aid.

Firms could take up all packages they are eligible for, and they were not mutually exclusive. Table 1 reports the set of firm characteristics that correlates with aid take-up of each type and combination of packages. We iterate across a set of indicators as the dependent variable and linear probability models starting with whether the firm took up any aid

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[10]The "normal times" data is from 2016 as that is the latest available date in the register data. It includes the population of limited liability firms in Denmark with more than 3 employees.

[11]We provide a more thorough descriptive exercise of the firm size and industry differences in the Data Appendix.

[12]The median firm reporting not receiving any aid has an expected revenue change of zero.

Figure 2: Share of firms taking up aid programs on industry and expected change in revenue.
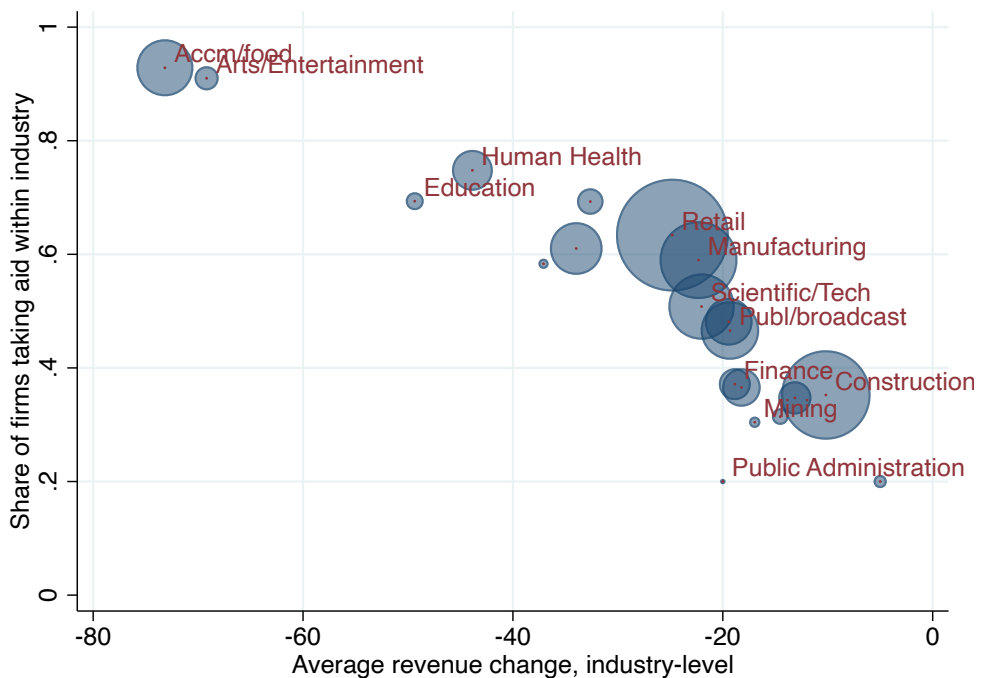
Notes: Data from author's COVID-19 survey. This graph reports the industry-level average revenue change (x-axis) and the industry-level average aid take-up (y-axis), weighted by industry size. Each circle represents an industry at the 1-digit NACE level, and the size of the circle shows the relative share of the economy accounted for by each industry.

package, and subsequently iterating through the possible package combinations. Column (1) includes all firms in the sample, while the remaining columns include only the firms that took on any aid at all. The last rows in the table indicates the share of firms and employment that account for each of the policy types.

Column (1) reports that approximately 56 percent of firms took on aid, and they were less likely to do so if they reported no change, or an increase in revenues. Larger firms were slightly more likely to take up aid, and more affected industries were more likely to take up aid. Column (2) shows that nearly 11 percent of all firms took on all three aid types (20 percent of aid-taking firms), relative to choosing only one or two bundles. This choice was more common for hard-hit sectors, but we find no relationship with firm size.

The outcome variables of Columns (3) through (5) take on a value of one if the firm took on only either labor, cost or fiscal aid, respectively. While a sizeable share of aid-takers chose only labor aid (about 19 percent) or only fiscal aid (22 percent), a much smaller share (4 percent) took on only cost aid. In general, industry characteristics predict take-up of labor-only and fiscal-only aid, while they fail to do so for cost-only aid. The direction of revenue change is not correlated with take-up of labor-only aid, but firms not experiencing a decrease are less likely to take up cost-only aid and more likely to take up fiscal-only aid. The most affected industries are also much less likely to take up fiscal-only aid. The patterns are relatively consistent when we consider the possible bundles including two types of aid in Columns (6) through (8).

In all, these correlations suggest that firms not experiencing distress are less likely to take up most types of aid (with the exception of fiscal aid), especially in bundles of two or three types. The relationship between firm size is economically small and mixed, and industry is most often the strongest predictor of taking a particular type of bundle.

Table 1: Regression results: policy choice

	All types		Only one type			2 types		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any aid	All three	Labor	Cost	Fiscal	Labor+Cost	Labor+Fiscal	Cost+Fiscal
Revenue change								
Increase	-0.459***	-0.181***	0.042	-0.030***	0.336***	-0.123***	0.002	-0.046***
	(0.016)	(0.011)	(0.030)	(0.008)	(0.035)	(0.006)	(0.029)	(0.008)
No change	-0.420***	-0.164***	0.018	-0.045***	0.369***	-0.115***	-0.009	-0.053***
	(0.011)	(0.007)	(0.018)	(0.004)	(0.020)	(0.006)	(0.016)	(0.004)
Firm characteristics								
Ln(employment)	0.022***	0.005	0.007*	-0.015***	0.003	-0.030***	0.044***	-0.014***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)
Industry								
Manufacturing	0.128***	0.048	0.100***	0.006	-0.237***	0.053**	0.108***	-0.079**
	(0.033)	(0.033)	(0.036)	(0.023)	(0.058)	(0.025)	(0.034)	(0.039)
Construction	0.015	-0.018	0.180***	0.008	-0.175***	0.025	0.078**	-0.098**
	(0.033)	(0.033)	(0.039)	(0.024)	(0.060)	(0.025)	(0.035)	(0.039)
Retail	0.178***	0.100***	0.121***	-0.013	-0.308***	0.087***	0.104***	-0.092**
	(0.032)	(0.032)	(0.035)	(0.023)	(0.057)	(0.024)	(0.033)	(0.039)
Accm/Food	0.366***	0.373***	-0.040	0.017	-0.441***	0.222***	-0.050	-0.081**
	(0.033)	(0.039)	(0.035)	(0.025)	(0.057)	(0.032)	(0.033)	(0.040)
Professional	0.086***	0.048	0.069*	-0.004	-0.199***	0.075***	0.070**	-0.059
	(0.033)	(0.034)	(0.037)	(0.024)	(0.059)	(0.027)	(0.035)	(0.040)
Education	0.267***	0.234***	0.111***	-0.013	-0.458***	0.242***	0.006	-0.123***
	(0.036)	(0.043)	(0.042)	(0.025)	(0.057)	(0.036)	(0.036)	(0.040)
Arts	0.228***	0.091*	0.098*	0.009	-0.359***	0.215***	0.066	-0.120***
	(0.046)	(0.053)	(0.054)	(0.034)	(0.066)	(0.053)	(0.048)	(0.042)
Observations	10505	5868	5868	5868	5868	5868	5868	5868
Share of firms (total)	0.555	0.107	0.106	0.023	0.124	0.077	0.092	0.027
Share of empl (total)	0.569	0.101	0.141	0.006	0.159	0.028	0.127	0.007
Share of firms (aid)	1.000	0.193	0.190	0.041	0.223	0.138	0.165	0.049
Share of empl (aid)	1.000	0.177	0.248	0.010	0.280	0.049	0.223	0.012

Notes: ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels. Standard errors in parentheses. All columns are linear probability models, estimated with OLS. Each outcome variable is an indicator for each type of aid. The omitted category from revenue impact is "experienced a decrease in revenue". Log of employment is calculated based on reported employment in January. Regressions include industry dummies at the 1-digit NACE level, reporting only selected industries based on relevance (share of the economy) and relative impact.

4.3   The effects of aid on employment decisions

Firms that took aid were more likely to furlough and less likely to layoff workers relative to non-aid takers. Figure 3 shows that, among firms receiving aid, the share of workers furloughed is increasing with the firm's revenue losses, suggesting the policy is having the intended effect. The layoff shares for aid-taking firms seems largely independent of the size of the revenue loss. Firms that did not take aid enact more layoffs than furloughs if they experience a revenue decrease of more than 50 percent, but at lower distress levels the difference is not statistically significant.

However, we cannot draw conclusions about the effectiveness of aid policies from a simple comparison between aid takers and non-takers, as taking aid is naturally a choice and not a random assignment.[13] If firms taking aid were more likely to furlough workers in response to a revenue shock instead of laying them off, the observed differences in employment decisions could overstate the policy's effects.

Estimates based on stated counterfactuals

In an effort to address the self-selection of firms into the different aid packages, we asked respondents to report their expected counterfactual choices. Among firms that took aid, we asked what share of workers they would have laid off and furloughed in the absence of aid. Under the assumption that firms report counterfactual outcomes accurately, we can identify the average effect of treatment on the treated for each of the policy options. Furthermore, we can also observe how firm's adoption of different aid packages is correlated with their outcomes in the absence of treatment.

Our analysis requires an assumption that the reported counterfactuals are correct. While this may seem strong, in the absence of clear experimental variation in aid packages our alternative is to assume that selection of these aid packages is random (conditional on observable covariates in the data). A simple comparison between aid takers and non-takers would imply an assumption that the counterfactual outcomes for a firm that took aid can be proxied by the outcomes of a firm with similar characteristics that did not take aid. Economic models of selection are predicated on the notion that firms know their business, and as such should be able to foresee immediate alternative outcomes. In this sense, our approach could be superior to a quasi-experimental designs. The primary concern in this scenario is that firms may not report their counterfactuals carefully, even if they are capable of doing so. In this

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[13]In time we may be able to observe identifying thresholds of eligibility, but our data suggests that 53 percent of firms that were eligible to take aid chose not to do so.

Figure 3: Labor Response to Revenue Change by firms aid taker status
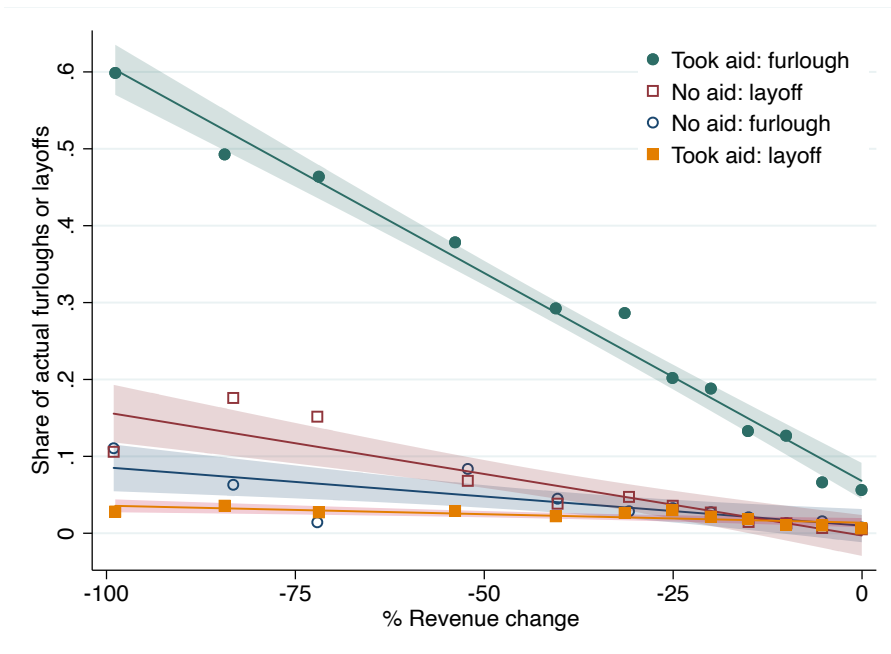
Notes: This graph shows the binned scatterplot of the simple relationship between the percentage revenue change in firms and the share of employees that they report actually furloughing or laying off. Squares show the relationships for the outcome of actual layoffs. Solid squares represent firms that took at least one type of aid, while hollow squares represent firms that did not take aid. Circles show the relationships for the outcome of actual furloughs. Solid circles represent firms that took at least one type of aid, while hollow circles represent firms that did not take aid.

section, we consider evidence about the validity of the counterfactual reports and alternative estimates based on more conventional assumptions about selection on observables.

Table 2 reports estimates of the effects of the effects of labor aid, cost aid, and fiscal aid on the share of workers furloughed and laid off. Columns (1) and (2) focus only on aid-takers, and the dataset includes two observations for each firm: one corresponding to their actual furloughs and layoffs, and one that reports their counterfactual furloughs and layoffs they say they would have chosen in the absence of aid. Using these data, we estimate a model:

$$Y_{jT} = \alpha + \beta_0^L L_j + \beta_0^C C_j + \beta_0^F F_j + T \times \left(\beta_1^L L_j + \beta_1^C C_j + \beta_1^F F_j \right) + X_j \gamma + \varepsilon_{js} \qquad (1)$$

where firms are indexed by j, and $T = 0$ if the observation measures the firm's reported outcomes in the absence of aid, and $T = 1$ if it measures the firm's actual outcomes. The key variables are binary indicators for whether the firm took labor aid (L_j), cost aid (C_j), or fiscal aid (F_j). Recall that these aid packages are not mutually exclusive; firms can take up any combination of the three. The coefficients $\beta_0^L, \beta_0^C, \beta_0^F$ measure differences in counterfactual outcomes for firms that took up particular aid packages. The coefficients $\beta_1^L, \beta_1^C, \beta_1^F$ measure the difference in observed outcomes, relative to counterfactuals, for a given aid package. Firm-specific controls, X_j, include log of January employment, the size of the revenue change, and industry at the 2-digit NACE level. The term ε_{jT} captures idiosyncratic reporting error and other factors that affect layoff and furlough decisions.

We interpret $\beta_1^L, \beta_1^C, \beta_1^F$ as effects of treatment on the treated — that is, the average effect of each policy on the firms that take them up.[14] Firms that took labor aid increase the share of furloughs by 25.6 percentage points; a magnitude consistent with the evidence in Figure 3. The reduction in layoffs from taking labor aid is -6.0 percentage points. Cost aid also increases the furlough share, but by a smaller margin: 3.9 percentage points.[15] Cost aid also reduces layoffs by 6.8 percentage points. For labor aid and cost aid, the effects have the signs that would be predicted by theory, and intended by policymakers. Fiscal aid, however, is estimated to increase layoffs by 1.1 percentage points, and we cannot rule out negative effects on furloughs. While unclear, this could be simply reflecting selection into this type of aid.

Our estimates of $\beta_0^L, \beta_0^C, \beta_0^F$ measure selection into treatment on the basis of counterfactual outcomes. The coefficients suggest that firms choosing labor aid expected 4.8 percentage points more furloughs, and 13.5 percentage points more layoffs, relative to firms that also

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[14] Under the aforementioned assumption that firms accurately report counterfactuals.

[15] Firms that want to furlough workers can pair cost aid and labor aid.

took aid but chose different packages. Hence, the firms that took labor aid are those that also had expected to enact relatively high layoffs and furloughs. Firms that took cost aid had expected significantly higher layoffs, but not furloughs. Firms taking fiscal aid also expected slightly higher furlough share (1.6 pp) and layoff share (2.4 pp).

Table 2: Regression results: aid takers and non aid takers

	Only Aid Takers		All firms	
	(1) Furlough	(2) Layoff	(3) Furlough	(4) Layoff
Aid eligible			-0.020*** (0.004)	0.014*** (0.002)
Observed outcomes				
Labor aid	0.256*** (0.008)	-0.060*** (0.005)	0.269*** (0.006)	-0.044*** (0.003)
Cost aid	0.039*** (0.010)	-0.068*** (0.005)	0.057*** (0.009)	-0.001 (0.004)
Fiscal aid	-0.011 (0.007)	0.011*** (0.004)	-0.008 (0.006)	0.007*** (0.002)
Reported counterfactuals				
Labor aid	0.048*** (0.008)	0.135*** (0.007)		
Cost aid	-0.000 (0.010)	0.122*** (0.008)		
Fiscal aid	0.016** (0.008)	0.024*** (0.006)		
Firm controls	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Observations	10540	10678	9267	9267
# Firms	5270	5339	9267	9267

Notes: ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels. Standard errors in parentheses. Columns (1) and (2) are estimated on a sample that only includes workers who actually took aid. Each firm has two observations: one with its actual outcomes, and one with the outcome in the absence of aid, as reported in the survey. The coefficient estimates for labor, cost, and fiscal aid in the top panel correspond to actual firm outcomes. The bottom panel corresponds to counterfactual outcomes, as described in equation (1). Columns (3) and (4) use data on observed outcomes for all firms. All models also include: revenue loss, log of January employment, and unrestricted industry effects at the 1-digit NACE level.

Estimates based on selection on observables

Columns (3) and (4) in Table 2 are based on comparisons of actual reported outcomes between firms that took aid and firms that did not. These are identified under the assumption that firms' counterfactual outcomes in the absence of aid are well-proxied by the actual outcomes of the firms that did not take aid. This assumption, albeit implausible, is a useful benchmark model to compare against our analysis based on stated counterfactuals.

For this analysis, we are estimating a standard cross-sectional model:

$$Y_j = \alpha + \beta^L L_j + \beta^C C_j + \beta^F F_j + X_j \gamma + \varepsilon_j \tag{2}$$

where the variables and parameters have interpretations analogous to equation (1). We assume $E[\varepsilon_j | L_j, C_j, F_j, X_j] = 0$.

Under these modeling assumptions, the estimated effects of the different aid packages on the share of workers furloughed and laid off are, in fact, similar to those estimated based on stated counterfactuals in Columns (1) and (2). Comparing the two sets of estimates is useful to help us understand the nature of the selection bias introduced by firms' choice of aid packages. Under both models, labor aid leads to large increases in the share of workers furloughed and substantial reductions in the share of workers laid off, albeit smaller. This is what the policy is intended to do: firms that take labor aid would have laid off more workers without aid, but they cut layoffs roughly in half and substantially increased furloughs. If the counterfactuals are accurate, firms furloughed significantly more workers than they had planned to lay off, suggesting that the policy not only saved employment matches, it also encouraged firms to put workers on leave who might have otherwise stayed on the job. While under normal circumstances inducing furloughs would be undesirable, it is certainly not so in the context of the pandemic, where a key goal is to encourage social distancing.

With regard to cost aid, the picture is somewhat less clear. Both models indicate that cost aid increases the furlough share by 3.9 to 5.7 percentage points, but the models disagree about the effect on layoffs. In the model based on stated counterfactuals (Columns 1 and 2), cost aid is estimated to reduce layoffs by 6.8 percentage points. In the model of selection on observables (Columns 3 and 4), cost aid has no discernible effect on layoffs.

This difference could arise if firms taking cost aid would have higher layoffs in the absence of aid than firms that did not take aid. The evidence on selection in Column (2) suggests this could be the case. Focusing on the results for cost aid in Columns (1) and (2), we would conclude that cost aid encourages reduced layoffs and increased furloughs. Unlike the case for labor aid, cost aid seems to reduce layoffs by more than it increases furloughs. One

interpretation is that taking cost aid encouraged firms to keep workers on the job that they might otherwise have been forced to lay off. When firms can offset payments of rent or other fixed costs, they may redirect funds to keeping workers employed who might have been laid off. To be sure, less than 1 percent of workers are employed in firms that only take cost aid, as most firms that take cost aid bundle it with another policy (see Table 1).

The results for fiscal aid consistently indicate that it has no effect on furloughs, and a small, but statistically significant positive effect on layoffs. Firms that take only fiscal aid employ around 16 percent of all workers, so even this small increase in layoffs could have a significant impact on the total number of workers who lose their jobs. Furthermore, taking fiscal aid alone is more likely among firms who did not experience revenue declines, and that are not in the most affected industries (see Table 1, Column 5). Still, the mechanism through which increased fiscal aid would lead firms to lay off a larger share of their workforce is not clear. Perhaps firms that defer tax payments or take government-backed loans lay workers off to restructure in anticipation of future loan payments. As the goal of fiscal-type aid is targeted at non-labor outcomes — such as, for example, firm survival and longevity — we will only be able to evaluate these relationships with additional data in due time.[16]

5   Conclusion

The COVID-19 pandemic has caused widespread disruption to lives and livelihoods across the world. We analyzed its reported impact on firm outcomes and the likely effect of firm-based aid programs. Our survey sample covers approximately 24 percent of firms in Denmark with more than 3 employees, and it is representative for the population with respect to size and industries.

The crisis was hard hitting for nearly 70 percent of firms, with the median firm experiencing a decline of 20 percent of revenue. Over one quarter more firms reported revenue declines in this period relative to firms in 2016. Firms experiencing declines in revenue were the primary takers of government aid, standing is in stark contrast to the reports of aid take-up in other countries, such as the United States.[17] The most common aid package taken up included support for labor furloughs and delays in VAT payments, with a non-trivial share of firms also taking on aid to cover fixed costs.

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[16]Our survey included questions on cost changes, cost shares and firm liquidity. However, these questions had much lower response rates relative to the rest of the survey. As such, we leave exploring this type of outcome to future work including register data and leave some exploratory basic descriptive statistics in our Data Appendix.

[17]Reports such as Silver-Greenberg et al. (2020) are widespread in the US news media.

We have documented that receiving government aid has a strong impact on reported labor choices: firms that took up aid report furloughing more and laying off fewer workers than they would have, absent government aid. However, the relationship varies with the kind of aid that firms take-up: we find a strong and clear relationship between taking up labor aid and reporting lower layoffs and more furloughs, while the relationship for firms taking up cost aid is mixed, with lower layoffs but lower furloughs contingent on also taking on labor aid. While we do not find the same relationship for firms taking up fiscal aid, the most expensive aid program, the effect is hard to cleanly identify. We report that financial distress is not correlated with higher take-up of fiscal aid, nor is being in a hard-hit industry. Further, while it is not clear that take-up of fiscal aid is correlated with furloughs, it is too early to detect the potential impact on liquidity, costs and survival. These outcomes are more likely to be the goal of the fiscal aid subsidy, and we leave the effect of these policies as important questions for future work.

Our analysis is important and, we hope, useful for policymakers in this turbulent time. As our survey response rate was high and yielded a highly representative sample across firm size and industry, we have one of the best datasets available today to examine the impact of COVID-19 pandemic on firms and their responses to government policy. The policy program implemented in Denmark is quite similar to policy programs in many other countries, including Germany, the United Kingdom and Sweden. Further, some portions of the program are similar to others beyond Europe across the world. As such, our results can be helpful as economists consider the potential effects of such programs across countries with different institutional contexts.

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A   Data Appendix

A.1   Sample characteristics

The Danish COVID-19 survey was sent to 44,374 firms; effectively the entire population of firms with more than 3 employees in Denmark. The survey was sent out on 23 April 2020, and by 1 June 2020 we had received 10,642 responses, yielding an overall response rate of 24 percent. This Data Appendix provides details on the sample characteristics and how representative the sample is relative to the Danish population of firms with more than 3 employees.

Table A.1: Distribution of Survey Responses

	Resp N	Popn N	Response rate	Share in sample	Share in popn
Firm size					
3-5 emp	3202	15768	0.20	0.30	0.36
6-9 emp	2283	10488	0.22	0.22	0.24
10-25 emp	2817	10860	0.26	0.27	0.24
26-50 emp	1063	3801	0.28	0.10	0.09
51+ emp	1200	3457	0.35	0.11	0.08
Industry					
Accommodation/Food	472	2840	0.17	0.04	0.06
Construction	1477	7182	0.21	0.14	0.16
Manufacturing	1561	5416	0.29	0.15	0.12
Other	2406	10497	0.23	0.23	0.24
Professional/Technical	1116	3892	0.29	0.11	0.09
Publishing/Broadcasting	788	3001	0.26	0.07	0.07
Wholesale/Retail	2745	11546	0.24	0.26	0.26
Total	10565	44374	0.24	1.00	1.00

Notes: This table reports the sample counts and response rate for our COVID-19 impact survey. The top panel reports the respondent numbers across firm size bands, and the bottom panel reports the respondent numbers across different industries. Column "Resp N" reports the total number of survey respondents. Column "Popn N" reports the total number of firms in the population. Column "Response rate" reports the response rate as the difference between the number of respondents and the population within the firm size band or industry. Column "Share in sample" reports the share of firms represented in each size band or industry relative to the entire sample — the number of respondents divided by the total sample. Column "Share in popn" reports the share of firms represented in each size band or industry relative to the entire population of firms — the number of respondents divided by the total population count.

Table A.1 shows the number of respondents within each employment size band, the response rate and the proportion of each set of firms in our sample and in the population. While we had a higher response rate among larger firms relative to small firms, the final share of firms sampled from each size band is not vastly different from the share of firms in

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the total population. Figure A.1 shows the cumulative distribution function for our sample and the population firm size. In all, approximately 45 percent of the firms in our sample have fewer than 10 employees, while 40 percent have between 10 and 50, and 15 percent have more than 50 employees.

Figure A.1: Cumulative Distribution Function of Firm Employment
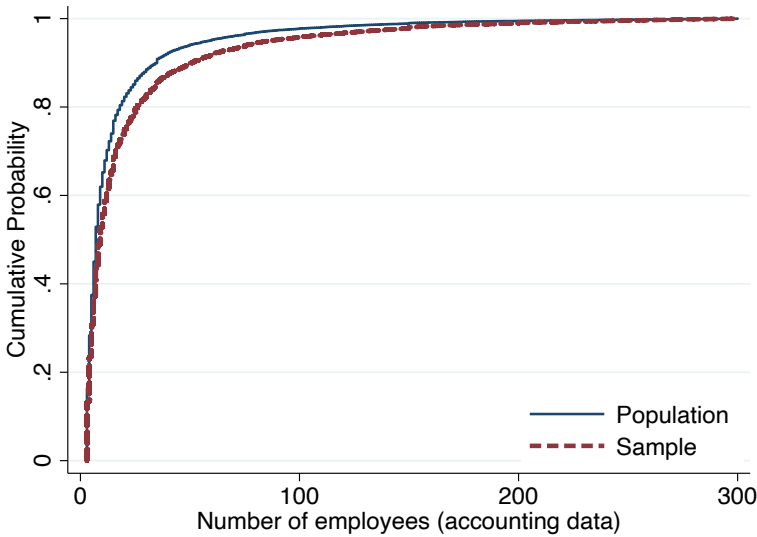
Notes: The red line represents the cumulative distribution function of firm employment in our survey sample. The blue line represents the cumulative distribution function of the remainder of the population of firms in Denmark with more than 3 employees. Employment truncated at 99th percentile (300 employees) for exposition. Population N = 33,513. Sample N = 10,642.

Similarly, the industry mix in our sample is relatively similar to the industry mix in the total population, and with fairly similar response rates across industries. The bottom panel of Table A.1 reports the response rates, sample and population shares for the largest industries in the sample. The representative nature of our sample in terms of industry composition is depicted in Figure A.2, where we plot the share of firms within each of the NACE 1-digit industries in our sample and in the population. Some industries were slightly over-sampled (like manufacturing and professional/technical services) while others were slightly under-sampled (like construction), but all are quite close to the 45-degree line.

A.2 Response rates

The overall response rate we received was relatively high for this type of non-incentivized, voluntary survey. As all questions were voluntary, not all survey questions had the same response rate. Table A.2 reports the response rates by firm size and industry for our main

App. 2

Figure A.2: Industry Composition of Sample Firms
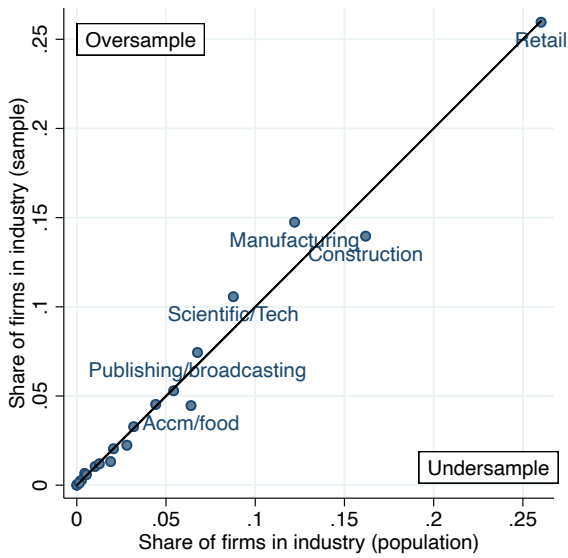
Notes: Each circle marker in the graph represents an industry-level share of firms, as they appear in the sample and in the full population. Industry markers above 45-degree line means industry is over-sampled. Industry markers below the 45-degree line means the industry is under-sampled. Population N = 33,513. Sample N = 10,642.

App. 3

Figure A.3: Firm size distribution within industry, population

(a) Population
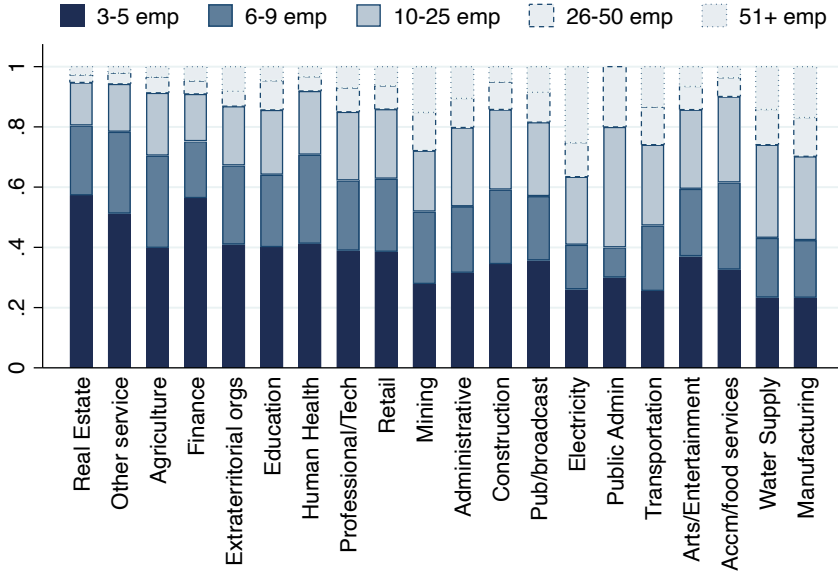
(b) COVID-19 Survey Sample
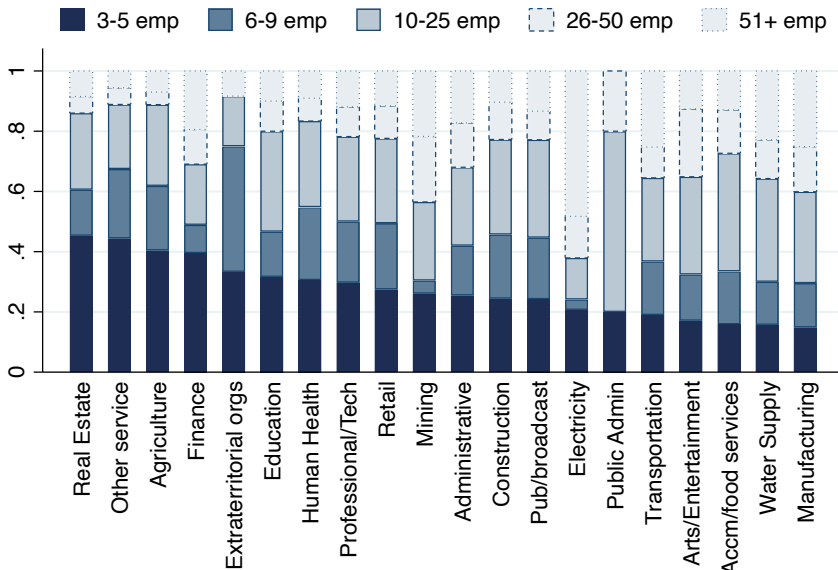
App. 4

Notes: Population N = 33,513. Sample N = 10,642. Industry defined by 1-digit NACE codes. Graph shows the distribution of firm size (number of employees) in the population and in the sample for each industry.

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variables. Effectively all respondents provided answers to the establishment employment size, share of furloughed workers and share of laid off workers. Less than half, however, responded to the labor cost share, fixed cost share and liquidity questions. If there was selection in the type of firm that chose to respond to these questions, it does not seem to have been across firm size and industry. The share of respondents across the various size bands and industry categories is relatively similar.

Table A.2: Survey Response Rates

	N	Empl	Furlough	Layoff	Labor Costs	Fixed Costs	Liq
Firm size							
3-5 emp	2652	1.00	0.99	0.99	0.39	0.38	0.38
6-9 emp	2039	1.00	0.99	0.99	0.40	0.39	0.41
10-25 emp	3110	1.00	1.00	1.00	0.39	0.38	0.37
26-50 emp	1217	1.00	0.99	0.99	0.40	0.39	0.40
51+ emp	1534	1.00	1.00	1.00	0.37	0.36	0.35
By industry							
Accommodation/Food	472	0.99	0.98	0.98	0.51	0.51	0.44
Construction	1477	0.99	1.00	1.00	0.27	0.26	0.31
Manufacturing	1560	0.99	1.00	1.00	0.33	0.32	0.37
Other	2419	0.99	0.99	0.99	0.39	0.38	0.36
Professional/Technical	1118	0.99	0.99	0.99	0.50	0.48	0.43
Publishing/Broadcasting	787	1.00	1.00	1.00	0.54	0.52	0.47
Wholesale/Retail	2746	0.99	1.00	1.00	0.38	0.36	0.38
Total	1511	0.99	0.99	0.99	0.42	0.41	0.40

Notes: As survey questions cannot be mandatory, the response rates of individual questions vary. This table reports the response rates of the main variables in our analysis for each size band and industry group. Column "N" reports the number of observations in each group. "Empl" reports the share of firms that responded to the question on the number of employees question. "Furlough" reports the share of firms that responded to the question on the share of employees that were furloughed. "Layoff" reports the share of firms that responded to question on the share of employees that were laid off. "Labor costs" reports the share of firms that responded the question on labor cost shares. "Fixed costs" reports the share of firms that responded the question on fixed cost shares. "Liq" reports the share of firms that responded the question on liquidity availability.

A.3 Direction of revenue change

We document that, in general, the direction of the revenue change is relatively similar across firm size bands, and the majority of the variation is driven by industry. Figure A.4a shows

Figure A.4: Expected Direction Change in Revenue

(a) By firm size

Expected direction of revenue change, by firm size

(b) By industry

Expected direction of revenue change, by industry
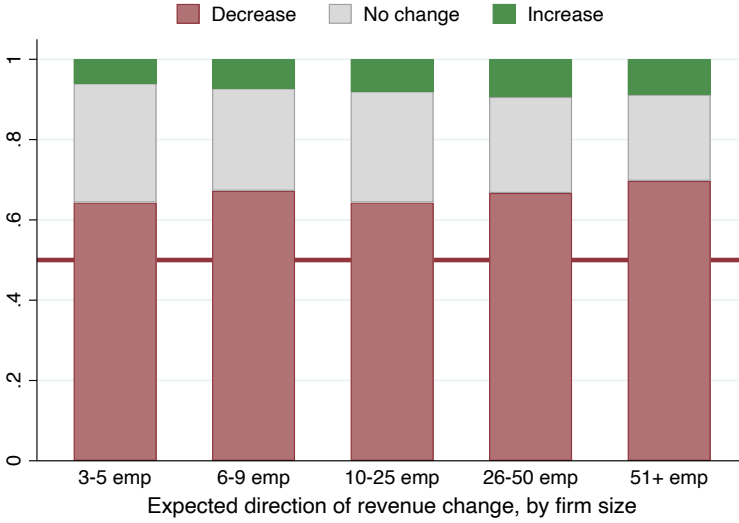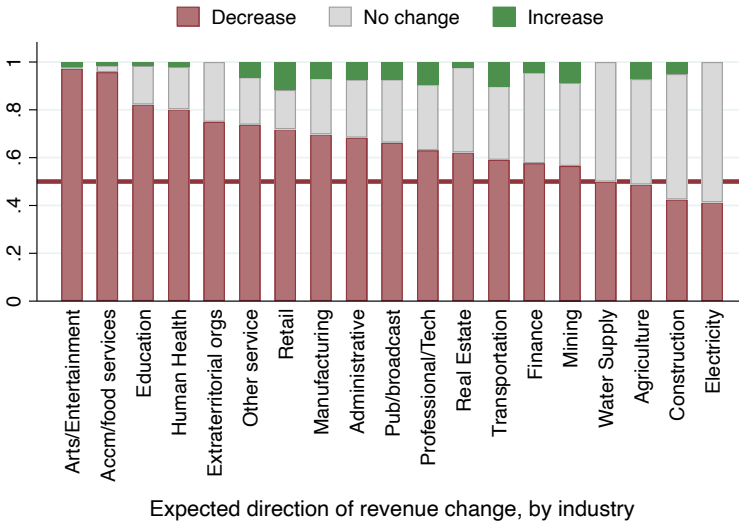
Notes: See Table A.1 for the sample size of each industry and size band in the sample. The figure shows the share of firms reporting an expected decrease, increase or no change in revenue as a result of the pandemic. Panel (A) shows the distribution across firm size bands, and Panel (B) shows the distribution across industries.

App. 6

the expected change in revenue across the firm size bands, and Figure A.4b shows the same data across industries.

A.4 Other outcomes: costs, liquidity and survival expectations

Cost and liquidity

Approximately 40 percent of the respondents chose to report their monthly costs in January and April, as well as the share of their costs accounted for by labor and fixed costs, and their available liquidity (including cash-on-hand and available loans). Table B.3 reports the average value of these responses by three different types of firms: firms experiencing different levels of revenue change, by their aid recipient status, and by firm size.

All firms reported lower costs in April relative to January, though the share of costs taken up by labor or fixed expenses remained relatively similar. Likewise, liquidity remained stable across the two months.

B Policy Appendix

On 14 March 2020, the Danish government, labour unions and employer organizations reached an agreement that included temporary salary compensation for employees at risk of losing their jobs, effective for the period from 9 March 2020 to 9 June 2020 (Ministeriet; 2020). On 18 April 2020 the government aid packages were extended to 8 July 2020 and also substantially expanded (Regeringen; 2020).

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Table B.3: Costs and liquidity, averages

	Mo. costs (Jan)	Mo. costs (April)	Lab. share cost (Jan)	Lab. share cost (Apr)	Fix share cost (Jan)	Fix share cost (Apr)	Liq (Jan) 100k Kr.	Liq (Apr) 100k Kr.
Decrease	31.43	21.98	0.58	0.59	0.31	0.35	45.87	44.12
Increase	40.68	28.75	0.56	0.58	0.29	0.30	50.06	52.32
No change	31.96	24.20	0.57	0.59	0.29	0.31	50.05	51.20
By aid recipient								
Did not take aid	37.02	26.22	0.58	0.60	0.29	0.31	52.21	52.46
Took aid	29.49	21.06	0.58	0.58	0.31	0.35	43.95	42.49
By firm size								
3-5 emp	4.85	2.89	0.58	0.59	0.32	0.35	19.06	18.22
6-9 emp	8.09	5.58	0.59	0.60	0.30	0.33	22.10	21.70
10-25 emp	17.89	12.83	0.59	0.60	0.30	0.33	38.85	38.01
26-50 emp	39.78	27.10	0.57	0.58	0.29	0.33	67.66	66.73
51+ emp	140.22	106.08	0.54	0.55	0.30	0.33	139.10	138.00
Total N	4225	3971	4017	3897	3894	3782	4083	4039

Notes: The table reports financial indicators of surveyed firms in terms of monthly cost in January(column 1), monthly cost in April (column 2), labor cost shares in January (column 3), labor cost shares in April(column 4), fixed cost shares in January(column 5), fix cost shares in April (column 6), liquidity in January (column 7) and liquidity in April (column 8) across groups with different revenue change expectations, aid recipients and firm size. Last row of the table reports number of total observations for each indicator.

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Table B.4: Summary of firm aid government programs.

Country	Furlough support	Loan and grant	Cost subsidy	Others
Denmark	- 75% of employee salaries are covered by the government, up to DKK30,000 per employee per month. Eligibility: firm would layoff at least 30% of its workers. Firm covers the remaining 25% of the salaries.	Loan guarantee on 70% of new corporate loans related to COVID-19. Eligibility: SMEs with losses of 50% or more. Large: revenue losses of 30% or more.	Between 25% and 80% of fixed costs for firms experiencing between 35 and 100% decreases in turnover, but remaining open. 100% of fixed costs are compensated for firms forced to close.	Employers are paid sickness reimbursement for salaries and benefits from to first day of absence instead of the 30th. 30 day VAT payments delay.
Germany	- Govt covers up to 80% (87 if family) of salaries and 100 % of the social-security contributions for reduced working hours. Working hours can be reduced with reduced wages. Eligibility: at least 10 % of workers affected	100% - loan guarantee up to 25% of the revenue of 2019. Max EUR 500k in loans for firms with 10-50 employees and 800k for > 50 employees.	Direct payment to self-employed and firms with 10 employees or less, up to EUR 15,000.	Reduced VAT rate to 7% for restaurants for 12 months
Sweden	- Employers can cut the working hours by 80%. Government covers most of the salary, workers receive 90%.	- Loan guarantee of 70% to companies, up to SEK 75 million in loans per company. No legal company size limit	Between 22.5% and 75% of fixed costs for firms with min SEK 250k in turnover and a decrease of at least 30% this year.	VAT by sole proprietors might be postponed.
Netherlands	Up to 90% of wages are compensated. If: At least 20% decreases in revenue in March to May compared to 2019 and the workers are not laid off.	- Loan guarantee of 50%, min EUR 1.5m and max EUR 150m per company.	Firms forced to close can apply for EUR 4000 lump-sum payment	VAT, income, corporate and turnover taxes might be deferred.
France	70% of wages, up to EUR 45.68 per hour not worked, are compensated, if a business is forced to close or reduce activities due to COVID-19.	- 70 % to 90% of loans might be guaranteed by the State. - Different percentages of guarantees apply to different sizes of firms	Lump-sum transfer of up to EUR 1500. For: Very small businesses, self-employed etc., if decreases of 70% in revenue or forced to closure	Early corporate tax repayment, postponed employers social security contribution
Italy	- 80% of salaries covered, with a maximum of EUR 1.200 for a maximum of 9 weeks.	Fee-free loan guarantee for SMEs, EUR 5m max guarantee	regional fund to assist firms with redundancy payments for 9 weeks of suspension for a max of 5 employees	6 months suspension of loan repayment for SMEs
UK	Up to 80% of salaries with a maximum of 2,500 GBP are paid for the next three months for retained workers. All employers are eligible to apply	- Guarantee of loan repayments up to GBP 5m for SMEs. Loan guarantee of 80% for loans up to GBP 25m for large firms, between GBP 45m - GBP 500m in turnover	Cash grant between GBP 10,000 and GBP 25,000, if firm uses properties for retail, hospitality or leisure and a property value of maximimum GBP 51,000.	VAT deferral for the second quarter of 2020
USA	Unemployment insurance payments plus USD 600 per month, under it the majority of workers get a replacement rate over 100	Low interest federal loans to affected small businesses	50% payroll tax reduction for affected firms that do not layoff workers	Tax payments deferred

COVID ECONOMICS
VETTED AND REAL-TIME PAPERS

Corporate bond liquidity during the COVID-19 crisis[1]

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We study liquidity conditions in the corporate bond market since the onset of the COVID-19 pandemic. We find that in mid-March 2020, as selling pressure surged, dealers were wary of accumulating inventory on their balance sheets, perhaps out of concern for violating regulatory requirements. As a result, the cost to investors of trading immediately with a dealer surged. A portion of transactions migrated to a slower, less costly process wherein dealers arranged for trades directly between customers without using their own balance sheet space. Interventions by the Federal Reserve appear to have relaxed balance sheet constraints: soon after they were announced, dealers began absorbing inventory, bid-ask spreads declined, and market liquidity started to improve. Interestingly, liquidity conditions improved for bonds that were eligible for the Fed's lending/purchase programs and for bonds that were ineligible. Hence, by allowing dealers to unload certain assets from their balance sheet, the Fed's interventions may have helped dealers to better intermediate a wide variety of assets, including those not directly targeted.

> So when Mr. Rao called senior executives for an explanation on why [broker-dealers] wouldn't trade, they had the same refrain: There was no room to buy bonds and other assets and still remain in compliance with tougher guidelines imposed by regulators after the previous financial crisis [...] One senior bank executive leveled with him: "We can't bid on anything that adds to the balance sheet right now."—**The Wall Street Journal**, (May 20, 2020, "The Day Coronavirus Nearly Broke The Financial Markets" Baer, 2020)

1   Background and Motivation

The COVID-19 pandemic has wrought havoc on the global economy. In mid-March, as both the scope of the pandemic and the duration of its effects became apparent, financial markets around the world entered a period of turmoil. As the price of equities and debt plummeted, reports of illiquidity in key financial markets emerged.[1] In the United States, the Federal Reserve responded with a variety of interventions aimed at different markets within the financial sector.

In this note, we attempt to shed light on recent trading conditions in one such market: the market for US corporate bonds. This market, nearly $10 trillion in size, serves as a primary source of funding for large US corporations. However, with the prospect of widespread downgrades and possible defaults, the cost of issuing debt increased dramatically in mid-March, and investors withdrew their money from corporate bond funds in record numbers.[2] In the midst of this turmoil, former Federal Reserve chairs Bernanke and Yellen described the corporate bond market as "under significant stress" (Bernanke and Yellen, 2020), while a March 18 report from Bank of America deemed the market "basically broken" (Idzelis, 2020).

In response, the Federal Reserve introduced several facilities to lower the costs of intermediating corporate debt and to bolster liquidity. On the evening of March 17, the Federal Reserve introduced the Primary Dealer Credit Facility (PDCF), offering collateralized overnight and term lending to primary dealers. By allowing dealers to borrow against a variety of assets on their balance sheets, including investment grade corporate debt, this facility intended to reduce the costs associated with holding inventory and intermediating transactions between customers. On March 23, the Federal Reserve proposed even more direct interventions in the corporate bond market through the Primary and Secondary Market Corporate Credit Facilities (PMCCF and SMCCF, respectively). These facilities were designed to make outright purchases of corporate bonds issued by investment grade US companies, along with US-listed exchange-traded funds (ETFs) that invested in US

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[1]In fact, reports of trading difficulties even reached the market for Treasuries, in what Chappatta (2020) described as a "stunning lack of liquidity in what's often billed as the world's deepest and most liquid bond market."

[2]For example, between March 5 and March 20, the ICE Bank of America AAA US Corporate Index Option-Adjusted spread increased by about 160 basis points (bps), while the corresponding spread for high yield corporate debt (HY) increased by more than 500 bps. See Ebsim, Faria-e Castro, and Kozlowski (2020) for a comprehensive analysis of credit spreads during this time period. Also see Haddad, Moreira, and Muir (2020) for a study of credit market disruptions during the COVID-19 crisis. They document large discounts for corporate bonds and bond ETFs relative to their CDS spreads and NAVs, respectively, which are more pronounced for the safer end of the credit spectrum.

investment grade corporate bonds. On April 9, these corporate credit facilities were expanded in size and extended to allow for purchases of ETFs that invested in high yield corporate bonds.[3]

To study the effects of these interventions on trading conditions, we explore several dimensions of market liquidity. We start with perhaps the most common metric, the bid-ask spread, which Demsetz (1968) famously defined as "the cost of making transactions *without delay*."[4] However, in the corporate bond market, dealers actually offer two types of transaction services: "principal trades," where the customer trades quickly against dealers' inventory; and "agency trades," where the customer typically waits for dealers to locate another customer to take the other side of the trade. Principal trades are fast, high quality transaction services as envisioned by Demsetz, while agency trades represent a slower, lower quality version.[5] Naturally, then, the prices of these distinct transaction services can differ significantly, and the frequency with which each type is used can depend on both market conditions and prevailing regulatory requirements.

At the height of the COVID-induced panic, with investors rushing to sell assets as quickly as possible and dealers hesitant to absorb assets directly onto their balance sheets, how much did dealers charge customers to trade immediately via principal trades? What was the cost of trading at a delay, via agency trades, that spared dealers from holding assets on their balance sheets? How did the Fed's interventions affect dealers' willingness to accumulate inventory, the price they charged for their transaction services, and the composition of principal vs. agency trades? These are the empirical questions that we attempt to answer below, as we provide an account of trading conditions in the corporate bond market that allows for this crucial distinction between different types of transaction services. In the Appendix, we provide a simple theoretical framework to help interpret some of our empirical observations.

2   The Costs of Trading, Fast and Slow

To capture the average transaction cost for principal trades alone, we calculate the measure of spreads proposed by Choi and Huh (2018). More specifically, we calculate the average spread between the price that customers pay or receive when trading with a dealer, relative to a reference inter-dealer price, calculated each day for each bond and weighted by trade size. Importantly, we do *not* include trades in which the dealer who buys the bond from a customer holds it for less than 15 minutes. In doing so, we leave out those trades where the dealer had pre-arranged for another party (either a customer or another dealer) to buy the bond immediately.

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[3]The April 9 update also allowed the SMCCF to make direct purchases of bonds that had been downgraded from investment grade to high yield status (so-called "fallen angels") after March 22.

[4]The italics are part of the author's quotation.

[5]See, e.g., An and Zheng (2018) and An (2019) for formal models.

To capture the average transaction cost of agency trades, we calculate a modified version of the Imputed Roundtrip Costs measure described in Feldhütter (2012).[6] To construct this modified imputed roundtrip cost (MIRC), we first identify roundtrip trades, defined as two trades in a given bond with the same trade size that take place within 15 minutes of each other: a sale from a customer to a dealer, and a purchase by a customer from a dealer. Then, for each roundtrip trade, we calculate the MIRC as the percentage difference between the maximum and minimum prices. A daily estimate of average roundtrip cost is the average MIRC on that day across bonds, weighted by the value of each trade.

We construct the two series using dealers' reports to the Trade Reporting Compliance Engine (TRACE), which is made available by the Financial Industry Regulation Authority (FINRA), and plot the output in Figure 1.[7] In all of our plots, we include vertical dashed lines to highlight several key dates: February 19, when stock markets reached their all-time peaks; March 5, which marks the beginning of the extended fall in equity prices and rise in corporate credit spreads; March 9, the first day of trading after Saudi Arabia initiated an oil price war with Russia; March 18, the first day of trading after the announcement of the PDCF; March 23, the day that the PMCCF and SMCCF were announced; and April 9, the day that the size and scope of the corporate credit facilities were expanded.

The two measures of transaction costs are relatively similar, and stable, through February 19. However, the cost of principal trades rises dramatically over the ensuing weeks, while the cost of agency trades is more muted. In particular, between Thursday, March 5, and Monday, March 9, the cost of principal trades roughly triples, to approximately 100 bps; over these three trading days, the S&P 500 Index declined more than 12%. A week later, during the most tumultuous period of March 16-18, this series continues to rise, reaching a peak of more than 200 bps, before beginning a steady decline after the announcement of the SMCCF on March 23. The MIRC measure, in contrast, increases from a baseline of approximately 20 bps to just under 40 bps, before receding back to pre-crisis levels.

To highlight the relative costs of principal and agency trades, we plot the ratio of the two series in Figure 2. One can see that the cost of trading immediately was considerably more responsive to both the heightened selling pressure induced by the pandemic in mid-March and the Fed's interventions which followed. This evidence is broadly consistent with anecdotes from dealers (such as the one in the epigraph) that ascribe a central role to balance sheet costs in the determination of market liquidity. Moreover, despite considerable improvement in both metrics during the month of April, note that the price of trading immediately remains elevated, which suggests that liquidity conditions remain somewhat strained.

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[6] We provide additional details on the construction of this measure in the Appendix.

[7] We describe the data in greater detail, along with the specifics of our calculations, in the Appendix.
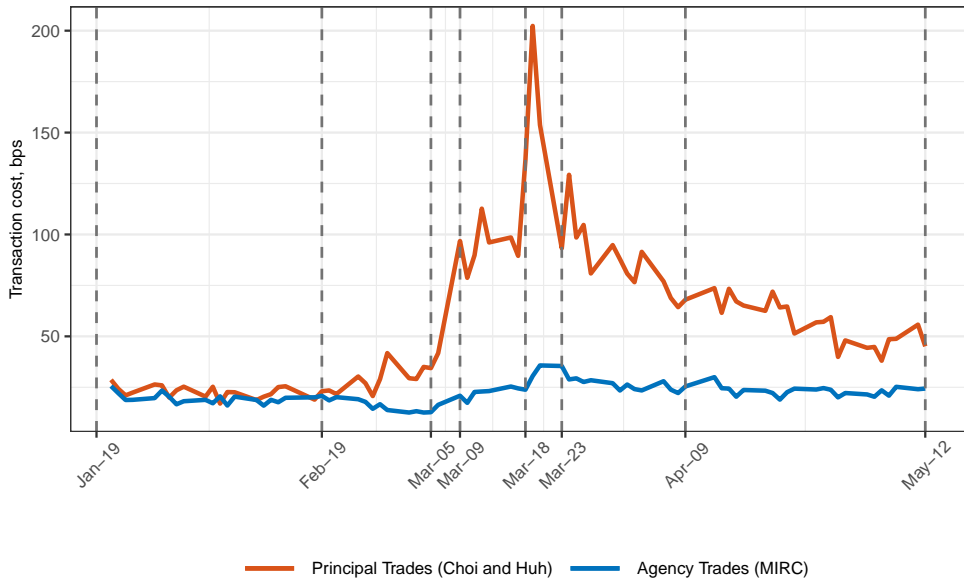
Figure 1. Transaction costs (Choi and Huh (2018) vs MIRC).
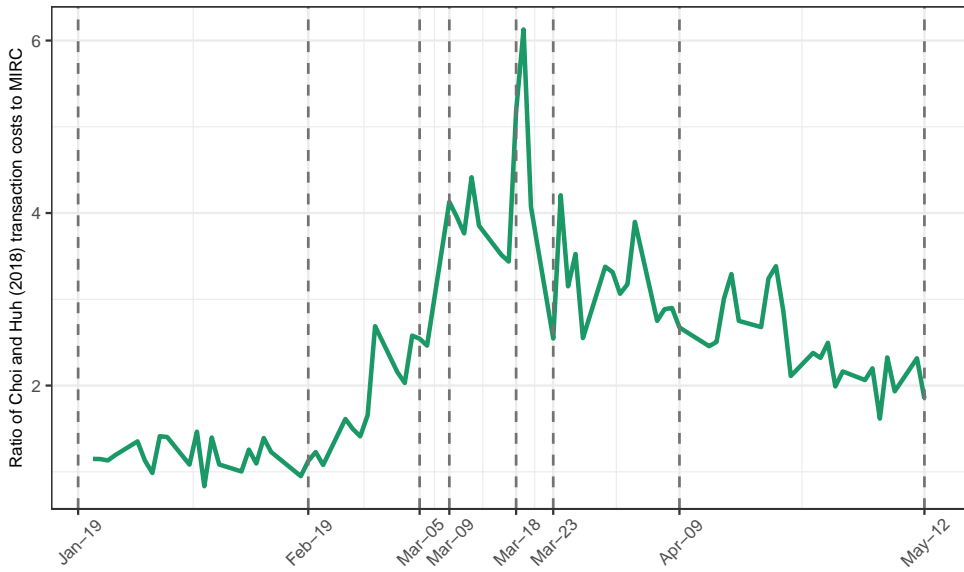
Figure 2. Ratio of Choi and Huh (2018) transaction costs to MIRC
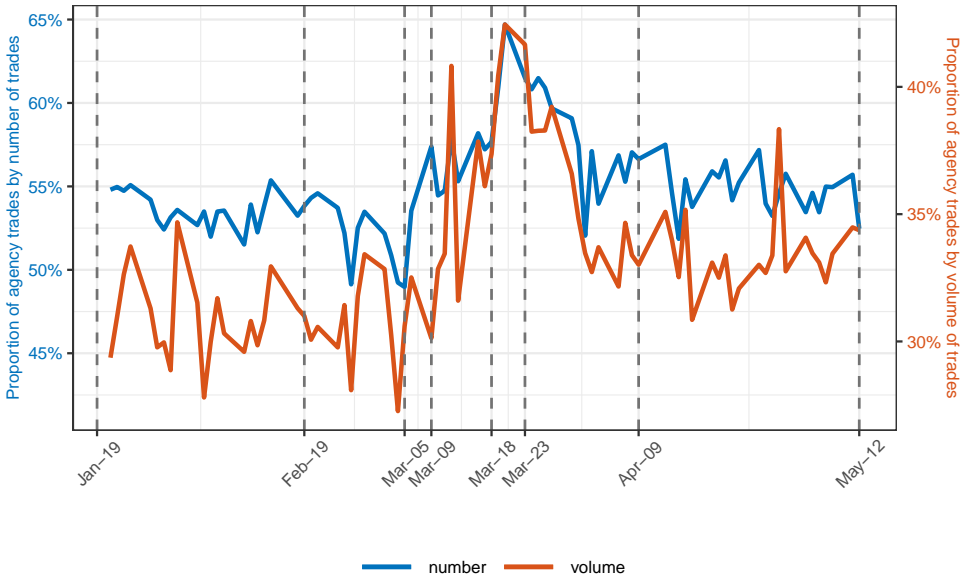
Figure 3. Proportion of Agency Trades, all bonds.

3 Did Dealers Lean Against the Wind?

Since dealers were charging considerably higher prices to trade immediately, one might expect customers to respond by substituting towards slower, agency trades. Figure reffig:agency-principal-All-EOD confirms that this was indeed the case during the most tumultuous weeks of trading in mid-March. For example, between March 5 and March 23, the fraction of agency trades measured by both number (left axis) and volume (right axis) increased by about 10 percentage points, before receding after the March 23 announcement of the corporate credit facilities. As a result, if one were to measure trading costs across all trades, they would underestimate the erosion in liquidity as the composition of trades shifted from faster, more expensive principal trades to less costly, but slower agency trades.

To summarize our results thus far, at the height of massive selling pressure in mid-March—when funds investing in investment-grade corporate bonds faced withdrawals of almost $100 billion alone (Scaggs, 2020)—the price of trading immediately increased substantially, and the fraction of principal trades declined. In light of these observations, one might naturally wonder: who was providing liquidity in the corporate bond market? Were dealers "leaning against the wind" and absorbing some of the inventory during the selloff, as described in Weill (2007)? Or was the shift to agency trades sufficiently large that other customers were ultimately providing liquidity?
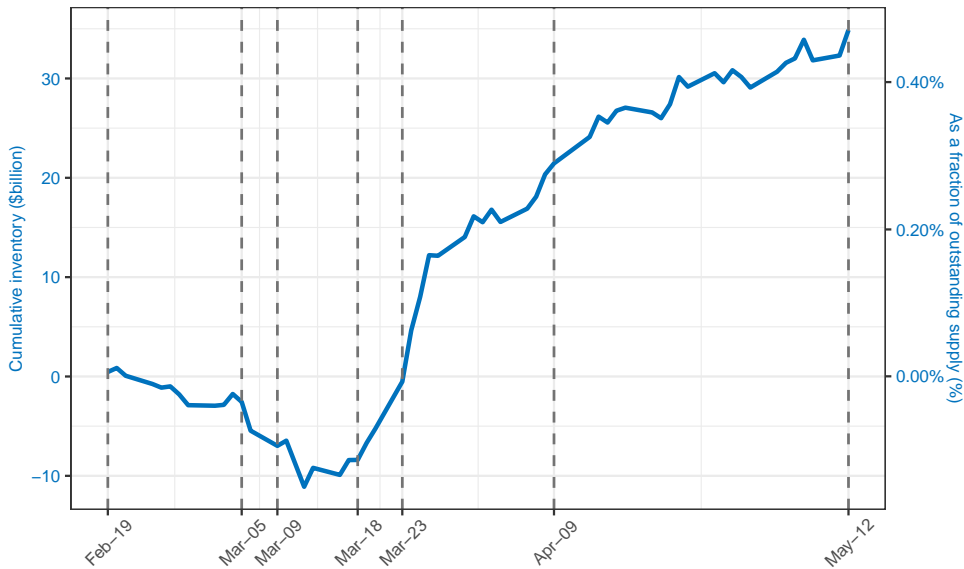
Figure 4. Cumulative inventory change (USD billions) in the dealer sector and as a fraction of total supply, according to FINRA market sentiment tables.

To answer this question, we construct a measure of the (cumulative) value of bonds that were absorbed over time by the dealer sector. In particular, using the daily Market Sentiment data from FINRA, we subtract the value of bonds that dealers sell to customers from the value of bonds that they buy from customers each day, and then calculate the cumulative sum of the net changes.[8] Figure 4 plots the cumulative net change in inventory held in the dealer sector, both in levels (left axis) and as a fraction of pre-crisis outstanding supply (right axis), starting on February 19, 2020.

Several aspects of Figure 4 are striking. First, during the most tumultuous period of trading, the dealer sector absorbed, on net, *no* additional inventory despite the considerable selling pressure. Hence, during this period, it was indeed other customers that were supplying liquidity to the market. Second, dealers' reluctance to absorb inventory appears to have changed substantially around the dates corresponding to the Fed's announcement of the Primary Dealer Credit Facility (March 18) and the Primary and Secondary Market Corporate Credit Facilities (March 23). Lastly, dealers have continued to accumulate inventory through April and the first half of May. Indeed, since March 18, the data indicates that dealers have absorbed nearly

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[8]See FINRA TRACE Market Aggregate Information.

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$50 billion in corporate debt, or roughly double the amount they held before the pandemic.[9]

4   Liquidity Across Ratings and Maturity

The evidence above suggests that improvements in corporate bond market liquidity coincided with the announcements of several significant interventions by the Federal Reserve, such as the PMCCF and the SMCCF. When these programs were first announced on March 23, the term sheets specified that the facilities could only purchase investment grade corporate debt with a maturity of five years or less (the possiblity of purchasing ETFs holding high yield corporate debt was introduced later, on April 9). To better understand the sources of illiquidity in the corporate bond market, and the potential effects of these interventions, we now explore the cost of trading eligible and non-eligible bonds since the onset of the pandemic.

To start, Figure 5 plots the Choi and Huh (2018) measure of transaction costs for investment grade (IG) and high yield (HY) corporate bonds (left axis), along with the ratio of the two (right axis). Roughly speaking, the spreads for IG and HY bonds exhibit similar patterns over the sample period: they increase considerably between March 5 and March 23 (with HY bonds issued by firms in the energy sector spiking dramatically on March 9), before gradually receding through April and May. Interestingly, during the week of March 16-20, when markets were most illiquid, IG and HY bonds were *equally* illiquid. This observation is consistent with anectodal evidence that dealers were unwilling to add *any* assets to their balance sheets in mid-March. It is inconsistent with, e.g., a theory of illiquidity based on adverse selection, since typically adverse selection would be more severe (and hence spreads would be larger) for more information-sensitive, HY bonds.

It is also noteworthy that the announcements of the Fed's interventions did not have drastically different effects on eligible and non-eligible bonds, as both IG and HY bonds spreads fell significantly after March 23, though the fall was more pronounced for eligible, IG bonds. This observation suggests that bond purchases could have important indirect effects, i.e., that enabling dealers to unload IG bonds from their balance sheet freed them up to intermediate all bonds (and, perhaps, other assets, too). We reach similar conclusions when we examine eligibility restrictions based on maturity. Figure 6 plots the transaction costs of principal trades for bonds with time-to-maturity (TTM) of less than 5 years (which were eligible for purchase by the SMCCF) and more than 5 years (which were not). Again, the ratio of spreads between the two classes of bonds does not indicate that liquidity conditions for eligible bonds improved more drastically than those for ineligible bonds.

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[9]From Table L.130 of the Flow of Funds, at the end of 2019Q4, security brokers and dealers held $54 billion in corporate and foreign bonds on the asset side of their balance sheets.
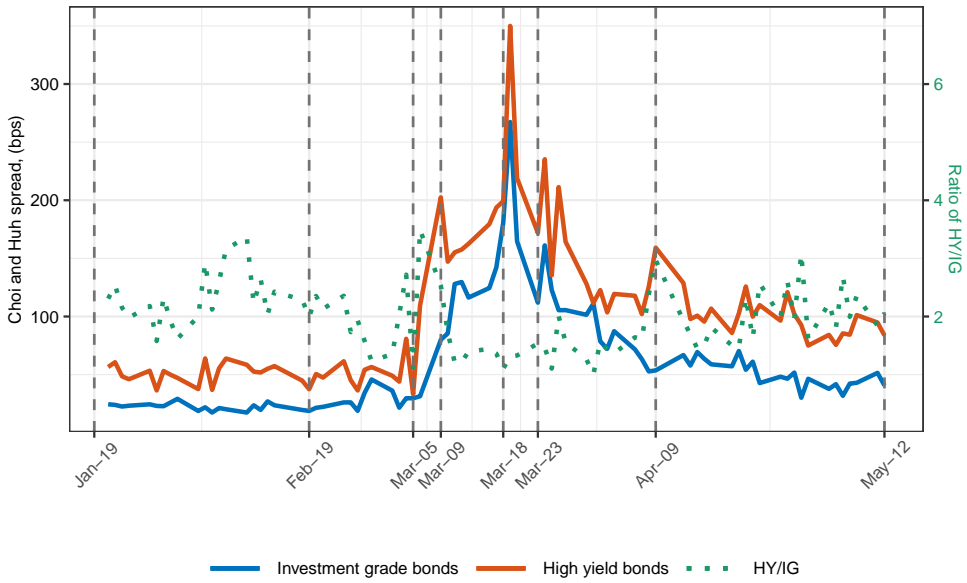
Figure 5. Choi and Huh spread across rating categories
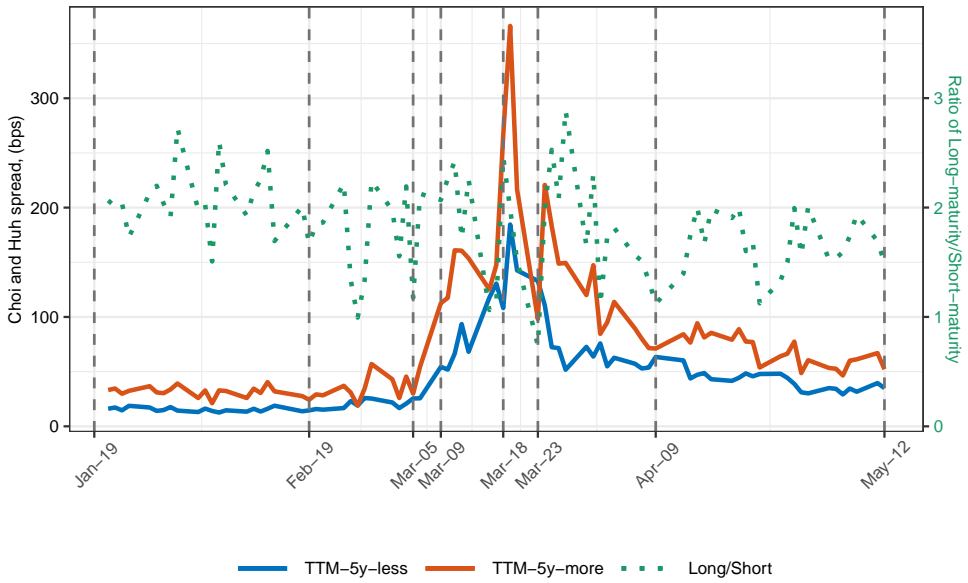
Figure 6. Choi and Huh spread across maturities

5 Conclusion

This note explores liquidity conditions in the corporate bond market during the COVID-19 pandemic. As is well known theoretically, illiquidity can have a direct negative effect on bond prices: for example, Amihud and Mendelson (1986) have shown that, under natural conditions, illiquidity creates a price discount equal to the expected present value of transaction costs incurred by successive buyers. There are important indirect effects too: for example, He and Xiong (2012) and He and Milbradt (2014) have shows that liquidity price discount creates rollover losses and bring a firm closer to default, which can increase the discount, deteriorate liquidity further, and so on.

Moreover, there are indications that the main source of illiquidity in the corporate bond market—namely, the inability of dealers to absorb inventory onto their balance sheets—was also an important factor in the markets for Treasuries, municipal bonds, and asset-backed securities.[10] Hence, by understanding the behavior of dealers in the corporate bond market, and the effects of the Fed's various interventions, we hope to provide insight into these other important, dealer-intermediated over-the-counter markets as well.

While the data provides an interesting, real-time assessment of market conditions, much work remains to be done. First, we would like to explore empirical strategies to better determine the causal relationship between policy interventions and market outcomes, as the current analysis is only suggestive, at best. Second, we would like to compare both credit spreads and transaction costs during the recent market turmoil to those observed during the Global Financial Crisis of 2008. By comparing the market's reaction during these two episodes—which were induced by different shocks amid different regulatory regimes—we hope to shed light on the extent to which each episode should be viewed as a solvency crisis, as opposed to a liquidity crisis.

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[10]See, e.g., Cheng, Wessel, and Younger (2020).

6 Appendix

6.1 Data Filtering

We first filter the report data following the procedure laid out in Dick-Nielsen (2014). We merge the resulting data set with the TRACE master file, which contains bond grade information, and with the Mergent Fixed Income Securities Database (FISD) to obtain bond fundamental characteristics. Following the bulk of the academic literature, we exclude bonds with optional characteristics, such as variable coupon, convertible, exchangable, and puttable, as well as on-the-run bonds (issued less than 90 days ago), asset-backed securities, and private placed instruments. The final sample contains 6,104,089 transactions in 34,407 bonds, for a sample period running from January 1 to May 12, 2020.

6.2 Dates Highlighted in the Figures

We choose the following dates to highlight in the figures with vertical, dashed lines:

January 19: beginning of the series, chosen to start the sample period one month before the stock market peak.

February 19 stock market peak.

March 5: beginning of extended fall in equity prices and rise in corporate credit spreads.

March 9: first day of trading after Saudi Arabia initiated an oil price war with Russia.

March 18: first day of trading after announcement of Primary Dealer Credit Facility (announced evening of March 17).

March 23: announcement of Primary and Secondary Market Corporate Credit Facilities.

April 9: expansion of PMCCF and SMCCF (in both size and scope).

6.3 Modified Imputed Roundtrip Trading Costs

We first construct pairs of Imputed Roundtrip Trades (IRT) as in Feldhütter (2012), but with several additional restrictions. To construct an IRT, we match a customer-sell trade with a customer-buy trade of the same size that takes place in a time window of 15 minutes. We do not include interdealer trades in IRTs, so that each IRT only includes one customer buy trade and one customer sell trade. Note that a particular bond may have multiple IRTs in a single day. Then, to compute the modified imputed roundtrip cost (MIRC), we calculate $(P_{max} - P_{min})/P_{max}$, where P_{max} is the largest price in the IRT and P_{min} is the smallest price in the IRT. Within each bond, we calculate the daily average roundtrip cost as the average of the bond's IRCs on that day, weighted by trade size. Finally, a daily estimate of average roundtrip cost is the average of roundtrip costs on that day across all bonds, weighted by bonds' total trading volumes.

6.4 Choi and Huh's Measure of Spreads

Following Choi and Huh (2018), we calculate $spread1 = 2Q \times \frac{\text{traded price} - \text{reference price}}{\text{reference price}}$, where Q is equal to $+1$ for a customer buy and -1 for a customer $sell$. For each customer trade, the reference price is taken to be the volume-weighted average price of interdealer trades larger than $\$100,000$ in the same bond-day, excluding interdealer trades executed within 15 minutes. The measure $spread1$ is calculated at the trade level for all customer principal trades (held in dealer inventories for more than 15 minutes) and is also calculated at the bond-day level by taking the volume-weighted average of trade level spreads.

6.5 A Simple Theoretical Framework

In this Appendix we develop a simple theoretical framework to intepret our empirical findings. We represent the COVID-19 crisis as an exogenous shock to the aggregate demand for transaction services in the corporate bond market.[11] We study the impact of this shock on the equilibrium quantities and prices of agency and risky-principal trades.

The Model

There are two types of agents: a measure N of customers and a measure one of dealers, all price takers. Each customer seeks to make a number of transactions normalized to one: therefore, in this model, the aggregate transaction demand is exogenous and equal to N. Although the total number of transaction is exogenous, the composition of transactions is not. Namely, we assume that customers demand vertically differentiated transaction services supplied by dealers at a convex cost: low-quality transaction services, interpreted as agency trades, and high-quality, interpreted as risky-principal trades.

Customers have quasi-linear utility for transaction services and for cash. Specifically, the problem of a customer is to choose how much low- and high-quality transaction services to demand from dealers in order to maximize:

$$u(x_l, x_h) - p_l x_l - p_h x_h,$$

subject to the constraint that the total number of transactions adds up to the exogenously desired level, $x_l + x_h = 1$. We assume that $u(x_l, x_h)$ is increasing, concave, twice continuously differentiable, and satisfies $u_h(x_l, x_h) - u_l(x_l, x_h) \geq 0$, where the h and l subscripts are short-hands for first partial derivatives with respect to x_h and x_l, respectively. This condition simply means that the customer values more high- than low-quality transaction services.

Assuming from now on interior solutions, the first-order optimality condition of the customer is:

$$u_h(x_l, x_h) - u_l(x_l, x_h) = p_h - p_l, \quad \text{where} \quad x_l + x_h = 1.$$

On the other side of the market, dealers choose their supplies of transaction services, X_l and X_h, in order to maximize profits:

$$p_l X_l + p_h X_h - C(X_l, X_h),$$

where $C(X_l, X_h)$ is some continuous, convex, and twice continuously differentiable cost function. This leads to the first-order optimality conditions

$$p_l = C_l(X_l, X_h) \quad \text{and} \quad p_h = C_h(X_l, X_h).$$

Finally, the market clearing conditions for transaction services are simply:

$$X_l = N x_l \quad \text{and} \quad X_h = N x_h.$$

An equilibrium given aggregate transaction demand N is a tuple $(x_l, x_h, X_l, X_h, p_l, p_h)$ solving the first-order optimality conditions of customers and dealers, and the market clearing conditions.

The impact of a shock to aggregate transaction demand

The COVID-19 crisis created unprecedented increase in aggregate transaction demand, with a corresponding rise in trading volume. In our model, we represent this shock by an increase in N. The following Proposition characterizes

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[11] According the FINRA market sentiment tables referenced above, volume increased by about 50 percent between February 19th and March 31st, relative to the January 19th to February 19th period.

the impact of this shock on the equilibrium prices and quantities of low- and high-quality transaction services.

Proposition 1. *Let* $(x_l, x_h, X_l, X_h, p_l, p_h)$ *be an equilibrium for a given aggregate transaction demand, N. Then, in response to a marginal increase in N:*

- $p_h - p_l$ *increases and x_h decreases if $C_h(Nx_l, Nx_h) - C_l(Nx_l, Nx_h)$ is, locally, increasing in N.*

- p_l *increases if $C_l(Nx_l, Nx_h)$ is, locally, increasing in N.*

The first bullet point characterizes the impact of the shock on the equilibrium premium, $p_h - p_l$, and quantity, x_h, of high-quality transaction servies. To understand it, combine the first-order conditions of the customers and the dealers, together with the market-clearing condition:

$$u_h(1 - x_h, x_h) - u_l(1 - x_h, x_h) = p_h - p_l = C_h(N(1 - x_h), Nx_h) - C_l(N(1 - x_h), Nx_h).$$

The left-hand side defines a downward-sloping schedule for the per-customer demand of high-quality intermediation sevices, represented by the orange solid curve in Figure 7. The right-hand side defines an upward-slopping supply schedule, represented by the blue solid curve.[12] The intersection of the two curve determines the equilibrium given some aggregate transaction demand.

The condition stated in the first bullet point of the proposition ensures that, when there is a shock to the aggregate transaction demand, the supply schedule shifts up – in the Figure, from the blue solid to the green dashed supply curve. If the demand stays the same, the premium for high-quality transaction services increases, along the vertical red arrow. In response, of course, customers change their demand: they substitute towards low-quality transaction services. The premium decreases, along the diagonal red arrow, but remains elevated relative to its pre-shock level.

The second bullet point provides a natural sufficient condition for the price of low-quality intermediation services, p_l, to go up with N. Figure 8 illustrates. The solid-blue and solid-green curves are the marginal cost for low- and high-quality transaction services. The aggregate transaction demand shock shifts the two curves up, leading to an increase in both prices.

These comparative statics can be mapped to (at least some of) our empirical observations. Drawing the analogy of $p_l \approx IRC$ and $p_h \approx CH$, we have the $p_l < p_h$ pre-crisis; that, upon impact, both p_l and p_h spiked, but the magnitude of the p_h spike was larger; and, in the new equilbrium, p_l remains only slightly elevated (if at all), while p_h remains more significantly elevated. And, of course, this coincides with an decrease in risky-principal trades.

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[12]Notice that both schedules are defined by differences in marginal values and marginal costs: this is because each customer has a fixed total demand of intermediation services, so a marginal increase in the demand of high-quality services induces a corresponding decrease in the demand of low-quality services.
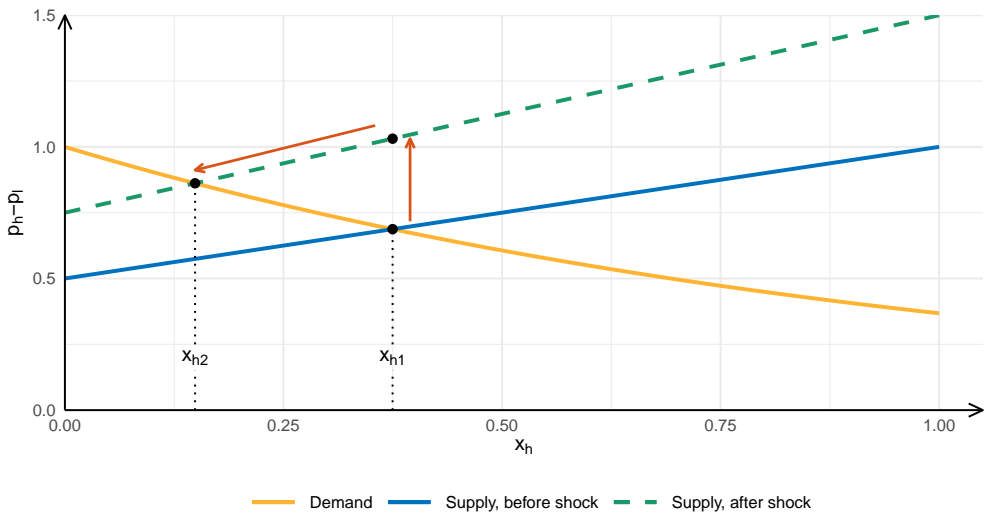
Figure 7. The determination of the price difference between high- and low-quality transaction services
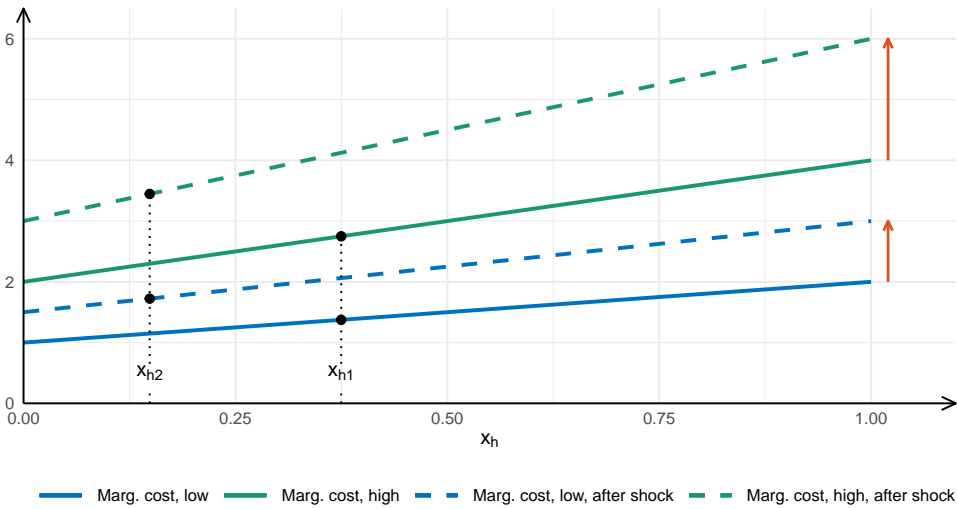
Figure 8. The determination of the price level of high- and low-quality transaction services

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The challenge of protecting informal households during the COVID-19 pandemic: Evidence from Latin America[1]

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Latin American countries introduced rapid emergency measures to sustain the income of informal workers and their families during shelter-in-place orders to contain COVID-19. The effectiveness of these measures is limited. The coverage and replacement rates of usual labor income are high among the first quintile of the population but fairly low in the second and third quintiles, where a substantial fraction of households are informal and have limited ability to telework. If governments plan to extend lockdown measures or reintroduce them in the future, they might need to consider broader income transfers for the lower-middle class.

COVID ECONOMICS
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1   Introduction

Governments around the world are taking measures to contain the spread of the new strain of coronavirus that causes COVID-19, prioritizing in almost all cases some form of social isolation or distancing. But the economic costs are not the same for everyone. The disease lays bare societies' inequalities, inflicting greater economic costs on the less economically fortunate across countries (Galasso 2020; Mongey, Pilossoph, and Weinberg 2020a). Latin America is no exception, where working at home is a luxury that most people cannot afford (Dingel and Neiman 2020; Delaporte and Peña 2020; Hatayama, Viollaz, and Winkler 2020). Data from online surveys show that, in every country of the region, the incidence of the lockdown on job losses has been heavily concentrated in the bottom half of the distribution (Bottan, Hoffmann, and Vera-Cossio 2020). Moreover, high levels of labor informality mean that large sections of the population are excluded from government safety nets.

To overcome the income losses among the most vulnerable households and workers, governments across the region have put in place a series of emergency social assistance programs.[1] Among the 10 countries considered in this study, 33 ad hoc programs were launched between March and the end of May of 2020.[2] Some of the programs are extensions of existing policies, most notably conditional and unconditional cash transfers that expanded considerably during the first decade of the 2000s (Levy and Schady 2013). However, preexisting programs have two limitations to reach all households at risk during the lockdown. First, they have well-known coverage limitations, even among the poor (Robles, Rubio and Stampini 2019). Second, the programs target the structurally poor and are not designed to mitigate temporary income shocks. Thus, many informal workers who are above the poverty line in normal times but would be severely affected by income losses during the lockdown

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[1] Governments put in place a much larger set of emergency measures (from soft credits to formal firms to adjustments to monetary policy). This paper evaluates the potential impact of the programs that target poor households and workers engaged in informal activities, which we broadly label as emergency social assistance programs.

[2] For data availability reasons, the analysis focuses on Argentina, Bolivia, Brazil, Chile, Colombia, the Dominican Republic, Ecuador, El Salvador, Peru, and Uruguay. These countries cover 60 percent of the population in Latin America.

are not eligible. To overcome these limitations, new programs targeting specific groups (e.g., self-employed, and unemployed who are not eligible for unemployment benefits) were added to the set of emergency measures.

This paper provides an ex-ante evaluation of the potential coverage and generosity of the COVID-19 emergency social assistance programs in 10 Latin American countries. The analysis maps the eligibility criteria of each program to the latest wave of nationally representative household surveys. We derive the coverage of the emergency programs across the income quintiles of each country's income distribution and a measure of the potential replacement rate that compares the total transfer that each household may receive as a share of its regular labor income.

We find that the potential coverage of the proposed emergency measures varies substantially by country, but in general it is fairly high among the poorest households that are in the first quintile of the income distribution, ranging from 68 percent in Chile to 100 percent (full potential coverage) in Brazil and Peru. Something similar happens with the replacement rate of potentially foregone labor incomes. With the exception of Uruguay, which introduced only selective lockdown in key sectors of economic activity and among vulnerable populations, the share of households with replacement rates below 25 percent in the first quintile of each country's income distribution does not exceed 20 percent. A different picture emerges in the second and third quintiles, which in all cases except Brazil and El Salvador present much lower replacement rates.

The paper makes two main contributions to the literature. First, Latin America was a pioneer in the development of conditional cash transfer (CCT) programs. By now they are ubiquitous and have rapidly expanded to the rest of the world (Fiszbein et al. 2009). These programs provide income support to households and, at the same time, introduce incentives for attending school and demanding health services. Many studies analyze the effects of CCT programs on labor supply, human capital, and welfare (to name but a few, Gertler 2004; Attanasio, Fitzsimons, and Gomez 2005; Barham and Maluccio 2009; Paxson

and Schady 2010) as well as features of their design (e.g., Attanasio, Oppedisano, and Vera-Hernández 2015; Dodlova, Giolbas, and Lay 2017). Our paper is the first to show the suitability of these programs to respond to an unexpected crisis. It shows that the existing safety nets have the potential to be expanded in times of crisis to make transfers more generous for those who are structurally poor. At the same time, the paper demonstrates the limitations of those safety nets to reach those who might fall into poverty temporarily. By doing so, it highlights the need for the region to develop a more robust system of automatic stabilizers that deal with the temporarily poor (e.g., unemployment insurance) that also accommodates the large existing informal economy (Alvarez-Parra and Sanchez 2009; Bosch and Esteban-Petrel 2013).

Second, this study contributes to the new literature on government responses to the COVID-19 crisis. Much of this literature focuses on developed countries (e.g., Faria-e-Castro 2020). The analysis in this paper has implications for the feasibility of sustaining a prolonged lockdown of economic activity in Latin America. But even beyond the initial lockdown period, strong social distancing may be sustained before a vaccine or viable cure becomes widely available. Self-enforcement and risk awareness have been key drivers of limited human interactions during the first wave of the pandemic (Maloney and Taskin 2020), suggesting that social distancing will continue independently of government interventions. In this context, labor demand in occupations and sectors that require high physical proximity (like retail, hotels, restaurants, and many personal services) may be substantially dampened even after the lockdown is lifted. Because these occupations and sectors are intensive in low-skilled labor (Mongey, Pilossoph, and Weinberg 2020b), they fundamentally employ informal workers in Latin America (Hatayama, Viollaz, and Winkler 2020). The challenges to sustain the incomes of these workers and their families highlighted here will be sustained over time.

The rest of the paper is organized as follows. Section 2 outlines the problem of implementing effective social distancing measures in economies with high rates of informality, such as those in Latin America. Section 3 describes the emergency social assistance pro-

grams in place in each country and how they were mapped to identify potential beneficiaries in household surveys. Section 4 discusses the potential coverage and replacement rate of the emergency measures. Section 5 concludes.

2 Social Distancing in an Informal Economy

Most of Latin America implemented strict social distancing policies relatively early during the pandemic. By mid-March, the 10 countries under analysis in this paper had fewer than 100 COVID-19 cases (Roser et al. 2020). Five days later, all 10 countries had closed their schools and a week later, there were strict lockdown measures in effect that required all non essential businesses to close temporarily and their populations to stay home, in many cases under strict penalties (Hale et al. 2020). The impacts of this widespread supply-side shock translated rapidly into a reduction of labor demand. Firm exits and job destruction amplified the initial effects of the lockdown, aggravating the recession (Guerreri et al. 2020).

In developing countries, the inability to telework combined with the high prevalence of labor informality imposes a limit to social distancing policies. Delaporte and Peña (2020) find that, for the sample of 10 countries used in this study, only 6.2 percent of individuals in the first quintile of the income distribution can work from home. The possibility of teleworking is also limited for individuals in the second and third quintiles (8.4 and 10.9 percent, respectively).

The limits on individuals teleworking are related to the task contents of their jobs, sector of economic activity, size and sophistication of employers, and formality status. Across occupations, only managers, professionals, technicians, and clerical workers are more amenable to teleworking. Across industries, it is only in finance, insurance, real estate and social services that the share of individuals who can telework exceeds 45 percent. Overall, only 6.7 percent of the informal workers are estimated to be able to work from home (Delaporte and Peña 2020).

At the same time, informal workers have very little space to face unexpected income losses. They have limited access to sick leave or unemployment benefits (Goni, Lopez, and Serven 2011), they have on average negative savings (Bebkzuk et al. 2015), and they have precarious access to health benefits. In the 10 countries under analysis, 41 percent of workers in the first and second quintile of the income distribution are self-employed. These workers most likely live hand-to-mouth.

Table 1: Percentage of Households without Formal Workers, by Country and Income Quintile

	Q1	Q2	Q3	Q4	Q5
Argentina	74	44	29	23	19
Bolivia	97	86	75	61	47
Brazil	67	31	19	14	9
Chile	46	24	16	14	11
Colombia	94	70	44	34	17
Dominican Republic	69	51	43	41	32
Ecuador	83	63	48	34	20
El Salvador	94	72	54	45	34
Peru	99	87	68	51	38
Uruguay	51	18	8	4	2
LAC	77	55	40	32	23

Note: Unweighted average for LAC. Data are from 2018 household surveys from Inter-American Development Bank–Harmonized Surveys for LAC, except Chile (2017). Income quintiles are calculated at the household level using monetary labor income per capita. LAC = Latin America and the Caribbean.

The severity of the problem is even greater considering assortative mating (Ganguli, Hausmann, and Viarengo 2014). Table 1 shows the share of informal households. That is, those in which no household member holds a formal job (defined as one where social security is being paid). On average, three in four households in the first quintile and more than half in the second quintile of the income distribution are fully informal. These shares decline for high-income households. This pattern is consistent across countries in the region, but the share of informal households declines with the level of development. Among the second quintile of each country's labor income distribution, more than 70 percent of the households

in Bolivia, Colombia, El Salvador, and Peru are fully informal. By contrast, the shares are 24 and 18 percent in Chile and Uruguay, respectively.

This highlights an additional cost that informality imposes when households face generalized and unexpected income losses. In a context of sudden crisis, full household informality severely limits the possibility of consumption smoothing through within-household risk-sharing mechanisms (as found by Pruitt, and Turner 2020). This limited within-household risk sharing is also observed in other developing regions (Dercon and Krishnan 2000; Robinson 2012).

Recognizing that social distancing would not be feasible without some sort of income support program, countries in Latin America moved swiftly to compensate households for their potential lost income.

3   Approximating Government Emergency Social Assistance Programs

Our analysis is based on two main sources of data. First, we collected and coded COVID-19 emergency assistance measures that were identified primarily through official government websites that track policy responses. The information in these websites has sometimes been incomplete or updated with some delay. To complete and validate this information, we used three sources. First, the main newspapers in each country were scraped, searching for specific keywords.[3] Second, we checked the "Weekly policymakers response against COVID-19 database" put together by the COVID-19 Policy Measures Team at the Inter-American Development Bank. Third, we checked the "ACAPS COVID-19: Government Measures Dataset". All sources are included in Table A1 in the Appendix. Our second source of data

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[3]We searched newspaper websites for the words "subsidy," "transfer," "coronavirus," and "aid" (in Spanish or Portuguese).

is harmonized household surveys from 2018[4] that were used to match the descriptions of the programs to household or individual characteristics in the survey.[5]

Table 2 shows a detailed view of the policies implemented by the 10 countries. The transfers are identified by the name the country gave them (e.g., Bono Universal in Bolivia) or by the beneficiaries targeted for the cash transfer. We identified the details of each policy (as described in the law or government announcement), targeted beneficiaries (households or individuals), amount and frequency of cash transfers, and eligibility criteria. A total of 33 programs were put in place in the 10 countries.

In 19 programs the identification of potential beneficiaries in the surveys is straightforward. This is the case for programs that expanded existing policies whose beneficiaries were already identifiable in the surveys, such as Familias en Accion in Colombia. Another 12 policies were reasonably approximated with survey respondents' characteristics. The details of the mapping between programs and household survey characteristics are provided in the Appendix.[6]

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[4]Except in Chile, where the National Socio-Economic Characterization Survey (CASEN) is bi-annual and the latest available wave was 2017.

[5]See Table A2 in the Appendix for a full list of the surveys used.

[6]We matched all programs except two in Argentina that target pregnant women, a characteristic we cannot observe in the surveys.

Table 2: Emergency Social Assistance Measures

Country	Policy	Beneficiary description	Transfer Level	Pre-existent social program
Argentina	1	Retirees, pensioners, and noncontributory pension beneficiaries receiving up to ARS$18,892 for their monthly pension	Individual	Yes
	2	Beneficiaries of Universal Child Allowance (AUH)	Household	Yes
	3	Per pregnant female at the household (AUE)	Individual	Yes
	4	Tarjeta Alimentar - for parents of children affiliated to AUH who are not over age 6 years	Household	Yes
	5	Tarjeta Alimentar - for pregnant women in their third trimester or more who have the AUE benefit	Household	Yes
	6	Ingreso familiar de emergencia - transfer for households with a household head between 18 and 65 who works in domestic service, is an informal worker, is a *monostributista social* (categories A and B), or households receiving AUH or Progresar social programs; household must not have a formal source of labor income or receive any pensions	Household	No
Bolivia	7	Bono Familia - transfer per child enrolled in school (does not include tertiary level)	Individual	No
	8	Bono Universal - for adults between ages 18 and 60 who do not receive any other government transfers (for retirement, widowhood, disability or meritorious), nor wages from public or private institutions, nor pensions or rents	Individual	No
	9	Canasta Familiar - transfer for older adults who receive Renta Dignidad but no other rent or pension; mothers who receive the Juana Azurduy transfer; or people with disability who receive the disability bonus	Individual	Yes
Brazil	10	Transfer for households with a single mother as household head, or with individuals whose main source of income comes from being informal workers or self-employed; unemployed; or microentrepeneurs; these households must not be beneficiaries of Bolsa Familia; their total income must not be more than R$3,135 or total per capita income above R$522.5	Household	No
	11	Beneficiaries of Bolsa Familia who do not receive other benefits; their total income must not be more than R$3,135 or total per capita income above R$522.5	Household	Yes
Colombia	12	Beneficiaries of Familias en Accion	Individual	Yes
	13	Beneficiaries of Jovenes en accion	Individual	Yes
	14	Beneficiaries of Colombia Mayor	Individual	Yes
	15	Ingreso Solidario - Households under extreme poverty, poverty, or economic vulnerability that do not receive any social program (Familias en accion, Jovenes en accion, Colombia Mayor) but belong to SISBEN	Household	No
Chile	16	Ingreso Familiar de Emergencia - transfer for households whose source of income is mainly from informal sources. The amount depends on the number of people in the household and decreases according to the percentage of income that is formal; pensioners from Pension Solidaria de la Vejez receive a smaller amount of aid	Household	No
	17	Bono Invierno - transfer for older adults who do not receive more than one pension or whose amount received is less than CLP$166,191 and who are retired from specific institutions (Instituto de Prevension Social, Instituto de Seguridad Laboral, Direccion de Prevision de Carabineros de Chile, Caja de Prevision de la Defensa Nacional, among others) or if they are beneficiaries of the program Pension Basica Solidaria de Vejez	Individual	Yes
	18	Bono de Emergencia COVID 19 - this transfer aims at households with individuals receiving Subsidio Familiar (SUF), households in the Sistema de Seguridades y Oportunidades database, households who belong to the 60% most vulnerable according to the Registro Social de Hogares database, and households who do not have a formal income through employment or pension and do not have any SUF beneficiaries	Household	Yes
El Salvador	19	Transfer for informal employees and self-employed workers with low social economic resources	Household	No
Ecuador	20	Transfer for affiliates to the unpaid work regime or self-employed; or affiliates to the Seguro Social Campesino, with income less than US$400 and who are not registered to the contributive social security and are not registered as dependents; individuals must not be beneficiaries of any other programs of the government	Individual	Yes
	21	Transfer for people not included in the previous subgroup whose income is lower than $400 and are below the poverty line	individual	No
Peru	22	Bono Quedate en Casa - Transfer for urban households below poverty line, who are not beneficiaries of Pension 65 or Juntos	Household	No
	23	Bono Independiente - transfer for households with main income source coming from self-employment and not in poverty; households cannot be beneficiaries of the Juntos, Pension 65, or Contigo programs; none of the household members can be registered as dependent workers of the public or private sector; household members cannot have income over PEN$1,200 and cannot be part of any local or central government	Household	No
	24	Bono Rural - transfer for rural households below poverty line, who are not beneficiaries of Pension 65 or Juntos	Households	No
	25	Bono Familiar Universal - transfer for households in poverty and extreme poverty; beneficiaries of the Juntos, Pension 65, or Contigo programs, and households above the poverty line and having no members registered as dependent workers of the public or private sector; none of the household members can have income greater than PEN $3,000; and only households who have not received previous transfers from COVID-19 aid (Policies (22) to (24)) can receive this transfer	Household	Yes
Dominican Republic	26	Beneficiaries of the Solidaridad social Comer es Primero program	Household	Yes
	27	Transfer for households who do not have any Solidaridad program Comer es Primero benefits and are under poverty and vulnerability according to SIUBEN	Household	No
	28	Additional transfer for groups in Policies (28) and (29) whose household head is vulnerable (age 60+ years)	Household	Yes
Uruguay	29	Extra transfer for Tarjeta Uruguay Social beneficiaries	Household	Yes
	30	Transfer for adults who are 65+ years and still working in the private sector (sickness benefit due to quarantine measures)	Individual	No
	31	Beneficiaries of Plan Equidad	Household	Yes
	32	Transfer for food purchases for informal and self-employed workers, with no other social program benefits and who do not have social security	Individual	No
	33	Transfer for a certain type of taxpayers (monotributistas sociales del MIDES)	Indiviidual	No

Using the household surveys, we then calculated potential coverage and replacement rates by household labor income quintile in each country. To approximate the replacement rates, we uniformly updated household labor incomes in the surveys to 2020 prices. Hence, our analysis shows the generosity of the intended programs as a percentage of the regular earnings of the households in each income quintile.[7]

Our estimates should be interpreted as an upper bound of the actual coverage and replacement rates in each country for two reasons. First, we focus on potential rather than actual beneficiaries. Implementing these programs with complex eligibility criteria during a pandemic is challenging. And so is the ability to receive aid in a region where less than 40 percent of the population has a bank account and bancarization is particularly low among households in the bottom half of the distribution (Demirgüç-Kunt et al. 2018). Despite these limitations, governments are innovating to expand the reach of the programs. For example, beneficiaries of several emergency programs in Colombia can opt to be enrolled in mobile wallet platforms and bank accounts to receive the aid. Yet, there is no doubt that some targeted families will end up not receiving aid.

Second, to calculate the replacement rate, we obtained the monthly stipend from all programs as a ratio of the regular monthly labor income of the household. At the time when we finished this paper (May 31), complete or soft lockdown measures were still in effect in the main cities of all the countries considered, except Uruguay. Our monthly stipends are calculated taking into account the projected duration of the lockdown. If governments were to decide to extend them without expanding the aid, the monthly stipends will decline.

4 Coverage and Generosity of the Transfers

Figure 1 summarizes the main results of the paper. It shows two indicators of the potential coverage of emergency transfers, measured as the share of households that are expected to receive them. One measure includes only emergency transfers that are extensions of programs

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[7]Households whose labor income was zero or negative in the survey are excluded from the analysis.

that existed before the COVID-19 crisis, and the other considers all emergency transfers. The third line shows the generosity of the emergency programs combined, calculated as the median emergency transfer received by households as a proportion of their regular monthly household labor income. The three measures are computed by quintile of the household labor income distribution of each country and averaged across the 10 countries.

Figure 1: COVID-19 Emergency Social Assistance Programs in LAC. Coverage and Replacement Rates
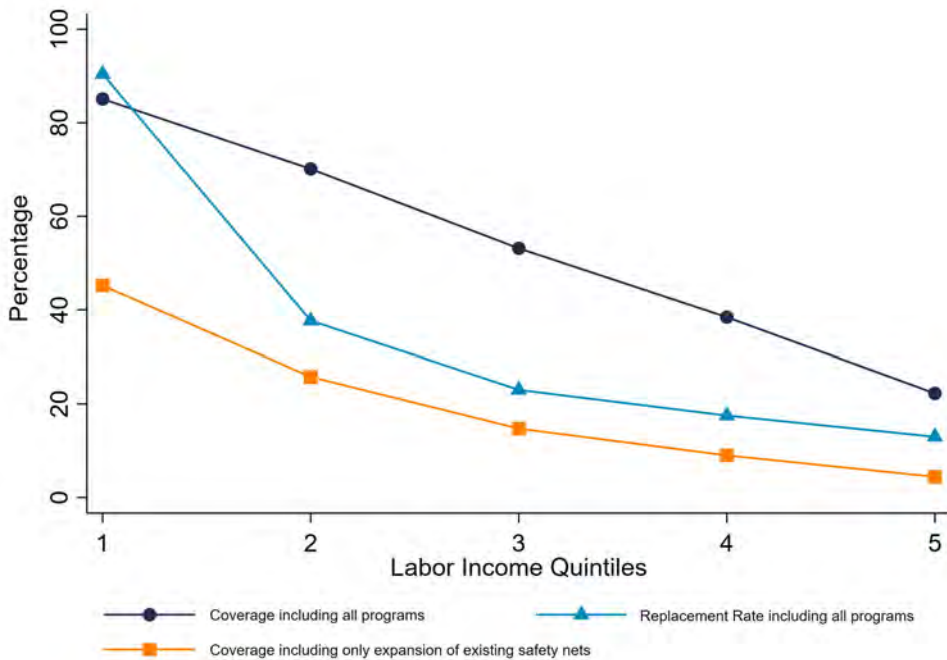
Note: Unweighted average for LAC. (i) Coverage is defined as the percentage of household receiving the aid (ii) Replacement Rate is the median of the monthly monetary transfer over the monthly monetary labor income for the targeted households. LAC average for coverage including only expansion of existing safety nets does not include El Salvador

The emergency transfers have the potential to reach a high proportion of households in the first quintile, but coverage drops linearly with income quintile. This leaves a substantial fraction of households in the second and third quintiles uncovered, although these quintiles have a high concentration of fully informal households (see Table 1), uncovered. The high coverage in the first quintile, potentially reaching 85 percent of households, hinges on the

set of ad-hoc measures introduced by the governments in the region. If governments were to rely only on the expansion of existing social programs, the coverage would have dropped to 45 percent.[8] The extension of the ad-hoc programs also shows potential leakages. Up to 22 percent of the households in the fifth quintile could become beneficiaries of one of these emergency social assistance programs.

Table 3: Percentage of Targeted Households by Type of Monetary Transfer, Country and Income Quintiles

	A. Preexisting social programs					B. All transfers				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Argentina	66	48	35	21	7	71	53	42	29	15
Bolivia	50	28	24	22	16	93	94	90	81	50
Brazil	80	23	0	0	0	100	97	68	21	4
Chile	32	20	12	7	4	68	43	30	20	7
Colombia	38	23	12	5	1	88	55	12	5	1
Dominican Republic	39	30	23	17	9	84	49	23	17	9
Ecuador	5	6	3	2	1	54	44	41	35	17
El Salvador	0	0	0	0	0	96	83	80	76	64
Peru	46	23	9	3	1	100	93	71	50	26
Uruguay	51	31	13	4	1	97	90	74	51	29
LAC	45	26	15	9	4	85	70	53	38	22

Note: LAC = Latin America and the Caribbean. Unweighted average for LAC. 2018 household surveys from IDB-Harmonized Surveys for LAC, except Chile (2017). Income quintiles are calculated at the household level using the distribution of monetary labor income per capita in each country. Panel A shows the percentage of targeted households receiving monetary transfers if countries only used preexistent social programs. The LAC average in panel A does not include El Salvador. Panel B shows the percentage of targeted households including all the policies implemented. The LAC average in panel B includes all 10 countries.

Moving to the detailed country results, Table 3 shows the share of households in each quintile of the income distribution of each country that was expected to receive an emergency social assistance transfer. Panel A considers the emergency transfers that were allocated to households via preexisting social programs. On average, 45 percent of the households in the first income quintile received an emergency transfer through the preexisting infrastructure of the social safety net, but this varies substantially across countries, with coverages as low as

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[8]This excludes El Salvador, which opted not to rely on its CCT program to cover the income losses of the COVID-19 lockdown measures.

5 percent in Ecuador and as much as 80 percent in Brazil. This is not surprising, given the low coverage of safety nets in the region. Robles, Rubio, and Stampini (2019) report that on average CCT programs in Latin America cover about 43 percent of households below the poverty line who have children. Similarly, noncontributory pension programs cover about 46 percent of the elderly who are under the poverty line.[9] Interestingly, Robles, Rubio, and Stampini (2019) report that among the CCT and non-contributory pension programs in the region the country with the lowest coverage is El Salvador, reaching as little as 11 percent of poor households with children and 9.4 of the elderly who are poor. El Salvador is the only country among those considered in this study that has not used targeting of its preexisting safety net to provide emergency transfers during the COVID-19 pandemic.

Being aware of the coverage limitations of preexisting social assistance programs, governments around the region expanded the eligibility criteria with a set of ad-hoc measures. Table 3, panel B, shows the coverage of all emergency transfers lumped together, which reaches more than 90 percent of the households in the first quintile in five of the 10 countries. Coverage drops in most countries for households in the second or third quintiles. Yet, in Bolivia, Brazil, El Salvador, Peru, and Uruguay it reaches on average 84 percent of the second and third quintiles, which allowed the emergency transfers to reach the lower-middle class.

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[9]The reasons for low coverage are many. Some of the programs are small due to fiscal constraints; targeting is based on proxy-means testing, which is imperfect; lack of connection or distrust of social services; and inability to comply with the eligibility criteria or conditionalities.

Table 4: Replacement Rate of COVID-19 Emergency Social Assistance by Country and Income Quintile

	A. Median					B. Less than 25%				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Argentina	60	24	15	10	6	15	52	93	100	100
Bolivia	97	22	12	7	4	5	58	95	100	100
Brazil	164	79	57	55	57	0	0	0	0	0
Chile	97	46	28	18	5	19	40	44	93	100
Colombia	61	27	9	5	3	15	46	99	100	100
Dominican Republic	41	21	13	10	7	19	60	84	89	99
Ecuador	79	28	12	8	5	4	46	84	92	100
El Salvador	189	101	67	50	32	0	0	1	4	30
Peru	100	23	14	10	9	4	56	84	89	100
Uruguay	18	6	3	2	1	63	94	94	94	87
LAC	90	38	23	17	13	14	45	68	76	82

Note: LAC = Latin America and the Caribbean. Unweighted average for LAC. Data are from 2018 household surveys from IDB-Harmonized Surveys for LAC, except Chile (2017). Income quintiles are calculated at the household level using monetary labor income per capita. The replacement rate is defined as total monthly transfer divided by regular monthly labor income in the household. Non-targeted households by the emergency programs and households with zero or negative regular labor income are excluded. Panel A shows the median of the replacement rate over the monetary labor income for targeted households. Panel B shows the percentage of targeted households for which the replacement rate is less than 25%.

Table 4 assesses the ability of the emergency transfers to replace potential labor income losses. Panel A shows the median replacement rate, and panel B shows the share of households for which the emergency transfer would replace less than 25 percent of their pre-COVID-19 income. Non-targeted households by the emergency programs and households with zero or negative regular labor income are excluded in the calculations.

The replacement rate is very high in the first quintile of all countries, in some cases more than compensating for the potential labor income loss. Notable exceptions are Uruguay (potential replacement rate of 18 percent) and the Dominican Republic (41 percent). Similarly, except in Uruguay, the share of households in the first quintile of the earnings distribution with a replacement rate below 25 percent is less than 20 percent.

However, the transfers replace a small share of the potential income losses of households in the second and third quintile. Brazil and El Salvador are the only exceptions. In the other eight countries, the median replacement rate does not reach 50 percent among households in

the second quintile, and it is below 30 percent in the third quintile. The emergency programs also leave a substantial share of households with replacement rates below 25 percent. More than 50 percent of the households are below this threshold in the second quintile in the same eight countries, and more than 80 percent in the third quintile would receive a transfer that replaced less than 25 percent of their labor income if this becomes zero during the lockdown. Having adopted social distancing measures later than most of the countries in the group, Brazil is an outlier. The two programs included in the emergency social assistance measures have a median replacement rate that is up to 57 percent of regular labor income in the richest quintile, leaving no household with a potential transfer that would cover less than 25 percent of its regular labor income. Potential beneficiaries in Brazil in all quintiles of the distribution would greatly benefit from the transfers.

5   Conclusion

Latin American governments have taken aggressive steps to save lives by ordering shelter-in-place regimes to stop the propagation of COVID-19. In most cases, they have swiftly implemented compensation programs to sustain incomes and facilitate stay-at-home orders. This paper highlights the strengths and limitations of these emergency programs by analyzing their potential coverage and generosity in 10 Latin American countries.

The proposed emergency measures do a good job in general in targeting the most vulnerable households: those in the first quintile of the country's labor income distribution. However, the coverage and replacement rates in the second and third quintiles are much more limited. With the notable exceptions of Brazil and El Salvador, emergency social assistance programs as currently formulated cannot replace the potentially foregone incomes of a large fraction of families in the informal workforce that are forced to shelter in place and cannot work. This insufficient compensation limits the ability of governments to sustain extended lockdown periods, and it may limit the ability to enforce another wave of lockdowns

due to contagion surges.

The government responses to the COVID-19 crisis highlight structural problems in the region: the fragmented and insufficient coverage of social protection systems. These limitations complicate the delivery of income support to informal workers who are not sufficiently poor to benefit from social assistance but lack other automatic stabilizers, such as unemployment insurance, that could alleviate the impact of temporary shocks.

The full impact of the shortcomings of the social protection systems during the course of the current outbreak is still unknown. Latin America needs to think seriously about reforms that would provide more effective and agile assistance to those falling through the cracks in times of crisis. Doing so would make the region more resilient.

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Appendix

Identifying COVID-19 Emergency Measures and Matching them to Household Surveys

We used several websites and news sources to identify the policies put in place in each country. Policies were identified primarily through official government websites that track countries' COVID-19 policy responses. Table A1 offers a full list of these websites. Sometimes the information in these websites is incomplete or updated with a delay. All the information was cross-checked with several sources. The main newspapers in each country were scraped, searching for the following keywords: "subsidy", "transfer", "coronavirus", "bonus", and "aid". We also checked policy makers' weekly response against the COVID-19 database put together by the COVID-19 Policy Measures Team at the Inter-American Development Bank (IDB). The last source for double checking and obtaining updates was the ACAPS COVID-19: Government Measures Dataset. All the sources are included in Table A1.

Table 2 in the main text presents a detailed view of the policies implemented by the 10 countries in our sample. We gathered information related to the beneficiaries (households or individuals), the amount and frequency of the emergency cash transfers and the eligibility criteria. Given the heterogeneity in the measures taken by governments concerning the implementation date, frequency (unique lump sum or monthly) and lockdown duration, our analysis focuses on a one-month time span.

To have a standardized measure across countries, we pro-rated the monetary amount to fit as a monthly transfer. We calculated the number of days the lockdown lasted, or is expected to last according to the information available by May 31. We take into account that some countries did not implement a total quarantine, and in these cases, we define it as the period when some sectors or capitals had stay-at-home orders. Then, for each policy, we divided the total cash transfer over the approximated months under lockdown. For example, in Peru the cash aid was a unique lump sum equivalent to PEN$760 and the quarantine is expected to last approximately 3.5 months (it started mid March and is expected to last until the end of June). This means that, for Peru, the monthly monetary transfer is equivalent to approximately PEN$217. In those countries where the transfer was designed as monthly and fits with the lockdown time estimated -such as Brazil, El Salvador, Uruguay and Ecuador- we used the amount as it was given by the governments, assuming the payment to all beneficiaries started with the quarantines.

Second, we identified the households beneficiaries using the variables from the 2018 household surveys harmonized by the IDB for all countries (except Chile, where the household survey is bi-annual and the latest available wave was 2017) [10]. To match the eligibility criteria with the surveys, we transformed the income variables to 2020 prices by multiplying them by the official inflation rates in 2019 and up to April 2020 for each country (for Chile, we added the 2018 inflation rate). As our analysis focuses on measuring the coverage and

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[10]See Table A2 for a full list of the surveys used.

generosity of the emergency measures, we worked with the usual labor income obtained by the household. Hence, we restricted the analysis to a sample of households with a monetary labor income per capita greater than zero, equivalent to 80 percent of the households.

To identify the policies' beneficiaries, we assessed whether this could be done directly using the household's survey variables or a set of variables and some assumptions that could help us approximate the targeted population. Table **??** shows that 19 policies in the 10 countries in our sample could be directly identified by specific questions in the survey. This is the case for most programs that target pre-existing social programs (such as Juntos or Pension 65 in Peru) or very specific segments of the population (like Bono Familia in Bolivia, which targets primary and secondary school students). For the other 12 policies, we made some assumptions to simulate, as close as possible, the potential households receiving the aid. To approximate the targeted households, we assumed that the complete eligible population for the regular cash transfer program was also the complete beneficiary population for the emergency transfer. A list of assumptions for each country are explained in the following list. Two policies for pregnant women in Argentina were not included, since we could not identify this population in the survey.

- *Argentina*. We approximated Policies (2), (4) and (6), since the survey does not have a variable to identify them directly. Policies (2) and (4) aim at Asignacion Universal por Hijo (AUH) beneficiaries, which is a program for unemployed; informal economy workers with incomes less than a minimum wage; a special category of taxpayers (monotributistas sociales); domestic service workers; and beneficiaries of Hacemos Futuro, Manos a la Obra, and Ministry of Labor (Secretaria de Gobierno de Trabajo) programs. All beneficiaries must have at least one child younger than 18 years. We were able to map most of all the conditions, except, due to lack of taxpayer data, we could not identify the specific taxpayers (monotributistas), instead we proxied it by including the self-employed. The household survey did not have variables to identify whether they participated in any of the Ministry of Labor programs.

  Policy (6), Ingreso Familiar de Emergencia, targets informal, domestic service and *monotributista social* in categories A-B household heads without unemployment aid or who have a dependent source of income in the household. As we could not identify the taxpayer criteria, we proxied it by including self-employed household heads earning less than ARS$26,092 per month. This aid is automatically given for AUH and PROGRESAR beneficiaries. As we could not identify the latter beneficiaries using the survey, we proxied it by assuming that all individuals who are elegible for PROGRESAR are beneficiaries. Hence, we include any household with at least one member between ages 18 and 24, who is unoccupied and with a household monthly total income less than three times the minimum wage, and who are enrolled in an educational program.

- *Brazil*. We made assumptions for policies (10) and (11). Policy (10) was aimed to help self-employed and informal workers who cannot work during the social distancing restrictions, especially informal households who are not part of Bolsa Familia. We assumed that all households that have at least one of the target beneficiaries re-

ceive R\$1,200. Further, we approximated households with a single female household head and at least one child and households whose household head works as an informal worker, is self-employed, or is an employer in a firm with 0-5 workers (microentrepreneurs). All households that are beneficiaries of this program must have total incomes less than R\$3,135.

Policy (11) targets Bolsa Familia Beneficiaries. The government gave them the option to receive R\$1,200 if it was higher than their usual transfer. Therefore, we assumed that both Bolsa Familia beneficiaries and informal households receive R\$1,200. We could not identify Bolsa Familia beneficiaries directly from the survey. Therefore, we approximated it with households under extreme poverty and households below the 2018 poverty line who have at least one child between 0 and 17 years.

— *Colombia.* Policy (15) targets three segments of the population. We identified the first two segment using the 2018 national poverty and extreme poverty lines to approximate them. We excluded the third segment, households under economic vulnerability in the SISBEN, as we could not identify them using survey data.

— *Chile.* The design of Policies (16 - 18) uses country-specific indexes or indicators, such as Registro Social de Hogares (RSH) and the Indicador Socioeconomico de Emergencia (ISE) to target vulnerable households. We do not have access to both indicators. However, since RSH is calculated using the total household income adjusted by the number of household members and other indicators, we used total income per capita to proxy the policy coverage. We cannot aproximate the ISE indicator.

Policy (16) established three subgroups of beneficiaries receiving differential monthly aid according to their vulnerability level and number of household members. The first two subgroups were a three-month aid program, which targets 90% of the most vulnerable households. We approximated it by including households below the 90th percentile of total income per capita. They also used as a criteria the 60% and 40% most vulnerable according to the ISE. As we could not observe it in the data or approximate it, we excluded this condition. The first subgroup received 100% of the cash aid, as it is also aimed for households without formal workers. The second subgroup received 50% of the benefit, as it is aimed at households with mainly informal income and income less than the aid they would receive if they were in the first subgroup. To avoid using an arbitrary criterion of mainly income, in the second subgroup, we considered households with at least one formal and one informal worker. Lastly, the third subgroup targets for the 80% most vulnerable households with at least one older adult benefitting from the Pension Basica Solidaria Vejez. The survey allowed us to identify the last two conditions but not the first, which we approximated using total income per capita. Furthermore, for all three subgroups, the transfer amount decreased each month, meaning that the first monthly transfer will be the highest of the whole. Hence, we used the amount given during the first month.

Policy (17), Bono Invierno, was a unique transfer allocated to retired people. The

variables in the survey data allow us to identify some of the beneficiaries directly, but there are some who are excluded for lack of data.

For policy (18), the Covid-19 emergency bonus, we used the survey to directly identify the beneficiaries of Asignacion Familiar program (SUF) and those who are part of the SSyOO database. Nonetheless, we approximated the 60% most vulnerable households according to the RSH database by including all households earning below the 60th percentile of the total income per capita.

— *El Salvador.* Policy (19) is designed to aid informal households and to cover at least 70% of the workers. Hence, we approximated informality as individuals without pension benefits or who were not affiliated to social security and, to reach the 70% objective, we also included in our proxy formal self-employed workers.

— *Ecuador.* Policy (20) has several subgroups of beneficiaries such as Seguro Social Campesino beneficiaries and affiliated to the unpaid work regimen. We were able to identify the first group but not the latter. Therefore, we approximated it by including all people working as nonremunerated and assumed everyone is under this regime. We also included self-employed workers as it has been stated that this is one of the policy objectives. Accordingly, following the policy design, we restricted the beneficiaries to have a labor income less than US$400, and not receive other government transfers, such as Bono de Desarrollo Humano or disability transfers and exclude those who are not contributing to social security. We restricted the sample of beneficiaries to be individuals of 18+ years.

— *Dominican Republic.* Policy (27) was a transfer intended for vulnerable and poor households according to SIUBEN (country-specific targeting indicator). We approximated the potential beneficiaries using the 2018 national poverty line. We could not approximate the vulnerable households in SIUBEN, as we did not have access to this indicator.

— *Uruguay.* For Policies (29) and (31) the survey had specific variables for directly identifying the beneficiaries. In Policy (29), we identify Tarjeta Uruguay Social beneficiaries and assign the current 2020 amount according to the number of children in the household. Nonetheless, as we could not identify whether there is a pregnant woman in the household, we only assigned the extra transfer of UYU$292 per child in the household and exclude the pregnant women benefits. Policy (31), Plan Equidad, is a conditional cash transfer program. The amount given depends on the number of eligible beneficiaries in the household and educational level, among others. The household survey allowed us to identify the targeted households but not the amount received. To avoid trying to approximate the amount each household receives, as it depends on a list of variables (for example, if the first beneficiary in the household was pregnant or was a child under five years old; information we do not have), we relied on the amount already stated in the survey but we approximated it to 2020 prices with the inflation rates of 2019 and up to April 2020.

Once all the groups of beneficiaries were identified, to compute the replacement rate, we obtained the total COVID-19 monthly monetary transfer at the household level by adding all

the individual and household transfers received and divided it by the total monthly monetary labor income.

Table A1: Covid-19 policies sources

Sources

1. Government web pages and newspapers

https://www.argentina.gob.ar/coronavirus/medidas-gobierno (Argentina)
https://www.argentina.gob.ar/economia/medidas-economicas-COVID19/ingresofamiliardeemergencia (Argentina)
https://www.boliviasegura.gob.bo/normativa.php (Bolivia)
https://id.presidencia.gov.co/especiales/200317-medidas-enfrentar-coronavirus/index.html (Colombia)
https://coronaviruscolombia.gov.co/Covid19/acciones/acciones-de-economia.html (Colombia)
https://www.chileatiende.gob.cl/fichas/77255-bono-de-emergencia-covid-19 (Chile)
https://www.gob.pe/busquedas?contenido[]=noticias&institucion[]=presidencia&reason=sheet&sheet=1 (Peru)
https://www.gub.uy/ministerio-salud-publica/coronavirus (Uruguay)
https://www.economiayfinanzas.gob.bo/ (Bolivia)
https://calendariobolsafamilia2020.net/quem-tem-direito-ao-bolsa-familia-2020/amp/ (Brazil)
https://www.elsalvador.com/noticias/negocios/el-salario-minimo-actual-solo-alcanza-para-cubrir-un-42-del-costo-de-la-vida-en-el-salvador/673786/2020/ (El Salvador)
https://www.prensalibre.com/internacional/coronavirus-el-salvador-ordena-cuarentena-de-30-dias-y-dara-subsidio-de-us300-a-los-mas-necesitados/ (El Salvador)
https://www.presidencia.gob.sv/presidente-nayib-bukele-confirma-la-entrega-del-subsidio-de-300-a-750000-familias/ (El Salvador)
https://www.elsalvador.com/eldiariodehoy/cuarentena-domiciliar-gobierno-bono/698888/2020/ (El Salvador)
https://www.eluniverso.com/sites/default/files/archivos/2020/04/decreto_ejecutivo_no._1026_20200324171450_20200324171526_20200324191332-1026-certificado_compressed.pdf (Ecuador)
https://www.produccion.gob.ec/wp-content/uploads/2020/03/Decreto_Ejecutivo_no._1022_20200227194449_compressed1.pdf (Ecuador)
https://www.gub.uy/ministerio-desarrollo-social/comunicacion/comunicados/beneficios-otorgados-monotributistas-sociales-mides (Uruguay)
https://www.180.com.uy/articulo/83151_aprobaron-subsidio-de-6779-pesos-por-dos-meses-a-monotributistas-del-mides (Uruguay)
https://ladiaria.com.uy/articulo/2020/4/coronavirus-gobierno-dara-1200-a-las-personas-que-no-reciben-ninguna-prestacion/ (Uruguay)
https://www.meganoticias.cl/dato-util/299030-bono-covid-19-coronavirus-pago-solo-con-el-rut-cuenta-rut-bancoestado.html (Chile)
https://ingresosolidario.dnp.gov.co/ (Colombia)
https://www.inclusion.gob.ec/gobierno-nacional-entregara-bono-de-contingencia-a-400-mil-familias-por-la-emergencia-sanitaria/
https://www.eluniverso.com/sites/default/files/archivos/2020/04/decreto_ejecutivo_no._1026_20200324171450_20200324171526_20200324191332 − 1026 − certificado_compressed.pdf
https://www.elcomercio.com/actualidad/coronavirus-covid-bono-emergencia-sanitaria.html
https://boliviaemprende.com/noticias/decreto-supremo-n-4215-bono-universal
https://www.periodicobolivia.com.bo/el-plazo-para-cobrar-la-canasta-familiar-de-bs-400-es-de-tres-meses/
https://libero.pe/ocio/1553756-bono-universal-bolivia-covid-19-beneficiario-bs-500-son-requisitos-bono-familia-carnet-identidad-fecha-link-bancos
https://www.opinion.com.bo/articulo/cochabamba/quienes-como-cobra-bono-canasta-familiar-hoy/20200402221439759940.html

2. Newspapers

El Comercio
El Tiempo
El Universo
El Peruano
El Observador
El Deber
La Nacion
La Republica
ElSalvador.com
El Desconcierto
Diario Financiero
Infobae
El Clarin
Valor Investe - Globo Noticias
Agencia Brasil

3. General datasets and publications

ACAPS COVID-19 Dataset (URL: https://data.humdata.org/dataset/acaps-covid19-government-measures-dataset)
Americas Society Council of the Americas Where is the Coronavirus in Latin America? from May 21, 2020 (https://www.as-coa.org/articles/where-coronavirus-latin-america)
IADB COVID-19 policy Measures by the Covid-19 policy Measures Team
https://www.ey.com/es_cr/tax/medidas-especiales-covid-19

4. Inflation data

https://rpp.pe/economia/economia/inei-peru-registro-una-inflacion-de-19-en-2019-noticia-1237290 (Peru)
Instituto Nacional de Estadistica Informatica (INEI - Peru)
Banco Central de Bolivia (Bolivia)
Banco de la Republica (Colombia)
Instituto Nacional de Estadistica (Bolivia)
Instituto Nacional de Estadistica (Uruguay)
Instituto Nacional de Estadistica y Censos (Ecuador)
Instituto Nacional de Estadistica y Censos (Argentina)
Instituto Brasileiro de Geografia e Estatistica (Brazil)
Banco Central (Dominican Republic)
Banco Central de Reserva (El Salvador)
Instituto Nacional de Estadistica (Chile)

Table A2: Household Surveys and Year by Country studied

Country	Household survey	Year
Argentina	Encuesta Permanente de Hogares (EPH)	2018
Bolivia	Encuesta Continua de Hogares (ECH)	2018
Brazil	Pesquisa Nacional por Amostra de Domiciolios (PNAD)	2018
Chile	Encuesta de Caracterizacion Socioeconomica Nacional (CASEN)	2017
Colombia	Gran Encuesta Integrada de Hogares (GEIH)	2018
Dominican Republic	Encuesta Nacional de Hogares - Fuerza de Trabajo (ENHFT)	2018
Ecuador	Encuesta Nacional de Empleo, Desempleo y Subempleo (ENEMDU)	2018
Peru	Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza (ENAHO)	2018
El Salvador	Encuesta de Hogares de Propositos Multiples (EHPM)	2018
Uruguay	Encuesta Continua de Hogares (ECH)	2018

COVID ECONOMICS
VETTED AND REAL-TIME PAPERS

Face masks considerably reduce Covid-19 cases in Germany: A synthetic control method approach[1]

Timo Mitze,[2] Reinhold Kosfeld,[3] Johannes Rode[4] and Klaus Wälde[5]

We use the synthetic control method to analyse the effect of face masks on the spread of Covid-19 in Germany. Our identification approach exploits regional variation in the point in time when face masks became compulsory. Depending on the region we analyse, we find that face masks reduced the cumulative number of registered Covid-19 cases between 2.3% and 13% over a period of 10 days after they became compulsory. Assessing the credibility of the various estimates, we conclude that face masks reduce the daily growth rate of reported infections by around 40%.

1 Introduction

Many countries have experimented with several public health measures to mitigate the spread of Covid-19. One particular measure that has been introduced are face masks. It is of obvious interest to understand the contribution made by such a measure to reducing infections.

The effect of face masks on the spread of infections has been studied for a long time. The usefulness in the clinical context is beyond dispute. There is also considerable evidence that they helped in mitigating the spread of epidemics such as SARS 2003 or influenza (see below). The effect of face masks worn in public on the spread of Covid-19 has not been systematically analyzed so far. This is the objective of this paper.

There is a general perception in Germany that public wearing of face masks reduces incidences considerably. This perception comes mainly from the city of Jena. After face masks were introduced on 6 April 2020, the number of new infections fell almost to zero. Jena is not the only city or region in Germany, however, that introduced face masks. Face masks became compulsory in all federal states between 20 April and 29 April 2020. Six regions made masks compulsory before the introduction at the federal level. These dates lay between 6 April and 25 April (see appendix A and Kleyer et al., 2020, for a detailed overview of regulations in Germany). This leads to a lag between individual regions and the corresponding federal states of between two and 18 days.

We derive findings by employing synthetic control methods (SCM, Abadie and Gardeazabal, 2003, Abadie et al., 2010, Abadie, 2019). Our identification approach exploits the previously mentioned regional variation in the point in time when face masks became compulsory in public transport and sales shops. We use data for 401 German regions to estimate the effect of this public health measure on the development of registered infections with Covid-19. We consider the timing of mandatory face masks as an exogenous event to the local population. Masks were imposed by local authorities and were not the outcome of some process in which the population was involved.[2] We compare the Covid-19 development in various regions to their synthetic counterparts. The latter are constructed as a weighted average of control regions that are similar to the regions of interest. Structural dimensions taken into account include prior Covid-19 cases, their demographic structure and the local health care system.

We indeed find strong and convincing statistical support for the general perception that public wearing of face masks in Jena strongly reduced the number of incidences. We obtain a synthetic control group that closely follows the Covid-19 trend before introduction of mandatory masks in Jena and the difference between Jena and this group is very large after 6 April. Our findings indicate that the early introduction of face masks in Jena has resulted in a reduction of almost 25% in the cumulative number of reported Covid-19 cases after 20 days. The drop is greatest, larger than 50%, for the age group 60 years and above. Our results are robust when we conduct sensitivity checks and apply several placebo tests, e.g. tests for pseudo-treatment effects in similarly sized cities in the federal state of Thuringia and for pseudo-treatment effects in Jena before the treatment actually started. We also test for announcement effects.

Constructing control groups for other single regions is not always as straightforward as for Jena. As a consequence, it is harder to identify the effect of face masks in these regions. When we

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[2] This is similar to the setup in Abadie et al. (2010), who study the effect of an increase in the tobacco tax in California. The tobacco tax was decided upon by the state government.

move from single to multiple treatment effects, we find smaller effects. They are still sufficiently large, however, to support our point that wearing face masks is a very cost-efficient measure for fighting Covid-19. When we summarize all of our findings in one single measure (we compare all measures in appendix B.4), we conclude that the daily growth rate of Covid-19 cases in the synthetic control group falls by around 40% due to mandatory mask-wearing relative to the control group.[3]

Concerning the literature (see appendix D for a more detailed overview), the effects of face masks have been surveyed by Howard et al. (2020) and Greenhalgh et al. (2020). Greenhalgh et al. (2020) mainly presents evidence on the effect of face masks during non-Covid epidemics (influenza and SARS). Marasinghe (2020) reports that they "*did not find any studies that investigated the effectiveness of face mask use in limiting the spread of COVID-19 among those who are not medically diagnosed with COVID-19 to support current public health recommendations*".

In addition to medical aspects (like transmission characteristics of Covid-19 and filtering capabilities of masks), Howard et al. (2020) survey evidence on mask efficiency and on the effect of a population. They first stress that "*no randomized control trials on the use of masks <...> has been published*". The study which is "*the most relevant paper*" for Howard et al. (2020) is one that analyzed "*exhaled breath and coughs of children and adults with acute respiratory illness*" (Leung et al., 2020, p. 676), i.e. used a clinical setting. Concerning the effect of masks on community transmissions, the survey needs to rely on pre-Covid-19 studies. We conclude from this literature review that our paper is the first analysis that provides field evidence on the effect of masks on mitigating the spread of Covid-19.

2   Identification, data and implementation

Identification. Our identification approach exploits the regional variation in the point in time when face masks became mandatory in public transport and sales shops. Given the federal structure of Germany, decisions are made by municipal districts (regions in what follows) and federal states. We can exploit differences by, first, identifying six regions (equivalent to the EU nomenclature of territorial units for statistics, NUTS, level 3) which made wearing face masks compulsory before their respective federal states. For all other regions, mandatory mask-wearing followed the decision of the corresponding federal state. Second, as Figure 1 shows, variation across federal states also implies variations across regions.

To identify possible treatment effects from introducing face masks, we apply SCM for single and multiple treated units. Our methodical choice is motivated as follows: First, the original goal of SCM to "*estimate the effects of <...> interventions that are implemented at an aggregate level affecting a small number of large units (such as cities, regions, or countries)*" (Abadie, 2019, p.3) clearly matches with our empirical setup. Compared to standard regression analyses, SCM is particularly well suited for comparative case study analyses with only one treated unit or a very small number thereof (Abadie and Gardeazabal, 2003, Becker et al., 2018). Second, the method is flexible, transparent and has become a widely utilized tool in the policy evaluation literature (Athey and Imbens, 2017) and for causal analyses in related disciplines

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[3] The main channel through which masks reduce transmission of SARS-CoV-2 is the reduction in aerosols and droplets, as argued by Prather et al. (2020).

(see, e.g., Kreif et al., 2015, for an overview of SCM in health economics, Pieters et al., 2017, for a biomedical application).[4]
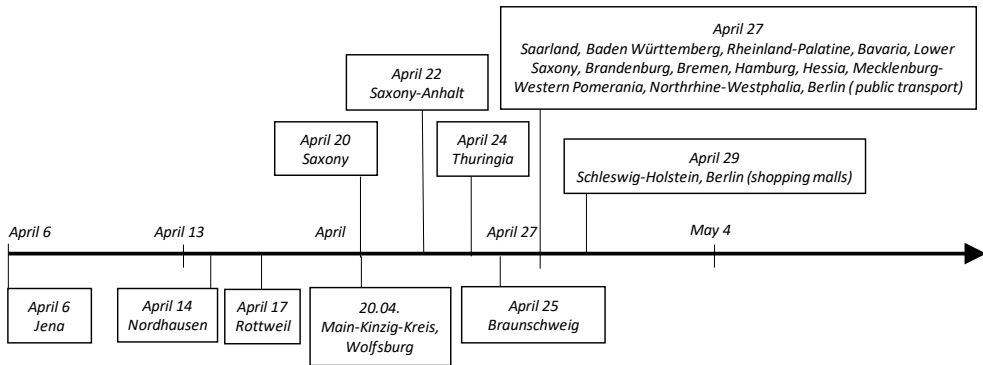
Figure 1: The timing of mandatory mask wearing in federal states (top) and individual regions (below)

SCM identifies synthetic control groups for the treated unit(s) to build a counterfactual. In our case, we need to find a group of regions that have followed the same Covid-19 trend as treated units before mandatory masks in the latter. This control group would then most likely have had the same behavior as treated unit(s) in the absence of the mask obligation. We can then use this group to 'synthesize' the treated unit and conduct causal inference. The synthetic control group is thereby constructed as an estimated weighted average of all regions in which masks did not become compulsory earlier on. Historical realizations of the outcome variable and several other predictor variables that are relevant in determining outcome levels allow us to generate the associated weights, which result from minimizing a pre-treatment prediction error function (see Abadie and Gardeazabal, 2003, Abadie et al., 2010 and Abadie, 2019 for methodical details).

Data. We use the official German statistics on reported Covid-19 cases from the Robert Koch Institute (RKI, 2020). The RKI collects the data from local health authorities and provides updates on a daily basis. Using these data (available via API), we build a balanced panel for 401 NUTS Level 3 regions and 95 days spanning the period from January 28 to May 1, 2020 (38,095 observations). We use the cumulative number of registered Covid-19 cases in each district as main outcome variable.[5] We estimate overall effects for this variable together with disaggregated effects by age groups (persons aged 15-34 years, 35-59 years and 60+ years). As an alternative outcome variable, we also use the cumulative incidence rate. Table 1 shows summary statistics for both variables for our sample period.

Table 1 also presents our other predictor variables. We focus on factors that are likely to describe the regional number and dynamics of reported Covid-19 cases. Obviously, past values

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[4] Friedson et al. (2020) employ the SCM to estimate the effect of the shelter-in-place order for California in the development of Covid-19. The authors find *inter alia* that around 1600 deaths from Covid-19 were avoided by this measure during the first four weeks.

[5] We are aware of the existence of hidden infections. As it appears plausible to assume that they are proportional to observed infections across regions, we do not believe that they affect our results. We chose the date of reporting (as opposed to date of infections) because not all reported infections include information about the date of infection.

of (newly) registered Covid-19 cases are important to predict the regional evolution of Covid-19 cases over time in an autoregressive manner. In addition, we argue that a region's demographic structure, such as the overall population density and age structure, and its basic health care system, such as the regional endowment with physicians and pharmacies per population, are important factors for characterizing the local context of Covid-19. Predictor variables are obtained from the INKAR online database of the Federal Institute for Research on Building, Urban Affairs and Spatial Development. We use the latest year available in the database (2017). We consider it likely that regional demographic structures only gradually vary over time such that they can be used to measure regional differences during the spread of Covid-19 in early 2020.

Table 1: Summary Statistics of Covid-19 indicators (outcome variables) and predictors characterizing the regional demographic structure and basic health care system

	Mean	S.D.	Min.	Max.
PANEL A: Data on registered Covid-19 cases				
[1] Newly registered cases per day	4.13	10.66	0	310
[2] Cumulative number of cases	120.86	289.07	0	5795
[3] Cum. cases [2] per 100,000 inhabitants	59.87	106.80	0	1,530.32
PANEL B: Regional demographic structure and local health care system				
Population density (inhabitants/km^2)	534.79	702.40	36.13	4,686.17
Population share of highly educated* individuals (in %)	13.07	6.20	5.59	42.93
Share of females in population (in %)	50.59	0.64	48.39	52.74
Average age of females in population (in years)	45.86	2.11	40.70	52.12
Average age of males in population (in years)	43.17	1.83	38.80	48.20
Old-age dependency ratio (persons aged 65 years and above per 100 of population age 15-64)	34.34	5.46	22.40	53.98
Young-age dependency ratio (persons aged 14 years and below per 100 of population age 15-64)	20.54	1.44	15.08	24.68
Physicians per 10,000 of population	14.58	4.41	7.33	30.48
Pharmacies per 100,000 of population	27.01	4.90	18.15	51.68
Settlement type (categorial variable$^\$$)	2.59	1.04	1	4

Notes: * = International Standard Classification of Education (ISCED) Level 6 and above; $ = categories are based on population shares and comprise 1) district-free cities *(kreisfreie Großstädte)*, 2) urban districts *(städtische Kreise)*, 3) rural districts *(ländliche Kreise mit Verdichtungsansätzen)*, 4) sparsely populated rural districts *(dünn besiedelte ländliche Kreise)*.

Implementation. The implementation of the SCM is organized as follows: As baseline analysis, we focus on the single treatment case for the city of Jena for three reasons. First, as shown in Figure 1, Jena was the first region to introduce face masks in public transport and sales shops on April 6. This results in a lead time of 18 days relative to mandatory face masks in the surrounding federal state Thuringia on April 24. By April 29, all German regions had introduced face masks (exact dates are provided in appendix A). A sufficiently long lag between mandatory face masks in the treated unit vis-à-vis the sample of control regions is important for effect identification.

Second, the timing of the introduction of face masks in Jena is -by and large- not affected by other overlapping public health measures related to the Covid-19 spread. Since March 22 the German economy had been in a general "lock down" coordinated among all federal states. Only from April 20 onwards has the economy been gradually reopening. Third, Jena is in various ways a representative case for studying the Covid-19 development: On April 5, which is one day before face masks became compulsory in Jena, the cumulative number of registered Covid-19 cases in Jena was 144. This is very close to the median of 155 for Germany. Similarly, the cumulative number of Covid-19 incidences per 100,000 inhabitants was 126.9 in Jena compared to a mean of 119.3 in Germany (compare Figure A1).

In our baseline configuration of the SCM, we construct the synthetic Jena by including the number of cumulative Covid-19 cases (measured one and seven days before the start of the treatment) and the number of newly registered Covid-19 cases (in the last seven days prior to the start of the treatment) as autoregressive predictor variables. The chosen period shall ensure that the highly non-linear short-run dynamics of regional Covid-19 cases are properly captured. We use cross-validation tests to check the sensitivity of the SCM results when we allow for a shorter training period in the pre-treatment phase by imposing longer lags. The autoregressive predictors are complemented by the cross-sectional data on the region's demographic and basic health care structure.

Although the case study of Jena can be framed in a clear identification strategy, the Covid-19 spread in a single municipality may still be driven by certain particularities and random events that may prevent a generalization of estimated effects. We therefore also test for treatment effect in districts that introduced face masks after Jena but still before they became compulsory in the corresponding federal state. More importantly, however, we apply a multiple treatment approach that takes all regions as treated units which introduced face masks by April 22. This results in 32 regions from Saxony and Saxony-Anhalt. All other regions apart from Thuringia introduced face masks on April 27. We employ this delay to study the effects of mandatory masks up to May 1st. We end on May 1st as we would expect that differences across treated and non-treated regions should disappear 5-7 days after April 27. This delay results from a median incubation time of 5.2 days (Linton et al., 2020 and Lauer et al., 2020) and around 2 days accounting for reporting to authorities (as assumed e.g. in Donsimoni et al., 2020a, b).

Although SCM appears to be a natural choice for our empirical identification strategy, we are well aware of the fact that its validity crucially depends on important practical requirements including the availability of a proper comparison group, the absence of early anticipation effects or interference from other events (Cavallo et al., 2013, Abadie, 2019). In the implementation of the single and multiple treatment SCM we check for these pitfalls through sensitivity and placebo tests. We deal with these issues in our baseline case study for Jena as follows:

1. We have screened the introduction and easing of public health measures, as documented in Kleyer et al. (2020), to ensure that no interference takes place during our period of study. This is the case at least until April 20 when exit strategies from public health measures started.

2. We make sure that the regions used to create the synthetic control, i.e. the donor pool, are not affected by the treatment (Campos et al., 2015). We eliminate the two immediate geographical neighbors of Jena from the donor pool to rule out spillover effects. We also exclude those regions for which anticipation effects may have taken place because face masks became compulsory in quick succession to Jena.

3. We account for early anticipation effects in Jena. Specifically, we take the announcement that face masks will become compulsory one week before their introduction as an alternative start of the treatment period.

4. We apply cross-validation tests to check for sensitivities related to changes in historical values in the outcome variables used as predictors. We also run placebo-in-time tests to check whether effects actually occurred even before the start of the treatment.

5. We test for the sensitivity of the results when changing the donor pool and run comprehensive placebo-in-space tests as a mode of inference in the SCM framework.

Inference thereby relies on permutation tests and follows the procedures suggested by Cavallo et al. (2013) and applied, for example, by Eliason and Lutz (2018) or Hu et al. (2018). For both the single and multiple treatment applications we estimate placebo-treatment effects for each district in which masks did not become compulsory early on. These placebo treatments should be small, relative to the treated regions. We calculate significance levels for the test of the hypothesis that the mask obligation did not significantly affect reported Covid-19 cases. This provides us with p–values for each day, which capture the estimated treatment effect on reported Covid-19 cases from placebo regions. The p-values are derived from a ranking of the actual treatment effect within the distribution of placebo treatment effects. We follow the suggestion in Galiani and Quistorff (2017) and compute adjusted p-values taking the pre-treatment match quality of the placebo treatments into account.[6]

3 The effects of face masks on Covid-19

Baseline results for Jena. Panel A in Figure 2 shows the SCM results for the introduction of face masks in Jena on April 6. The visual inspection of the development of cumulative Covid-19 cases shows that the fit of the synthetic control group is very similar to Jena before the treatment.[7] The difference in the cumulated registered Covid-19 cases between Jena and its corresponding synthetic control unit after the start of the treatment can be interpreted as the treatment effect on the treated.

The figure clearly shows a gradually widening gap in the cumulative number of Covid-19 cases between Jena and the synthetic control unit. The size of the effect 20 days after the start of the treatment (April 26) amounts to a decrease in the number of cumulative Covid-19 cases of 23%. For the first 10 days, the decrease amounts to 13%. Expressed differently, the daily growth rate of the number of infections decreases by 1.32 percentage points per day (see appendix B.4 for computational details and an overview of all measures). If we look at the estimated differences by age groups, Table A2 in the appendix indicates that the largest effects are due to the age group of persons aged 60 years and above. Here the reduction in the number of registered cases is even larger than 50%. For the other two age groups we find a decrease between 10 and 20%.

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[6] We conduct all estimations in STATA using "Synth" and "Synth Runner" packages (Abadie at al., 2020, Galiani and Quistorff, 2017). Data and estimation files can be obtained from the authors upon request.

[7] The pre-treatment root mean square prediction error (RMSPE) of 3.145 is significantly below a benchmark RMSPE of 6.669, which has been calculated as the average RMSPE for all 401 regions in the pre-treatment period until April 6. This points to the relatively good fit of the synthetic control group for Jena in this period.

If we consider a median incubation of 5.2 days plus a potential testing and reporting lag of 2-3 days, the occurrence of a gradually widening gap between Jena and its synthetic control three to four days after the mandatory face masks seems fast. One might conjecture that an announcement effect played a role. As shown in appendix B.7, online searches for (purchasing) face masks peaked on April 22, when it was announced that face masks would become compulsory in all German federal states.[8] A smaller peak (70% of the April 22 peak) of online searches appeared on March 31. This is one day after Jena announced that masks would become compulsory on April 6. The announcement was accompanied by a campaign "Jena zeigt Maske" to communicate the necessity to wear face masks in public[9] and was widely discussed all over Germany.

Panel B in Figure 2 therefore plots the results when we set the start of the treatment period to the day of the announcement on 30 March. The visual inspection of the figure shows the existence of a small anticipation effect (which is mainly driven by the relative development of Covid-19 age group 15-34 years (Panel B in Figure A2). Yet, the gap to the synthetic control significantly widens only approximately 10 days after the announcement. As this temporal transmission channel appears plausible against the background of incubation times and given that no other intervention took place around this time in Jena or the regions in the synthetic control group, we take this as first evidence for a face mask-effect in the reduction of Covid-19 infections. Appendix B.6 shows similar SCM results for the incidence rate (overall and by age groups). We find a reduction of approximately 30 cases per 100,000 of population.
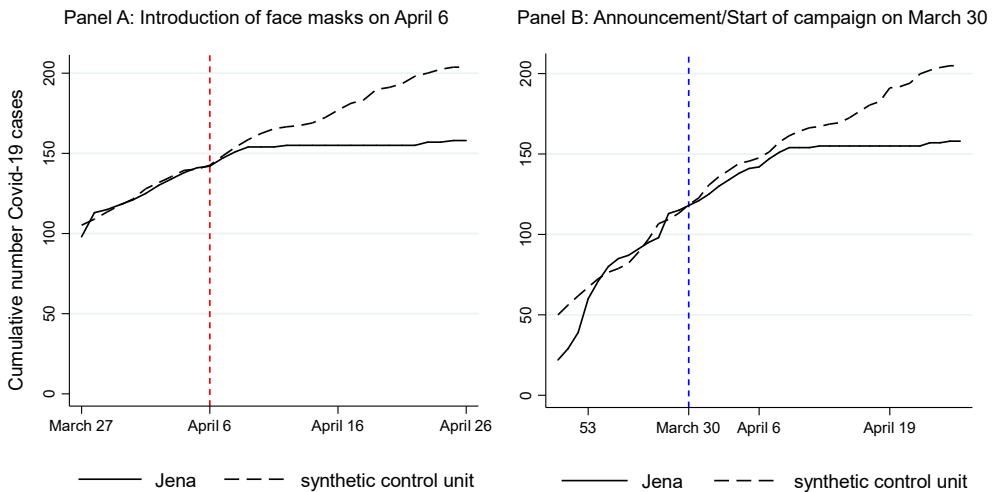
Figure 2: Treatment effects of mandatory face masks in Jena on April 6 and start of campaign on March 30 (see Table A3 and appendix B.2 for details)

[8] See https://www.tagesschau.de/inland/corona-maskenpflicht-103.html. Last accessed May 05, 2020.

[9] See https://www.jenaer-nachrichten.de/stadtleben/13069-jena-zeigt-maske-kampagne-f%C3%BCr-mund-schutz-startet. Last accessed May 05, 2020.

Obviously, the estimated differences in the development of Jena vis-à-vis the synthetic Jena is only consistently estimated if our SCM approach delivers robust results. Accordingly, we have applied several tests to check for the sensitivity of our findings.

Cross-validation and placebo-in-time test. One important factor is that our results are not sensitive to changes in predictor variables. We therefore perform cross-validation checks by modifying the length of the training and validation periods before the start of the treatment. Panel A in Figure 3 shows that lagging the autoregressive predictor variables further in time only slightly changes our results. Importantly, we do not find a systematic downward bias of our baseline specification (cumulative number of reported Covid-19 cases: one and seven days before start of treatment; number of newly registered Covid-19 cases: last seven days before start of treatment) compared to an alternative specification. The latter trains the synthetic control on the basis of information on cumulative Covid-19 cases 7 and 14 days prior to the treatment together with the development of newly register cases between day 7 and 14 prior to the treatment. Given that regional Covid-19 cases developed very dynamically and non-linearly in this period, this is an important finding in terms of the robustness of our results.
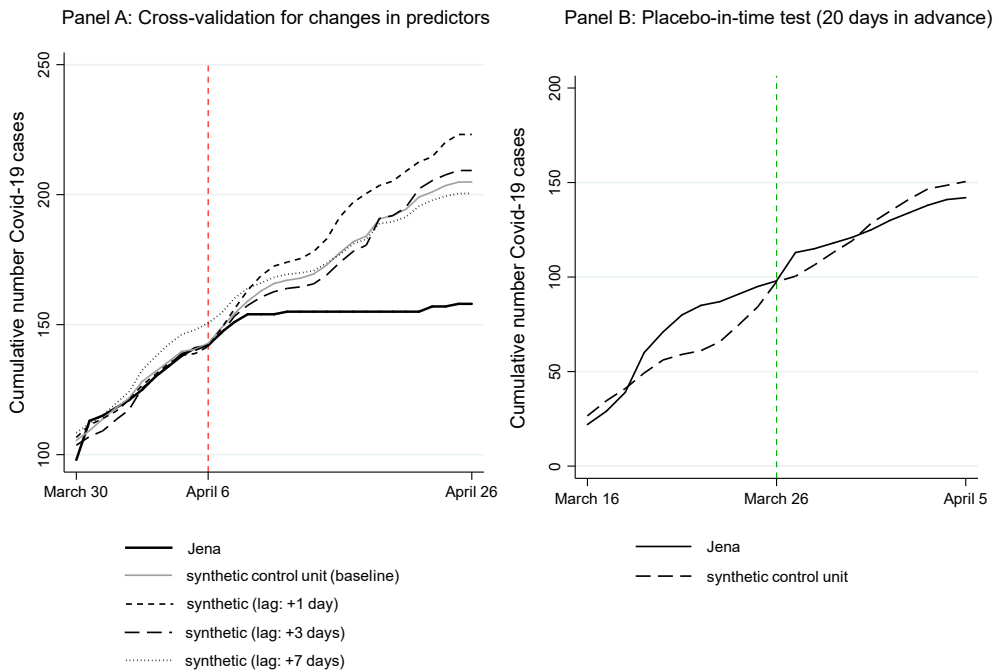
Figure 3: Cross-validation for changes in predictor variables and placebo-in-time test

Notes: In Panel A the baseline specification for the synthetic control group uses historical values of the outcome variable in the following way: i) number of cumulative Covid-19 cases (measured one and seven days before the start of the treatment), ii) the number of newly registered Covid-19 cases (in the last seven days prior to the start of the treatment); the alternative specifications lag these values by 1, 3 and 7 days.

Another important factor for the validity of the results is that we do not observe an anticipation effect for Jena prior to the announcement day. We test for a pseudo-treatment in Jena over a period of 20 days before the introduction of face masks. This period is equally split into a pre-

and pseudo post-treatment period. As Panel B in Figure 3 shows, there is no strong deviation from the path of the synthetic control group. This result needs to be interpreted with some care as the regional variation of Covid-19 cases in Germany is very heterogeneous the longer we go back in time. This is indicated by the generally lower fit of the synthetic control group in matching the development in Jena in mid-March when the absolute number of Covid-19 cases was still low.

Changing the donor pool. In addition, we also check for the sensitivity of the results when changing the donor pool. This may be important as our baseline specification includes the region of Heinsberg in the donor pool used to construct the synthetic Jena (with a weight of 4.6%; compare Table A3). As Heinsberg is one of the German regions which was significantly affected by the Covid-19 pandemic during the Carnival season, this may lead to an overestimation of the effects of face masks. Accordingly, appendix B.8 presents estimates for alternative donor pools. Again, we do not find evidence for a significant bias in our baseline specification. By tendency, the treatment effect becomes larger, particularly if we compare Jena only to other regions in Thuringia (to rule out macro-regional trends) and to a subsample of larger cities (*kreisfreie Städte*). Both subsamples exclude Heinsberg. We also run SCM for subsamples excluding Thuringia (to rule out spillover effects) and for East and West Germany (again in search for specific macro regional trends). Generally, these sensitivity tests underline the robustness of the estimated treatment effect for Jena.

Placebo-in-space tests. A placebo test in space checks whether other cities that did not introduce face masks on April 6 have nonetheless experienced a decline in the number of registered Covid-19 cases. If this had been the case, the treatment effect may be driven by other latent factors rather than face masks. Such latent factors may, for instance, be related to the macro-regional dynamics of Covid-19 in Germany. Therefore, appendix B.9 reports pseudo-treatment effects for similarly sized cities in Thuringia assuming that they have introduced face masks on April 6 although −in fact− they did not. As the figure shows, these cities show either a significantly higher or similar development of registered Covid-19 compared to their synthetic controls. This result provides further empirical support for a relevant effect in the case of Jena.

As a more comprehensive test, we also ran placebo-in-space tests for all other regions that did not introduce face masks on April 6 or closely afterwards. Again, we estimate the same model on each untreated region, assuming it was treated at the same time as Jena. The empirical results in Figure 4 indicate that the reduction in the reported number of Covid-19 cases in Jena clearly exceeds the trend in most other regions – both for the overall sample in Panel A and the subsample of large cities (*kreisfreie Städte*) in Panel B.

As outlined above, one advantage of this type of placebo-in-space-test is allows us to conduct inference. Accordingly, Panel C and Panel D report adjusted *p*-values that indicate the probability if the treatment effect for Jena was observed by chance given the distribution of pseudo-treatment effects in the other German regions (see Galiani and Quistorff, 2017). For both samples, the reported *p*-values indicate that the reduction in the number of Covid-19 cases in Jena did not happen by chance but can be attributed to the introduction of face masks, at the latest - roughly two weeks after the start of the treatment. This timing is again in line

with our above argument that a sufficiently long incubation time and testing lags need to be considered in the evaluation of treatment effects.[10]
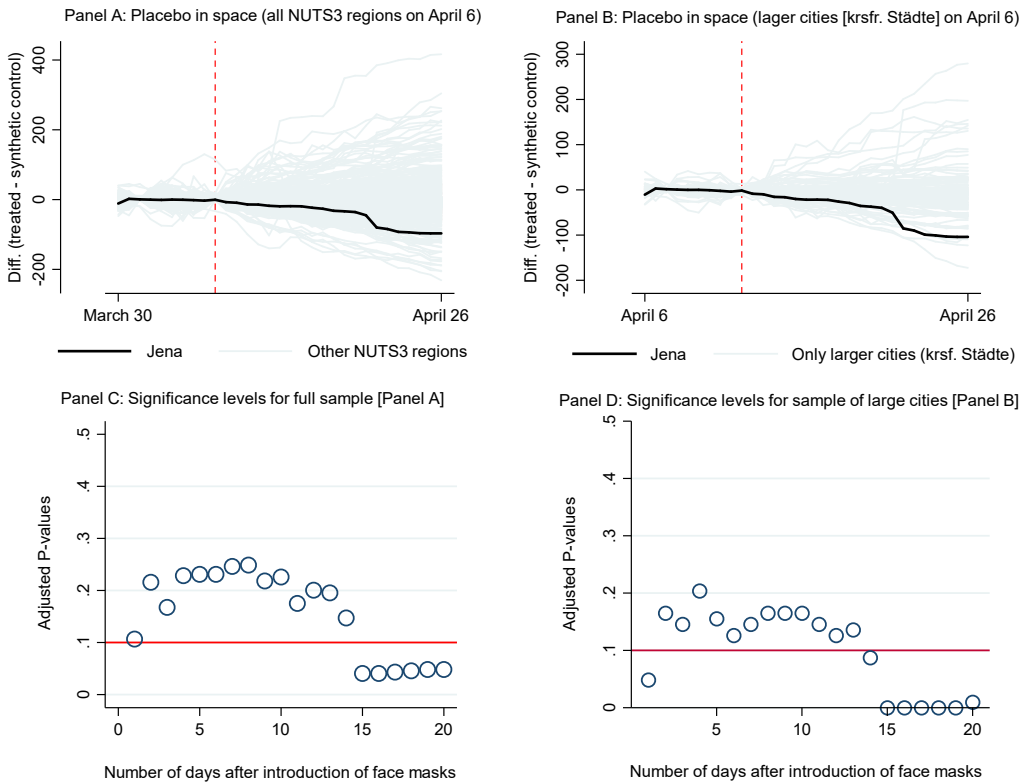
Figure 4: Comprehensive placebo-in-space tests for the effect of face masks on Covid-19 cases

Notes: Graphs exclude the following regions with a very large number of registered Covid-19 cases: Hamburg (2000), Berlin (11000), Munich (9162), Cologne (5315) and Heinsberg (5370). In line with Abadie et al. (2010), we only include placebo effects in the pool for inference if the match quality (pre-treatment RMSPE) of the specific control regions is smaller than 20 times the match quality of the treated unit. *P*-values are adjusted for the quality of the pre-treatment matches (see Galiani and Quistorff, 2017).

Treatment in other districts. Jena may be a unique case. We therefore also study treatment effects for other regions that have antedated the general introduction of face masks in Germany. Further single unit treatment analyses are shown in appendix C. Multiple unit treatments are studied in two ways. The first sample covers all 401 regions and 32 treated units. The second focused on the subsample of 105 larger cities (*kreisfreie Städte*), of which 8 are treated units. Treated regions

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[10] As the reviewer pointed out, we analyse a measure that is introduced for the first time in this region. One might conjecture that our estimation measures both the true effect of a face mask but also any other change in behavior (washing hands, limiting interactions, stayed more at home...) that was triggered by this policy. This change in behaviour is known as the Hawthorn effect. Individuals in this pioneer region might take the crisis more seriously than in the other areas. Although German health authorities had been strongly recommending such behavioral changes in daily life since mid-march, we cannot fully rule out this mixing of effects and leave its decomposition for future research.

introduced face masks by April 22. The multiple treatment approach, visible in Figure 5, points to a significant face mask-effect in the reduction of Covid-19 infections. The adjusted *p*-values indicate that the estimated treatment effects are not random.

Face masks may have made a particular difference in the spread of Covid-19, particularly in larger cities with higher population density and accordingly higher intensity of social interaction.[11] Over a period of 10 days, we observe an average reduction of 12.3 cases between treated and control regions. Relative to the average number of cumulative Covid-19 cases on May 1 in control regions (295.6), this amounts to a reduction of 4.2% of cases. The daily growth rate of the number of infections correspondingly shrinks by 0.42 percentage points. For the entire sample, the reduction in the daily growth rate is estimated to be 0.23 percentage points (see again appendix B.4 for an overview of all measures).
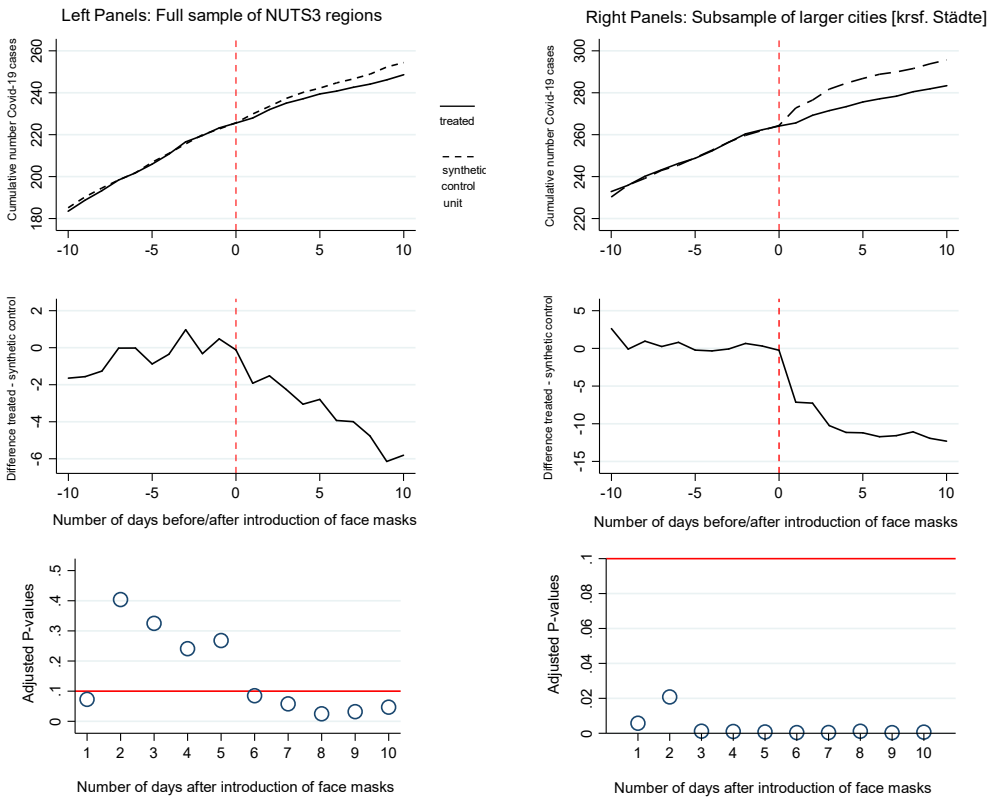
Figure 5: Average treatment effects for introduction of face masks (multiple treated units)

Notes Statistical inference for adjusted *p*-values has been conducted on the basis of a random sample of 1,000,000 placebo averages.

4 Conclusion

We set out by analyzing the city of Jena. The introduction of face masks on 6 April reduced the number of new infections over the next 20 days by almost 25% relative to the synthetic control

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[11] This is perfectly in line with Prather et al. (2020) given the reduction in aerosols and droplets via using masks.

group. This corresponds to a reduction in the average daily growth rate of the total number of reported infections by 1.32 percentage points. Comparing the daily growth rate in the synthetic control group with the observed daily growth rate in Jena, the latter shrinks by around 60% due to the introduction of face masks. This is a sizeable effect. Wearing face masks apparently helped considerably in reducing the spread of Covid-19. Looking at single treatment effects for all other regions puts this result in some perspective. The reduction in the growth rate of infections amounts to 20% only. By contrast, when we take the multiple treatment effect for larger cities into account, we find a reduction in the growth rate of infections by around 40%.

What would we reply if we were asked what the effect of introducing face masks would have been if they had been made compulsory all over Germany? The answer depends, first, on which of the three percentage measures we found above is the most convincing and, second, on the point in time when face masks are made compulsory. The second aspect is definitely not only of academic interest but would play a major role in the case of a second wave.

We believe that the reduction in the growth rates of infections by 40% to 60% is our best estimate of the effects of face masks. The most convincing argument stresses that Jena introduced face masks before any other region did so. It announced face masks as the first region in Germany while in our post-treatment period no other public health measures were introduced or eased. Hence, it provides the most clear-cut experiment of its effects. Second, as stated above, Jena is a fairly representative region of Germany in terms of Covid-19 cases. Third, the smaller effects observed in the multiple treatment analysis may also result from the fact that −by the time that other regions followed the example of Jena− behavioral adjustments in Germany's population had also taken place. Wearing face masks gradually became more common and more and more people started to adopt their usage even when it was not yet required.

We should also stress that 40 to 60% might still be a lower bound. The daily growth rates in the number of infections when face masks were introduced was around 2 to 3%. These are very low growth rates compared to the early days of the epidemic in Germany, where daily growth rates also lay above 50% (Wälde, 2020). One might therefore conjecture that the effects might have been even greater if masks had been introduced earlier.

We simultaneously stress the need for more detailed analyses. First, Germany is only one country. Different norms or climatic conditions might change the picture for other countries. Second, we have ignored spatial dependencies in the epidemic diffusion of Covid-19. This might play a role. Third, there are various types of face masks. We cannot identify differential effects since mask regulations in German regions do not require a certain type. This calls for further systematic causal analyses of the different health measure implemented to fight the spread of Covid-19. Our results provide some initial empirical evidence on this important matter.

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Supplementary Appendix
for

**Face Masks Considerably Reduce
Covid-19 Cases in Germany**

—

A synthetic control method approach

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A. Timing of introduction of mandatory face masks

Table A1: Overview of dates when masks became compulsory in federal states and districts

Federal State	Public transport	Sales shops	Individual NUTS3 region	Introduction of face masks	Difference in days to state
Baden-Wurttemberg	27.04.2020	27.04.2020	LK Rottweil	17.04.2020	10
Bavaria	27.04.2020	27.04.2020			
Berlin	27.04.2020	29.04.2020			
Brandenburg	27.04.2020	27.04.2020			
Bremen	27.04.2020	27.04.2020			
Hamburg	27.04.2020	27.04.2020			
Hesse	27.04.2020	27.04.2020	Main-Kinzig-Kreis	20.04.2020	7
Mecklenburg-West Pomer.	27.04.2020	27.04.2020			
Lower Saxony	27.04.2020	27.04.2020	Wolfsburg	20.04.2020	7
			Braunschweig	25.04.2020	2
North Rhine-Westphalia	27.04.2020	27.04.2020			
Rheinland-Pfalz	27.04.2020	27.04.2020			
Saarland	27.04.2020	27.04.2020			
Saxony	20.04.2020	20.04.2020			
Saxony-Anhalt	22.04.2020	22.04.2020			
Schleswig-Holstein	29.04.2020	29.04.2020			
Thuringia	24.04.2020	24.04.2020	Jena	06.04.2020	18
			Nordhausen	14.04.2020	10

Notes: A comprehensive overview of all public health measures introduced in German federal states and individual regions is given in Kleyer et al. (2020).

B. Background and additional estimates for SCM application to Jena

This appendix presents supporting findings for the comparative case study of Jena.

B.1. Covid-19 cases and cumulative incidence rate in Jena and Germany on April 5

Panel A: Cumulative number Covid-19 cases (April 5)   Panel B: Cumulative Incidence Rate (April 5)
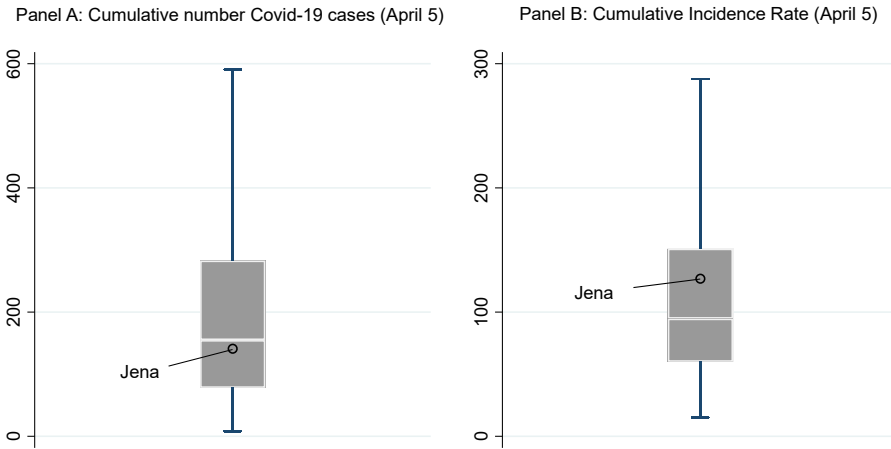
Figure A1: Box plots for distribution of Covid-19 cases across German NUTS3 regions (April 5)

B.2.   Evaluation of pre-treatment predictor balance and prediction error (RMSPE)

This appendix shows the balancing properties of the SCM approach together with the root mean square percentage error (RMSPE) as a measure for the quality of the pre-treatment prediction.

Table A2: Pre-treatment predictor balance and RMSPE for SCM in Figure 2

Treatment:	Introduction of face masks		Announcement/ start of campaign	
	Jena	Synthetic control group	Jena	Synthetic control group
Cumulative number of registered Covid-19 cases (one and seven days before start of treatment, average)	129.5	129.2	93	92.7
Number of newly registered Covid-19 cases (last seven days before the start of the treatment, average)	3.7	3.8	5	5.2
Population density (Population/km^2)	38.4	22.8	968.1	947.9
Share of highly educated population (in %)	968.1	1074.3	38.4	26.3
Share of female in population (in %)	50.1	50.1	50.1	50.1
Average age of female population (in years)	43.5	43.7	43.5	43.9
Average age of male population (in years)	40.5	40.6	40.5	40.8
Old-age dependency ratio (in %)	32.1	29.3	32.1	29.8
Young-age dependency ratio (in %)	20.3	19.6	20.3	19.5
Physicians per 10,000 of population	20.5	19.8	20.5	20.8
Pharmacies per 100,000 of population	28.8	28.7	28.8	28.6
Settlement type (categorial variable)	1	1.3	1	1.9
RMSPE (pre-treatment)	**3.145**		**4.796**	

Notes: Donor pool includes all other German NUTS3 regions except the two immediate neighboring regions of Jena (Weimarer Land, Saale-Holzland-Kreis) as well as the regions Nordhausen and Rottweil since the latter regions introduced face masks in short succession to Jen on April 14 and April 17.

B.3. Selected control regions and their associated sample weights

Table A3: Distribution of sample weights in donor pool for synthetic Jena

Introduction of face masks (Panel A in Figure 2)		
ID	**NUTS 3 region**	**Weight**
13003	Rostock	0.326
6411	Darmstadt	0.311
3453	Cloppenburg	0.118
7211	Trier	0.117
6611	Kassel	0.082
5370	Heinsberg	0.046

Note: Donor pools corresponds to SCM estimation in Panel A of Figure 2. Sample weights are chosen to minimize the RMSPE ten days prior to the start of the treatment.

B.4. Growth rates

Jena has 142 registered cases on April 6 compared to an estimated number of 143 cases in the synthetic control group. On April 26 Jena counts 158 cases and the synthetic control group reports 205 (again estimated) cases. The daily growth rate in Jena is denoted by x_{Jena} and can be computed from $142\,[1+x_{Jena}]^{20} = 158$. The daily growth rate in the control group is denoted by $x_{control}$ and can be computed from $143\,[1+x_{control}]^{20} = 205$. Hence, the introduction of the face mask is associated with a decrease in the number of infections of $x_{control} - x_{Jena}$ percentage points per day.

Table A4: Summary of treatment effects of face mask introduction in Germany

	Single Treatment (Jena)	Multiple treatments (all districts)	Multiple treatments (cities)
Percentage change in cumulative number of Covid-19 cases over 20 days	-22.9%	n.a.	n.a.
Absolute change in cumulative number of Covid-19 cases over 10 days	-23	-5.8	-12.3
Percentage change in cumulative number of Covid-19 cases over 10 days	-12.8%	-2.3%	-4.2%
Difference in daily growth rates of Covid-19 cases in percentage points	-1.32%	-0.23%	-0.42%
Reduction in daily growth rates of Covid-19 cases in percent	60.1%	18.94%	37.28%

These numbers are computed in an Excel-file available on the web pages of the authors.

B.5.   SCM results by age groups
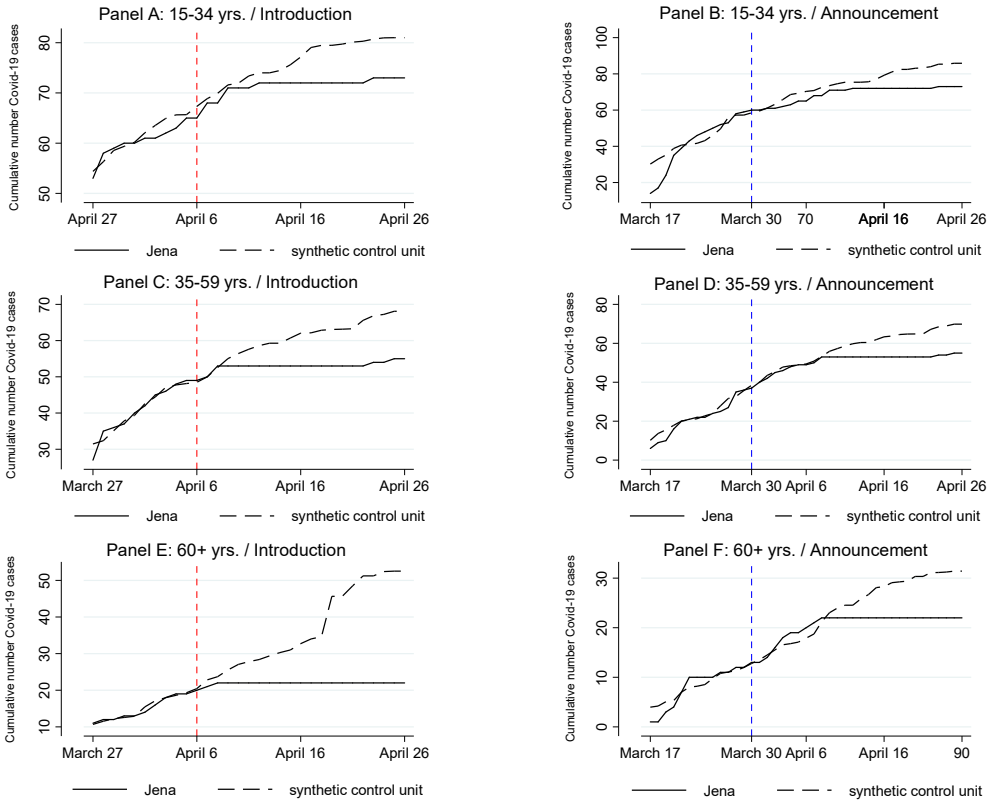
Figure A2: Treatment effects for introduction and announcement of face masks in Jena

Notes: Predictor variables are chosen as for overall specification shown in Figure 2.

Table A5: Sample weights in donor pool for synthetic Jena (cumulative Covid-19 cases; by age groups)

Age Group 15-34 years			Age Group 35-59 years			Age Group 60 years and above		
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
1001	Flensburg	0.323	6411	Darmstadt	0.528	6411	Darmstadt	0.522
7211	Trier	0.207	16055	Weimar	0.16	16055	Weimar	0.244
13003	Rostock	0.184	14511	Chemnitz	0.15	7316	Neustadt a.d. Weinstraße	0.068
5370	Heinsberg	0.142	8221	Baden-Baden	0.07	9562	Erlangen	0.06
3453	Cloppenburg	0.107	6434	Hochtaunus-kreis	0.062	3356	Osterholz	0.056
6413	Offenbach am Main	0.038	8435	Bodenseekreis	0.029	5515	Münster	0.027
			5370	Heinsberg	0.001	9188	Starnberg	0.022

Note: Donor pools corresponds to SCM estimations in Figure A2. Sample weights are chosen to minimize the RMSPE ten days prior to the start of the treatment.

B.6. Effects on cumulative number of infections per 100,000 inhabitants
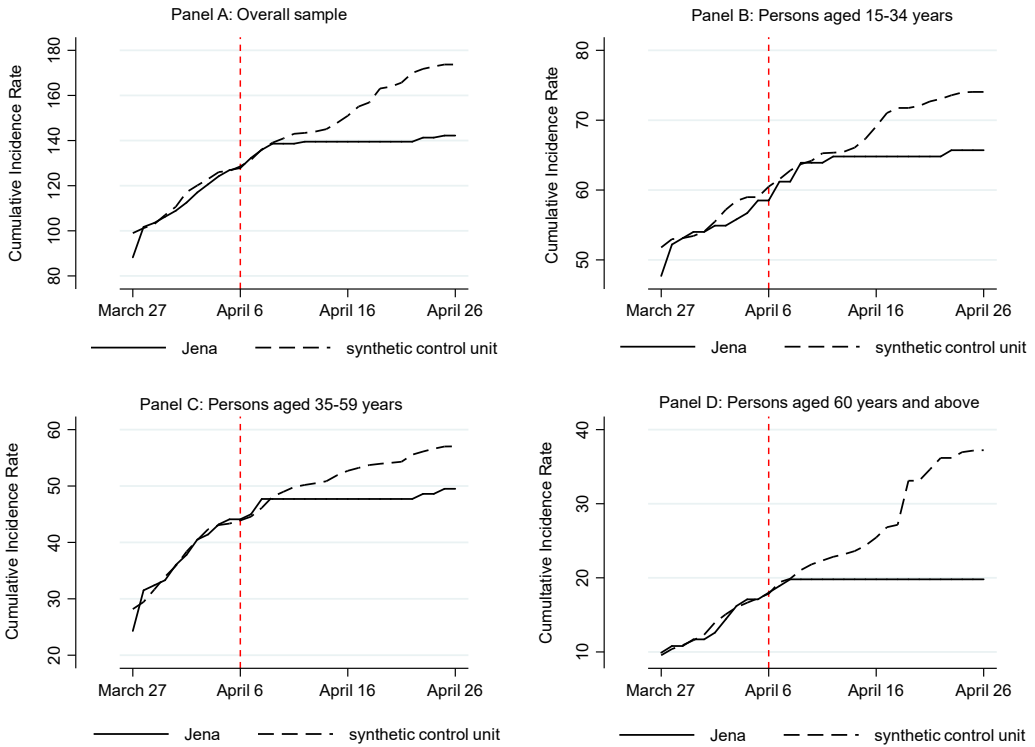
Figure A3: Treatment effects for introduction of face masks on cumulative incidence rate

Notes: See Table 1 for a definition of the incidence rate. Predictor variables are chosen as for overall specification shown in Figure 2.

Table A6: Sample weights in donor pool for synthetic Jena (cumulative incidence rate)

ID	NUTS 3 region	Weight
6411	Darmstadt	0.46
15003	Magdeburg	0.171
5370	Heinsberg	0.133
13003	Rostock	0.093
5515	Münster	0.066
11000	Berlin	0.035
12052	Cottbus	0.032
6611	Kassel	0.011

Note: Donor pools corresponds to SCM estimation in Figure A3. Sample weights are chosen to minimize the RMSPE ten days prior to the start of the treatment.

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Table A7: Sample weights in donor pool for synthetic Jena (cumulative incidence rate; by age groups)

Age Group 15-34 years			Age Group 35-59 years			Age Group 60 years and above		
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
5370	Heinsberg	0.377	6411	Darmstadt	0.419	6411	Darmstadt	0.448
13003	Rostock	0.288	14511	Chemnitz	0.184	14612	Dresden	0.313
1001	Flensburg	0.14	14612	Dresden	0.154	9188	Starnberg	0.071
6611	Kassel	0.138	8221	Heidelberg	0.138	16054	Suhl	0.069
11000	Berlin	0.058	9188	Starnberg	0.088	5515	Münster	0.06
			5370	Heinsberg	0.016	8221	Heidelberg	0.039

Note: Donor pools corresponds to SCM estimations in Figure A3. Sample weights are chosen to minimize the RMSPE ten days prior to the start of the treatment.

B.7.   Google trends and announcement effects
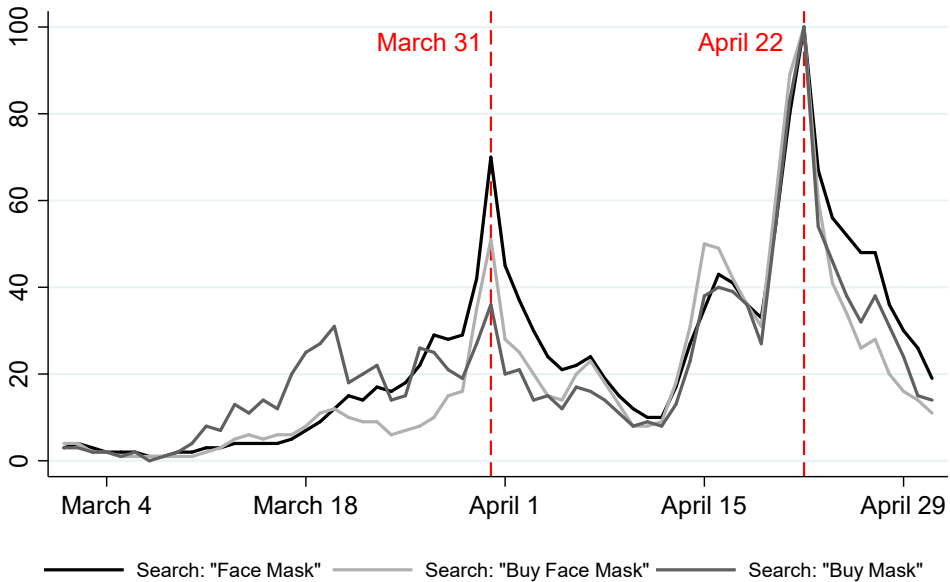
Figure A4: Online search for face masks and purchase options according to Google Trends

Note: Online search for keywords (in German) as shown in the legend as Face Mask ("Mund.-Nasen-Schutz"), Buy Face Mask ("Mundschutz kaufen") and Buy mask ("Maske kaufen"); alternative keywords show similar peaks but with a lower number of hits; based on data from Google Trends (2020).

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B.8. Changes in donor pool for synthetic Jena
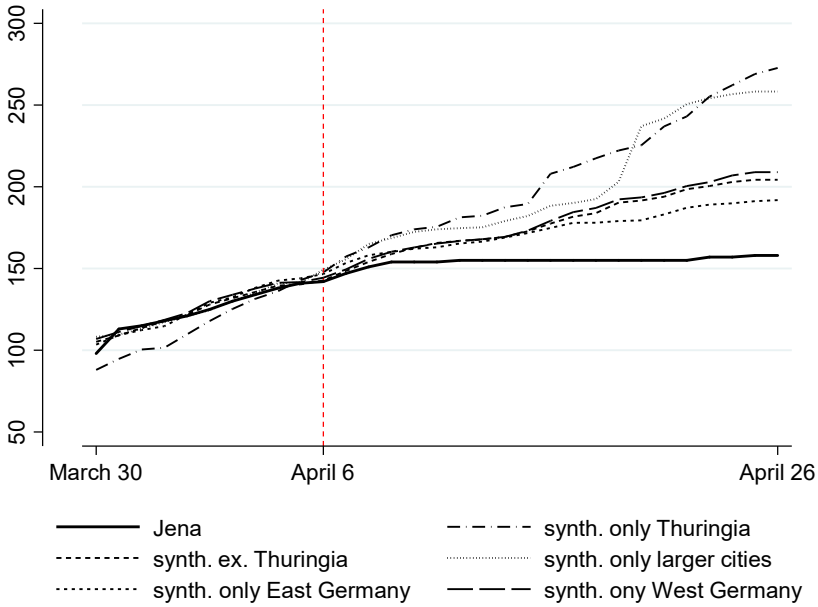
Figure A5: Treatment effects for changes in donor pool used to construct synthetic Jena

Notes: See main text for a detailed definition of the respective donor pools. Predictor variables are chosen as for overall specification shown in Figure 2.

Table A8: Sample weights for alternative donor pools used to construct synthetic Jena

Only Thuringia			Excluding Thuringia			Only larger cities		
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
16076	Greiz	0.533	13003	Rostock	0.318	6411	Darmstadt	0.504
16051	Erfurt	0.467	6411	Darmstadt	0.302	13003	Rostock	0.304
			7211	Trier	0.129	5113	Essen	0.192
			3453	Cloppenburg	0.122			
			6611	Kassel	0.083			
			5370	Heinsberg	0.046			

Only East Germany			Only West Germany		
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
16051	Erfurt	0.865	6411	Darmstadt	0.242
14612	Dresden	0.124	3402	Emden	0.198
11000	Berlin	0.011	6611	Kassel	0.169
			7211	Trier	0.168
			4012	Bremerhaven	0.167
			5370	Heinsberg	0.057

Note: Donor pools corresponds to SCM estimations in Figure A5. Sample weights are chosen to minimize the RMSPE ten days prior to the start of the treatment.

B.9. Place-in-space tests for other major cities in Thuringia
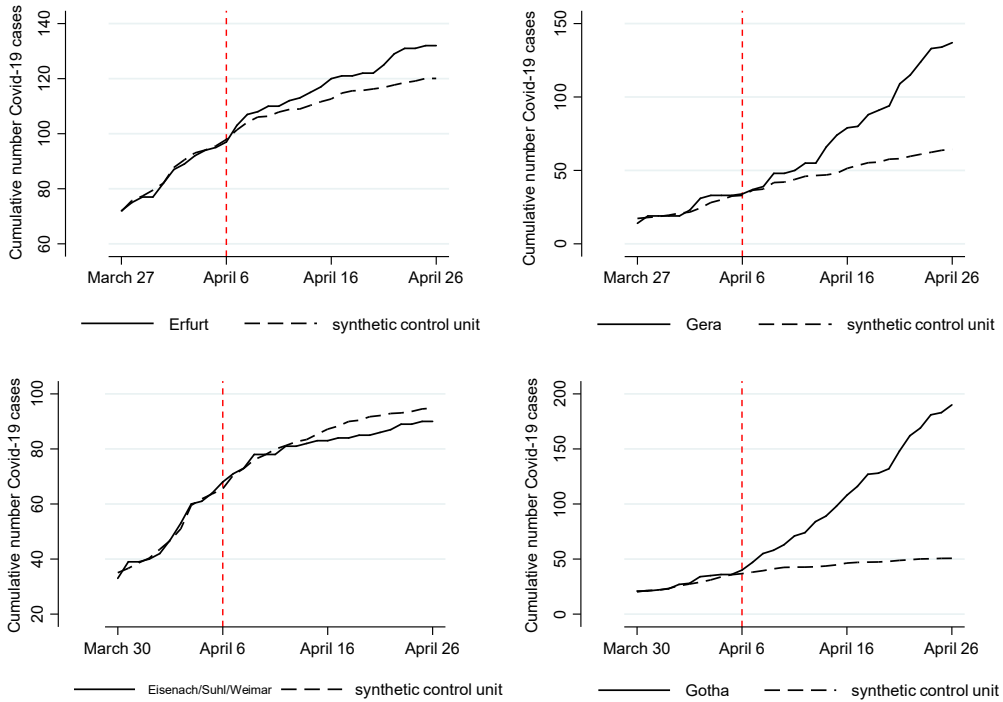
Figure A6: Placebo tests for the effect of face masks in other cities in Thuringia on April 6.

Notes: For the placebo tests in the other cities in Thuringia the same set of predictors as for Jena (Figure 2) has been applied. The reported regions cover all *kreisfreie Städte* plus Gotha (*Landkreis*). The cities Weimar, Suhl and Eisenach have been aggregated since the number of reported Covid-19 is low in these cities.

Table A9: Sample weights in donor pool for synthetic control groups (other cities in Thuringia)

Erfurt			Gera		
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
13003	Rostock	0.28	15001	Dessau-Roßlau	0.501
16055	Weimar	0.244	16054	Suhl	0.222
3356	Osterholz	0.212	7318	Speyer	0.162
7313	Landau in der Pfalz	0.154	8231	Pforzheim	0.061
6413	Offenbach am Main	0.078	7311	Frankenthal (Pfalz)	0.046
5370	Heinsberg	0.029	8211	Baden-Baden	0.005
5515	Münster	0.004	9662	Schweinfurt	0.003
			14521	Erzgebirgskreis	0.001
Weimar/Suhl/Eisenach			**Gotha**		
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
15001	Dessau-Roßlau	0.263	15081	Altmarkkreis	0.23
12052	Cottbus	0.236	16077	Altenburger Land	0.164
13004	Schwerin	0.202	15086	Jerichower	0.161
9361	Amberg	0.177	3402	Emden	0.111
14626	Görlitz	0.069	16071	Weimarer Land	0.108
9363	Weiden i.d. Opf.	0.036	16074	Saale-Holzland-Kreis	0.063
14521	Erzgebirgskreis	0.008	16061	Eichsfeld	0.058
9184	München	0.005	16070	Ilm-Kreis	0.055
6411	Darmstadt	0.005	3453	Cloppenburg	0.027
			15003	Magdeburg	0.017
			4012	Bremerhaven	0.007

Note: Donor pools corresponds to SCM estimations in Figure A6. Sample weights are chosen to minimize the RMSPE ten days prior to the start of the treatment.

C.   The effect in other German cities and regions (single treatment analyses)

In addition to Jena, we test for treatment effects in Nordhausen, Rottweil, Main-Kinzig-Kreis, and Wolfsburg (compare Figure 1). We ignore Braunschweig here as the introduction became effective only two days in advance of its federal state.
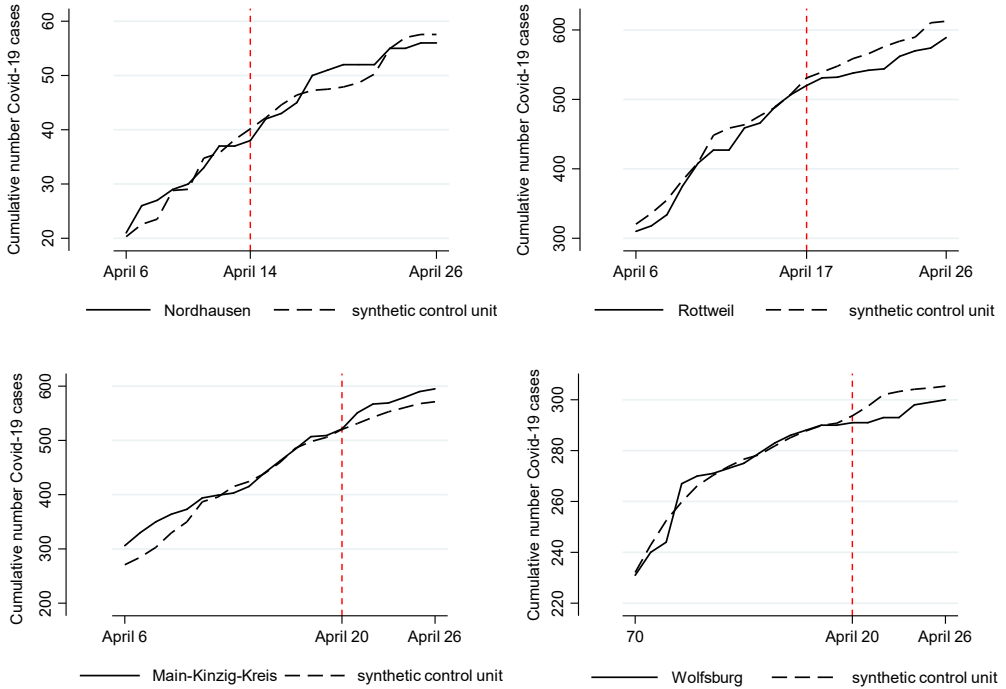
Figure A7: Treatment effects for introduction of face masks in other cities

Notes: Nordhausen (Thuringia, April 14, top left), Rottweil (Baden Württemberg, April 17, top right), Wolfsburg (Lower Saxony, April 20, middle left), Main-Kinzig-Kreis (Hessia, April 20, middle right). Predictor variables are chosen as for overall specification shown in Figure 2.

As the figure shows, the result is 2:1:1. Rottweil and Wolfsburg display a positive effect of mandatory mask wearing, just as Jena. The results in Nordhausen are very small or unclear. In the region of Main-Kinzig, it even seems to be the case that masks increased the number of cases relative to the synthetic control group. As all of these regions introduced masks after Jena, the time period available to identify effects is smaller than for Jena. The effects of mandatory face masks could also be underestimated as announcement effects and learning from Jena might have induced individuals to wear masks already before they became mandatory. Finally, the average pre-treatment RMSPE for these four regions (7.150) is larger than for the case of Jena (3.145). For instance, in the case of the region of Main-Kinzig it is more than three times as high (9.719), which indicates a lower pre-treatment fit. The obtained treatment effects should then be interpreted with some care as the pre-sample error could also translate into the treatment period. In order to minimize the influence of a poor pre-treatment fit for some individual regions, the main text therefore compares the results in Jena mainly with a multiple unit treatment approach.

Table A10: Sample weights in donor pool for synthetic controls (other treated NUTS3 regions)

	Nordhausen			Rottweil	
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
16069	Hildburghausen	0.228	8327	Tuttlingen	0.324
6636	Werra-Meißner-Kreis	0.209	5966	Olpe	0.216
16064	Unstrut-Hainich-Kreis	0.168	8136	Ostalbkreis	0.2
16054	Suhl	0.109	16071	Weimarer Land	0.063
3402	Emden	0.093	14521	Erzgebirgskreis	0.06
12073	Uckermark	0.071	3102	Salzgitter	0.043
12053	Frankfurt (Oder)	0.07	16061	Eichsfeld	0.035
3354	Lüchow-Dannenberg	0.051	9187	Rosenheim	0.031
			9279	Dingolfing-Landau	0.025
			3455	Friesland	0.003
	Main-Kinzig-Kreis			Wolfsburg	
ID	NUTS 3 region	Weight	ID	NUTS 3 region	Weight
8136	Ostalbkreis	0.193	8212	Karlsruhe	0.357
1062	Stormarn	0.168	8221	Heidelberg	0.189
5966	Olpe	0.113	8211	Baden-Baden	0.158
6433	Groß-Gerau	0.105	10046	St. Wendel	0.128
9473	Coburg	0.092	14511	Chemnitz	0.071
5562	Recklinghausen	0.063	5117	Mülheim an der Ruhr	0.059
7313	Landau in der Pfalz	0.059	5315	Köln	0.028
9171	Altrötting	0.056	15003	Magdeburg	0.007
7338	Rhein-Pfalz-Kreis	0.047	9663	Würzburg	0.004
6437	Odenwaldkreis	0.041			
8236	Enzkreis	0.041			
3159	Göttingen	0.023			

Note: Donor pools corresponds to SCM estimations in Figure A7. Sample weights are chosen to minimize the RMSPE ten days prior to the start of the treatment.

D. A brief survey of public health measures against Covid-19

Our approach goes in line with various studies that have already tried to better understand the effect of public health measures on the spread of Covid-19 (Barbarossa et al., 2020, Hartl et al., 2020, Donsimoni et al., 2020, Dehning et al., 2020, Gros et al., 2020, Adamik et al, 2020). However, these earlier studies all take an aggregate approach in the sense that they look at implementation dates for a certain measure and search for subsequent changes in the national incidence. There are some prior analyses that take a regional focus (Khailaie et al. 2020) but no attention is paid to the effect of policy measures.[12]

There are also many cross-country analyses, both in a structural SIR (susceptible, infectious and removed) sense (Chen and Qiu, 2020) and with an econometric focus on forecasting the end of the pandemic (Ritschl, 2020). Others draw parallels between earlier pandemics and Covid-19 (Barro et al., 2020). These studies do not explicitly take public health measures into account. Some studies discuss potential effects of public health measures and survey general findings (Wilder-Smith et al. 2020, Anderson et al., 2020, Ferguson et al, 2020) but do not provide direct statistical evidence on specific measures.

The synthetic control method (SCM) has been applied by Friedson et al. (2020) to estimate the effect of the shelter-in-place order for California, USA, in the development of Covid-19. The authors find *inter alia* that around 1600 deaths from Covid-19 have been avoided by this measure during the first four weeks. The effects of face masks have been surveyed by Howard et al. (2020) and Greenhalgh et al. (2020). Greenhalgh et al. (2020) mainly presents evidence on the effect of face masks during non-Covid epidemics (influenza and SARS). Marasinghe (2020) reports that they "*did not find any studies that investigated the effectiveness of face mask use in limiting the spread of COVID-19 among those who are not medically diagnosed with COVID-19 to support current public health recommendations*".

In addition to medical aspects (like transmission characteristics of Covid-19 and filtering capabilities of masks), Howard et al. (2020) survey evidence on mask efficiency and on the effect of a population. They first stress that "*no randomized control trials on the use of masks <…> has been published*". The study which is "*the most relevant paper*" for Howard et al. (2020) is one that analyzed *"exhaled breath and coughs of children and adults with acute respiratory illness"* (Leung et al., 2020, p. 676), i.e. used a clinical setting. Concerning the effect of masks on community transmissions, the survey needs to rely on pre-Covid-19 studies.

We conclude from this literature review that our paper is the first analysis that provides field evidence on the effect of masks on mitigating the spread of Covid-19.

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[12] In a short note, Hartl and Weber (2020) apply panel methods based on time dummies to understand the relative importance of various public health measures. They employ data at the federal state level and not at the regional level. As a detailed model description is not available, an appreciation of results is difficult at this point.

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The macroeconomics of pandemics in developing countries: An application to Uganda

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How do optimal policies to control the spread of SARS-CoV-2 vary across countries? In an influential recent paper, Eichenbaum, Rebelo, and Trabandt (2020) incorporate economic behavior into a standard epidemiological model calibrated to the United States, finding that spontaneous social distancing will fall short of the social optimum without policy intervention. In this paper, we apply and extend their model to explore how optimal policy varies across contexts depending on demography, comorbidities, and health system strength -- which affect the infection fatality rate -- as well as poverty -- which affects agents' willingness to forego current consumption to reduce disease risk. Calibrating the model to Uganda, we calculate an optimal path for a containment policy equivalent to a 4% consumption tax over one year (compared to a 40% tax in the U.S.), which reduces predicted mortality by roughly 5.5% (compared to 28.2% in the U.S.). Notably, the normative predictions of the model constitute poor positive predictions. Actual containment policies in Uganda and many other developing countries with high poverty and favorable demographics have been relatively severe, and have been met with broad public approval despite high economic costs. Within the model, widespread overestimation of the risk of contracting and dying from the disease provides one possible explanation for this pattern.

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COVID ECONOMICS
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an Application to Uganda

1   Introduction

The ongoing COVID-19 pandemic has led governments around the world to impose unprecedented restrictions on economic activity, with surprising uniformity across countries at all income levels (Figure 1). While economists in rich countries have largely spoken out in support of strict containment policies on the grounds that controlling the pandemic is a prerequisite for economic recovery (IGM Forum, 2020; Mahoney, 2020; Summers, 2020), development economists have expressed reservations about the paths taken by governments in poorer countries (Ray et al., 2020; Ray and Subramanian, 2020; Barnett-Howell and Mobarak, 2020; Ravallion, 2020). We explore two reasons why a unified economic framework might produce such different conclusions: demography and poverty.

We build on the recent model developed by Eichenbaum, Rebelo, and Trabandt (2020, henceforth ERT) to compare welfare-optimizing policies across contexts that differ in terms of these two factors. We replicate the authors' analysis of optimal policy in the United States, and compare it to results

Figure 1: OxCGRT Stringency Index in 2020 - selected countries and average per income group
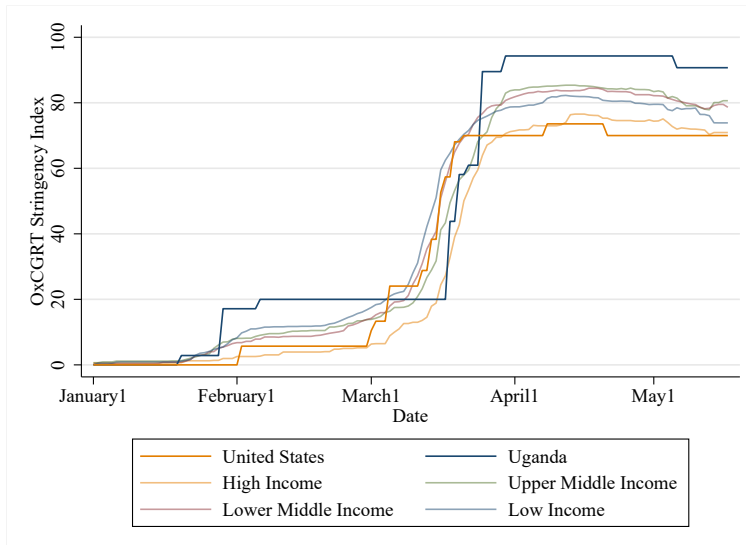
The figure shows the average level of restrictions over time in the four income groups defined by the World Bank and our study countries as measured by the Oxford Coronavirus Government Response Stringency Index. The index 'systematically collects information on several different common policy responses that governments have taken to respond to the pandemic on 17 indicators such as school closures and travel restriction'.

Figure 2: IFR estimates for US and Uganda, based on country-specific age and comorbidity distributions
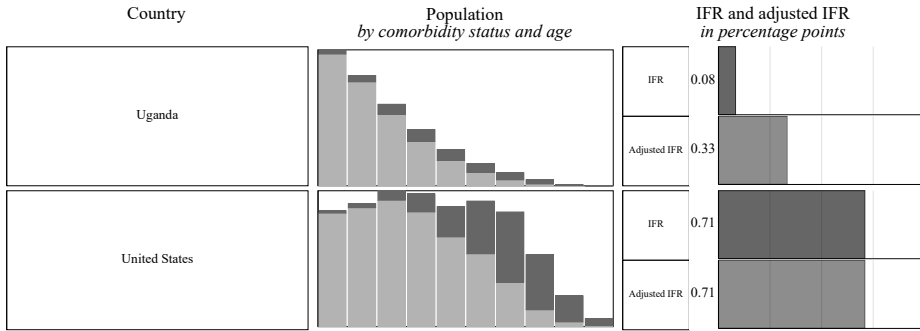
The figure shows the IFR estimates for US and Uganda, based on country-specific age and comorbidity distributions. The middle column reports population by 10-year age groups and by number of comorbidities (light grey - 0 comorbidities; dark grey - any comorbidity), the height of the bars is proportional to the number of people in the most populous age group. Dark grey bars in the right column report IFRs, calculated as an average of the IFRs by age and comorbidity weighed by the proportion of the population in each age and comorbidity group. Light grey bars show the IFR taking into account local health system capacity. See Ghisolfi et al. (2020) for further reference.

calibrated to Uganda. We focus on the latter as an example of a developing country highlighting the two salient features we seek to explore. First, Uganda's median age of 16 is less than half than that of the US, implying the share of infected who die from the disease may be considerably lower.[1] In the ERT framework, this risk differential affects agents' labor supply and consumption decisions, and in turn optimal policy. Second, the country's GDP per capita at $710 is a fraction of the US's at approximately $54,000.[2] At lower incomes foregone consumption due to pandemic control (voluntary or policy-induced) implies a larger welfare loss in the ERT framework, affecting agents' and policymakers' optimal choices. Despite these differences, Uganda's response to the virus has been relatively early and strict (see Figure 1), and available figures suggest successful containment: by early June, there had been 500 confirmed cases and no reported deaths[3]. There is however emerging evidence of widespread economic hardship as a result of the lockdown policies: Mahmud and Riley (2020) report that, while households have so far not begun to sell of productive assets, non-farm incomes have decreased by 60% in their sample from rural Western Uganda. Households have been forced to reduce their food expenditure by 40%, have used up half of their savings and work substantially more on their own farms.

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[1]For comparison, the average is 20 years in low-income countries and 40 in high-income countries. Source: https://apps.who.int/gho/data/view.main.POP2030

[2]The average among low-income countries according to the World Bank's World Development Indicators is $750, versus $43,000 among high-income countries.

[3]Source: ourworldindata.org, accessed June 4th, 2020

A key statistic for our analysis summarizing the above demographic differences is the infection fatality ratio (IFR), the share of people dying from an infection. In companion work, we show that a population's age and comorbidity structure predicts wide variation in this statistic across contexts (Ghisolfi et al., 2020). Even after adjusting for the lower capacity of health systems in Uganda than in the United States, we find that an infected person in Uganda is less than half as likely to die from COVID-19 compared to the US (Figure 2). We describe the construction of these numbers in Section 2.1.

In recent weeks, economists have put forward various ways to incorporate economic decision-making into standard epidemiological models, including the Susceptible-Infected-Recovered (SIR) framework. Studies have highlighted that voluntary adjustments of economic activity by agents facing contagion risk may go some way in containing the spread of the epidemic (Toxvaerd, 2020; Garibaldi et al., 2020; Chudik et al., 2020), and that, from a social welfare perspective, further government action can be justified by agents' failure to internalize their own contribution to the spread of the epidemic (Eichenbaum et al., 2020; Farboodi et al., 2020; Krueger et al., 2020; Glover et al., 2020; Alvarez et al., 2020). Few of these recent papers have focused on developing countries and the efficacy of the aforementioned mechanisms in their contexts (Alon et al. (2020) being a notable exception we discuss below). Our calibration exercise to a developing country, Uganda, focuses on inelastic consumption adjustments and implicit valuations of the utility of the living against the number of deaths. We further explore a simple extension to this model which can help explain the seemingly paradoxical observation from recent surveys in low-income countries, where respondents state high rates of agreement with lockdowns imposed by governments, while at the same time experiencing large income losses.

Our primary reference, the ERT model, posits a continuum of representative agents who value consumption and leisure. The agents expose themselves to infection risk when working and consuming, and, realizing this danger, reduce work hours and consumption as the risk of infection rises. However, they do not weigh the impact of their own labor and consumption decisions on the pandemic's spread, leading to an externality the social planner seeks to internalize. This is modeled via a discouragement on consumption, termed the 'containment rate' by the authors. The optimal policy here is one that maximizes the present value of societal utility. Components of this are i) the utility the agents derive from consumption, labor income, and leisure, ii) the disutility of foregone consumption from lower productivity when infected, and iii) the disutility of dying. The social planner thus strikes a balance between lost utility from containment policies, and lost utility from infection and death. In line with other studies, the authors show that the time path of the 'optimal containment rate' follows the share of infected in the population, i.e. it discourages economic activity more when the risk of contracting or

spreading the disease is higher. Although never restricting economic activity totally, their calibration yields a strong and sustained discouragement of consumption, equivalent to a 40% consumption tax over the first year of the epidemic.

Inherent in their analysis and most other recent modeling efforts of optimal lockdown policy is a trade-off between lives saved and foregone consumption. In the ERT framework, a central assumption, which we take on board here, is that the disutility of death is equal to the foregone utility of living. Placing a monetary value on a life is challenging, and some would even argue unethical. However, in all societies around the world, decision makers are making trade-offs that either implicitly or explicitly assign monetary values to lives. Examples are implicit valuations in budget posts for public health services and explicit valuations when using calculated risks of deaths in cost-benefit analysis of infrastructure projects such as roads. While the qualitative results of our study do not depend on the precise value put on a life by either the agent or the social planner, our quantitative statements do. In future work, we plan to explore the implicit valuations put on lives by policymakers, but for now we adhere to the ERT assumption, which is standard in macroeconomic models.

We find that the difference in terms of mortality between a simple SIR model and one integrating economic decision making is much smaller in Uganda than in the case of the United States. While ERT find that the optimal containment policy in the United States reduces mortality by 28% relative to the pure SIR model, we find the corresponding figure for Uganda is only 5.5%. Both of our suggested factors contribute to this result: First, lower infection fatality ratios (IFR) in developing countries make for a lower aggregate disutility of infection. Second, even in the face of contagion risk and containment measures, a poorer agent experiences larger relative utility losses when reducing their labor supply and consumption. The former makes the behavioral responses to any tax less efficient from a health perspective, and the latter makes the social planner less willing to introduce a tax that reduces the consumption. Thus, both forces suggest that optimal policies should be less restrictive in developing countries (characterized by lower incomes and younger populations with lower predicted IFRs) than in richer economies.

Given this discrepancy between observed and optimal policies, we highlight how a key assumption, that the agents are aware of the true transmission and death probabilities, may be adjusted to explain why acceptance of strict policies in many contexts appears surprisingly high: if agents perceive an exaggerated risk of contracting the disease and dying from it, their voluntary adjustment to protect themselves may coincide with the effects of the strict measures introduced by governments. Unless they updates their beliefs, agents may well agree with a painfully strict lockdown.

Our study complements independent research by Alon et al. (2020) who use a heterogenous agents

model including various characteristics of developing country state and health system capacity to assess how different levels of governmental restrictions affect welfare in rich and poor countries. While their model assumes that workers in the informal sector cannot be shielded from the disease by a lockdown, the authors argue that government policy will be less effective in containing the epidemic in countries with larger informal sectors. Our approach highlights a similar effect, though grounded in the utility maximization of the representative agent: When faced with a relatively large decrease in consumption, a poorer agent will rationally reduce her exposure to the epidemic less, requiring government efforts that are stricter than in richer contexts to achieve the same reduction in deaths. Alon et al. (2020) further emphasize that demographic differences, as captured by the country-varying IFR in our framework, account for most of the differences in mortality rates between their modeled rich and poor countries. In contrast, our approach highlights that lower mortality risk not only mechanically affects the overall death rate, but also individual-level optimization and adaptation behavior.

In the following section, we present in more detail the model by ERT and discuss our calibration procedure to the case of Uganda. In Section 3, we present the results before concluding in Section 4.

2   Model

Since the outbreak of the current pandemic, economists have quickly incorporated basic formulations of the SIR model into economic frameworks (Atkeson, 2020). In this, they have largely relied on an early formulation by Kermack and McKendrick (1927), where the share of the population that is currently either susceptible to, infected with or recovered from a disease, evolves according to a set of parameters. We first give a very short introduction to this class of models, and then discuss its incorporation into an economic framework.

The epidemic starts with some exogenous share of the population being infected. A parameter β denotes the rate at which infected people contact susceptibles and transmit the virus. Once infected, individuals recover at a rate γ and are thereafter assumed to be immune. Depending on the relative size of β and γ, the epidemic dies out quickly (if people recover at a higher rate than infecting new ones), or the number of infected rises exponentially, until there are only few susceptibles left. At that stage, a sufficiently large share of the population has acquired immunity to the disease and exogenous new infections will not cause a new epidemic. An extension also models the share of people that die from the epidemic as a simple share of those contracting the disease. We note that estimates of these parameters are still surrounded by significant uncertainty, and that the question of whether surviving an infection provides immunity is not settled (Avery et al., 2020).

The key variable in ERT linking the economy and the epidemic is the number of newly infected people in a given period, denoted by T_t:

$$T_t = \pi_{s1}\left(S_t C_t^s\right)\left(I_t C_t^i\right) + \pi_{s2}\left(S_t N_t^s\right)\left(I_t N_t^i\right) + \pi_{s3} S_t I_t \tag{1}$$

The first term on the right denotes new infections coming from interactions while consuming, or more broadly defined, spending money. This can include activities such as shopping, using services or leisure traveling. It is higher the more susceptible (S_t) and infected (I_t) people there are, and the more each of them consume $\left(C_t^s, C_t^i\right)$. Similarly, the second term describes infections from working, increasing in the number of hours worked by members of the susceptible and infected group $\left(N_t^s, N_t^i\right)$. The third term captures infections from random interactions outside of work or consumption activities. The π_s parameters govern the likelihood of getting infected from either source. Their estimation is key for the way the epidemic plays out. ERT assume that evidence from other epidemics also applies to the current one, in that 1/6 of infections take place at work or while consuming, and 2/3 from random interactions[4]. The authors furthermore target an immunity level of 60% in the population when the epidemic has run its course. Taking these targets, they calibrate the π_s using the steady state values of hours worked and consumption.

Turning to the economic side of the model, the economy consists of a continuum of representative agents whose behavior is modeled through a simple utility function, trading off consumption c and labor n.

$$u\left(c_t, n_t\right) = \ln c_t - \frac{\theta}{2} n_t^2$$

Agents face a budget constraint linking government action to individual consumption through a discouragement on consumption μ_{ct} (the containment rate), the proceeds of which are immediately rebated as a lump sum Γ_t:

$$\left(1 + \mu_{ct}\right) c_t = w_t n_t + \Gamma_t$$

In choosing the parameter θ and the wage rate, ERT target two readily available statistics: the average weekly income and the number of hours worked. The parameters can then be calculated from

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[4] The transmission probabilities in the ERT framework are, due to scarcity of reliable estimates, calibrated on a weak evidence base and on strong assumptions. In addition, it is unclear whether more or less infections in developing countries come through consumption and work: while crowded work places may well be more common in developing countries, work is also more likely to take place outdoors where transmission is lower. Absent better evidence, we have here copied the calibration exercise in ERT. We note that if transmissions from consumption and work are more important (and perceived so) in developing countries, the economic reactions modeled in this paper would be stronger, and vice versa. Collecting evidence on transmission through the various channels, and their perceptions would thus be an important avenue for future research.

the model's steady state.

Agents maximize their lifetime utility, the form of which differs by whether they are susceptible, infected, or recovered.

$$
\begin{aligned}
\text{Susceptible:} \quad U_t^s &= u\left(c_t^s, n_t^s\right) + \beta\left[(1-\tau_t)U_{t+1}^s + \tau_t U_{t+1}^i\right] \\
\text{with} \quad \tau_t &= \pi_{s1}c_t^s\left(I_t C_t^I\right) + \pi_{s2}n_t^s\left(I_t N_t^I\right) + \pi_{s3}I_t \\
\text{Infected:} \quad U_t^i &= u\left(c_t^i, n_t^i\right) + \beta\left[(1-\pi_r-\pi_d)U_{t+1}^i + \pi_r U_{t+1}^r\right] \\
\text{Recovered:} \quad U_t^r &= u\left(c_t^r, n_t^r\right) + \beta U_{t+1}^r
\end{aligned}
\tag{2}
$$

Here, τ_t represents the agents' probability of getting infected given their own and the infected's consumption and working activities, π_r is the probability of recovering, and π_d is the probability of death. We note here the strong assumption that agents know the 'true' infection probabilities - it seems likely that different parts of the population in all countries may over- or underestimate this probability, potentially by a large factor[5]. We present below an exercise illustrating the effects of varying perceived transmission probabilities on behavioral adjustment and agreement with lockdown policies. The formulation above furthermore expresses the assumption that the cost of death is the foregone utility of life. While common in macroeconomic research, it imposes a strict valuation of a life, on which optimal policy depends. As agents do not fully internalize their own contribution to the spread of the epidemic, the social planner can efficiently further discourage economic activity through the containment rate. In particular, ERT set the objective of the policy maker to maximize overall societal utility, including disutility of the dead.

2.1 Calibration

In our analysis below, we compare ERT's calibration to the United States to one for Uganda as our example of a developing country. As we show in companion research, a key difference between rich and poor countries is likely to lie in the lower share of infected succumbing to the disease in the latter, mostly driven by their younger and less vulnerable population (Ghisolfi et al., 2020). This difference remains even after adjusting for the capacity of health systems to deal with pulmonary diseases. We predict an IFR of 0.33% for Uganda and 0.71% for the United States. This figure takes into account the age and comorbidity distribution, as well as health system capacity of the countries. ERT assume an IFR of 0.5% for the US and for comparability reasons, we keep this rate for the US calibration.

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[5]Mahmud and Riley (2020) report that only 14% of households in their rural Ugandan sample find it likely that someone in their household will contract the virus - absent representative testing in Uganda, we cannot say whether this is an over- or underestimate of the true probability, which will also vary over time.

However, we can easily show qualitative robustness related to incorporating our estimated IFR of 0.71% for the United States. In fact, the differences in optimal policy we highlight are larger the greater the relative difference in IFRs between contexts.

An obvious difference between the two settings are incomes and hours worked. These are used to calibrate the disutility of labor parameter of the utility function and labor productivity. For the US, we again follow ERT, who target a yearly income of $58,000, earned during 28 hours of weekly labor. For Uganda, we take the median main job monthly nominal wage for wage employees from the 2016/17 Household Survey, converted to yearly dollar wages (UBOS, 2018), amounting to $535, and set weekly hours worked to 50, in line with evidence from Tanzania and Ethiopia presented in Charmes (2015). We take all other parameters from ERT. This includes an annualized discount rate of 0.96, and a recovery duration π_r of 18 days. Note that the model is set up with one time unit representing a week, so all parameters are converted accordingly. The model runs for 250 weeks, long enough to have the epidemic run its course. At the beginning of the epidemic, 1 in 1000 people are infected.
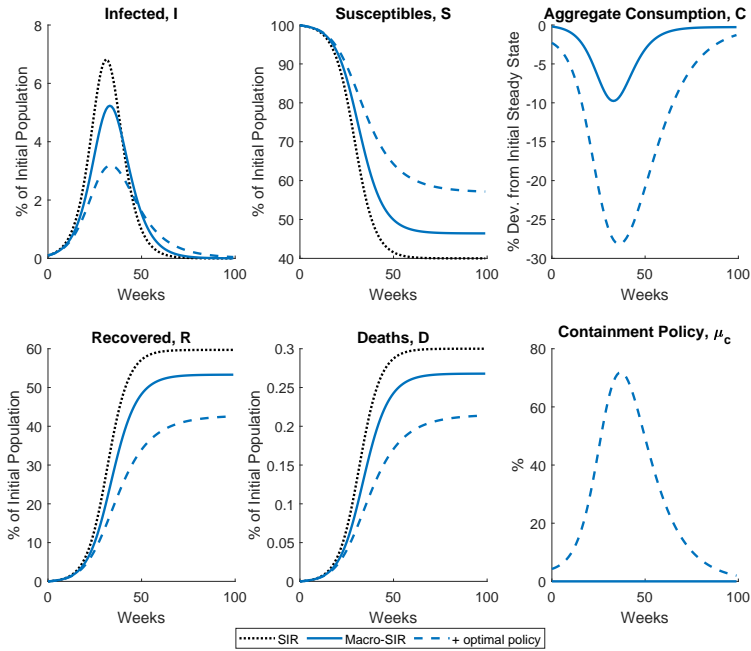
3   Results

In the following, we start by replicating Figure 2 and 3 from ERT to serve as a benchmark scenario and to explain the basic mechanisms of the model. We then proceed in steps towards a scenario calibrated to a low- income country setting. The first step is to change the income targets to the values described for Uganda in the calibration above, keeping the IFR at the US level. This comparison will highlight the role of income per se, holding constant the disutility of death relative to the utility of living. The second step, is to apply the IFR for Uganda and explore the role of a lower probability of deaths and subsequent lower aggregate disutility of infection/exposure. The third step is to introduce a subsistence constraint and by this deviate from ERT's formulation of the representative agents' utility function. Finally, we present a small extension highlighting the role of beliefs about transmission probabilities in agreement with lockdown policies.

3.1   Replicating ERT's calibration to the United States

Figure 3 replicates a combination of Figure 2 and 3 in ERT. The dotted black line represents the course of the epidemic without any behavioral adjustment or government intervention - the basic SIR model. As is common to these models, infections increase ever faster until a large enough share of the population has acquired immunity, such that the infected are less and less likely to interact with the remaining susceptibles. At the end of the epidemic, 60% of the population have ever been infected

Figure 3: Replication of ERT calibration to US economy

The figure shows the time path of epidemiological (left and middle panels) and economic components (right panels) of the ERT model calibrated to the United States. Dotted black line reports results from the basic SIR model. Solid line includes agents' voluntary adjustments. Dashed line shows results from social planner problem maximizing overall utility.

(targeted by the parameterization), and 0.3% have died (60% infected * 0.5% of the infected dead = 0.3% of the population).

The solid blue line presents the model estimates from augmenting the SIR-model with rationally adjusting agents. Focusing on the top-right panel, reductions in aggregate consumption amount to up to 8% and follow the infection rate. This is for two reasons: firstly, infected individuals are assumed to be 20% less productive and thus have less income to consume. With a peak infection rate of 5%, this amounts to a reduction of 1%. The larger share of the reduction comes from agents' voluntary adjustments of hours worked and consumption, in order to reduce the risk of infection. These adjustments slow the epidemic and reduce its peak infection rate, leading to a 10.7% reduction in death rates.

Besides this voluntary adjustment, the social planner can increase overall utility by internalizing the individual agents' contribution to the overall epidemic, which is otherwise not taken into account. This

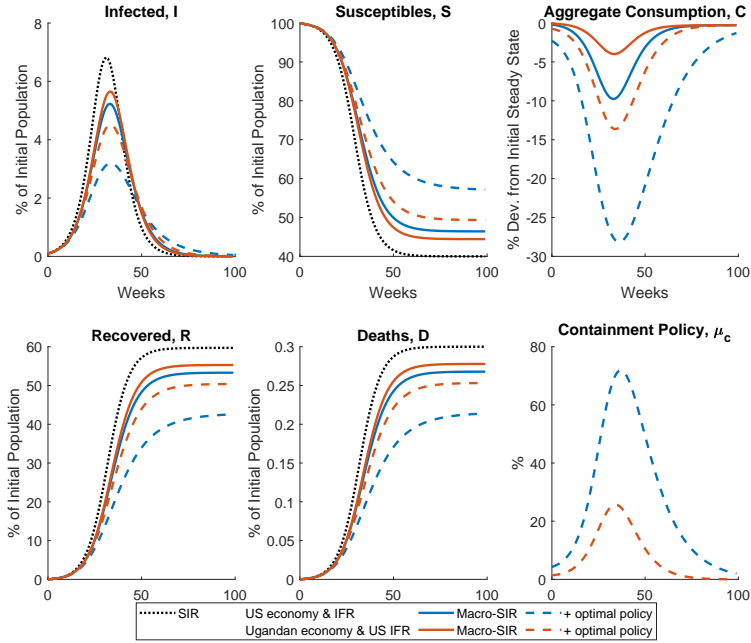Figure 4: Calibration to Ugandan economy with US IFR

The figure shows the time path of epidemiological (left and middle panels) and economic components (right panels) of the ERT model calibrated to the United States (blue) and Uganda (orange), holding constant the IFR. Dotted black line reports results from the basic SIR model. Solid lines include agents' voluntary adjustments. Dashed lines show results from social planner problem maximizing overall utility.

optimal policy, the dashed blue line in the bottom right panel amount to a tax on consumption equal to up to 70% at the peak of the epidemic or 40% over the first year, leading to an additional reduction in consumption of up to 28%. This slows the epidemic further, reducing deaths by an additional 17.5%.

Overall, the ERT calibration suggests that the policymaker can be effective at reducing deaths by reducing economic activity. Interestingly, their calculation implies that overall societal utility of the living between the voluntary adjustment and the optimal policy scenario is virtually unchanged, since agents are willing to reduce their working hours proportionately to the consumption reduction. This observation motivates our exercise in Section 3.4 where we introduce a subsistence constraint into the utility function, thus making the income elasticity of consumption dependent on baseline consumption.

3.2   The role of income levels in determining the optimal policy

We now take the first step of our calibration to Uganda by changing the economic targets of the model. Agents are now much poorer ($535 vs. $58,000) and less productive (working 50hrs/week vs. 28), but have the same, relatively high, probability of dying once infected as in the US calibration. Figure 4 repeats the graphs from the US calibration in Figure 3 in blue, and adds the same set of graphs for the Ugandan economy in orange. Focusing first on aggregate consumption adjustments without any containment policies, it is striking that the adjustments are less than half as strong than in the US economy. The adaptation still reduces peak infection and death rates substantially, though less so than in the US (7.4% reduction in death rate vs. 10.7%). We make a similar observation for the optimal policy, which now peaks at 26%: It reduces deaths, but much less so than in the US (additional 8.1% reduction vs. 17.5%). Both agents and the social planner are trading off mortality risk and utility losses from consumption reductions. When consumption is low already it becomes more costly to reduce it, reductions lead to relatively large losses in utility, and it becomes less optimal to avert deaths.

This exercise highlights that despite equal death risk, the social planner would choose less stringent containment measures in a poorer economy, where reduction in consumption is more costly in utility terms, i.e., an additional consumption reduction takes a relatively larger share of agents' utility.

3.3   The role of mortality risk in determining the optimal policy

The second step of the calibration keeps the Ugandan economy structure, and adds the estimated IFR for Uganda. The results are presented in Figure 5. Faced with a relatively low death rate, agents themselves find it rational to reduce consumption only marginally, reducing the death rate by 6.9% only. Optimal policy now peaks at 18% and reduces deaths by only an additional 6.1%. This difference to the US setting would be even starker if we used our estimates of the IFR for the US, which is 0.2 percentage points higher.
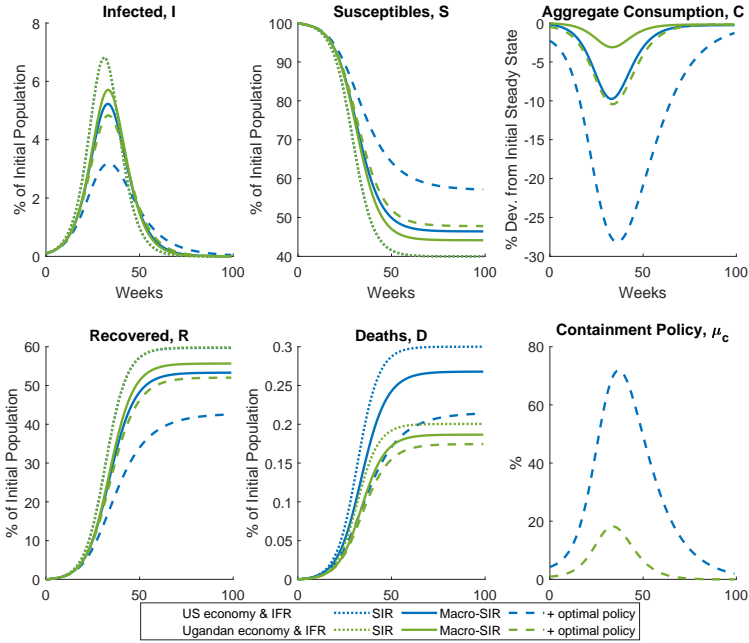
3.4   The role of subsistence constraints

The third step of the calibration to Uganda is to introduce a subsistence constraint into the utility function of the agent, which then becomes

$$u\left(c_t, n_t\right) = ln(c_t - \bar{c}) - \frac{\theta}{2}n_t^2.$$

We set the subsistence level at $200, in line with the median monthly nominal wage for female workers

Figure 5: Calibration to Ugandan economy with Ugandan IFR

The figure shows the time path of epidemiological (left and middle panels) and economic components (right panels) of the ERT model calibrated to the United States (blue) and Uganda (green). Dotted lines report results from the basic SIR model. Solid lines include agents' voluntary adjustments. Dashed lines show results from social planner problem maximizing overall utility.

without any formal education.

Introducing this constraint makes it even more costly for people with a low income to reduce their labor hours. In case of the United States, the introduction of such a subsistence level would not have any substantial effect as consumption is a lot larger than the threshold in the typical household. In Uganda however, the agents are relatively closer to the constraint and thus the introduction of a subsistence level of consumption in the model makes hours and consumption adjust even less in Uganda as a response to an increased tax. In total, deaths are only reduced by 5.5% relative to the pure SIR model.

While our calibration implies that agents are still well above the subsistence constraint, and we hence observe a small consumption adjustment, this extension would in principle allow for modeling of agents being pushed against their subsistence constraint by a containment policy.

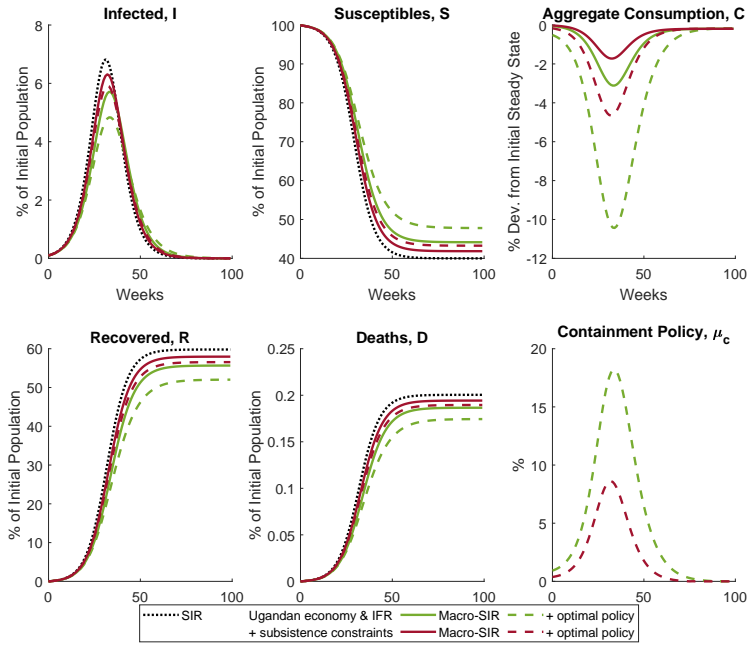Figure 6: Low income calibration with low income IFR and subsistence constraints

The figure shows the time path of epidemiological (left and middle panels) and economic components (right panels) of the ERT model calibrated to Uganda with (green) and without (red) subsistence constraints. Dotted black line reports results from the basic SIR model. Solid lines include agents' voluntary adjustments. Dashed lines show results from social planner problem maximizing overall utility.

3.5 The role of beliefs about transmission risk in the acceptance of lockdown policies

The previous subsections have explored optimal policy for overall utility from the perspective of a recent model. We found that for a calibration to Uganda, voluntary and even optimal adjustments are quite small. This stands in contrast to the strict lockdown policies imposed in many developing countries, among them Uganda. Given the large difference between optimal and observed policies, it may be surprising that recent surveys in Senegal and Pakistan have found broad agreement with the measures mandated by the government, despite households reporting substantial reductions in income. A clear majority of respondents (70%) of a nationally representative survey conducted in Senegal in the second week of April supported a then two-week lockdown to curb the spread of the epidemic (Moscoviz and Le Nestour, 2020). Interestingly, this number was similar among the people who had already seen income losses, and higher among those stating to be more worried about the

epidemic in general. At the time, the Senegalese government had already imposed a nightly curfew and closed public spaces, and more households than usually had cut down on the size of meals during the survey period. In a non-representative but geographically broad sample from Bangladesh (Brac, 2020), respondents similarly reported large decreases in income of up to 75% due to the drying up of casual labor markets, while at the same time generally supporting further restrictive measures.

A possible explanation for these findings lies in that people may or would have been reducing their economic activity even without stricter government measures, as suggested by the mobility data from the US and Sweden presented in Farboodi et al. (2020). Also in the case of Uganda, Mahmud and Riley (2020) report a large increase in protective behavior. In particular, this may be the case if agents overestimate the risk of getting infected and/or the risk of dying from an infection. Further restrictions would then either not be controversial – if their effect does not exceed the voluntary reductions–, or even welcome – if there is a belief that others are not reducing their activity enough. With a small extension, the ERT model lends itself to an analysis of the necessary overestimation.

In particular, we note that the 'true' infection risk from economic activity $(\pi_{s1}, \pi_{s2}, \pi_{s3})$ are, in reality, unlikely to be known by the agents. It appears more probable that beliefs on both the risk of contracting an infection and of dying from it, at least during early stages of the epidemic, often largely overestimate the true (unknown) parameters in both developing and developed countries. Within the model, we can thus introduce a factor ρ by which agents overestimate the true infection parameters from consumption or work. A similar exercise could be performed for the probability of death. This transforms Equation 2 into

$$
\begin{aligned}
U_t^s &= u\left(c_t^s, n_t^s\right) + \beta\left[(1-\tau_t)\,U_{t+1}^s + \tau_t U_{t+1}^i\right] \\
\text{with } \tau_t &= \rho\pi_{s1}c_t^s\left(I_t C_t^I\right) + \rho\pi_{s2}n_t^s\left(I_t N_t^I\right) + \pi_{s3}I_t
\end{aligned}
$$

In our calibration of the ERT model to Uganda using the Ugandan IFR, agents reduce consumption voluntarily by 1%, and the optimal policy increases this reduction to 4%. If, however, agents overestimate the infection risk from consuming and working by factor 20, they voluntarily reduce consumption by 10%, 10 times their original voluntary adjustment. This simple exercise illustrates that if agents are overly afraid of contracting the virus (or similarly, overestimate the IFR), their consumption reduction may exceed what the social planner mandates. In turn, this suggests that agreement with strict, (according to our model overly strict), lockdown policies in developing countries can be partly explained through an overestimation of the risks. The exercise also suggests that governments may find it harder to restrict economic activity once people get more accurate or even too optimistic beliefs about the

Figure 7: Optimal policy with inaccurate beliefs about transmission probabilities
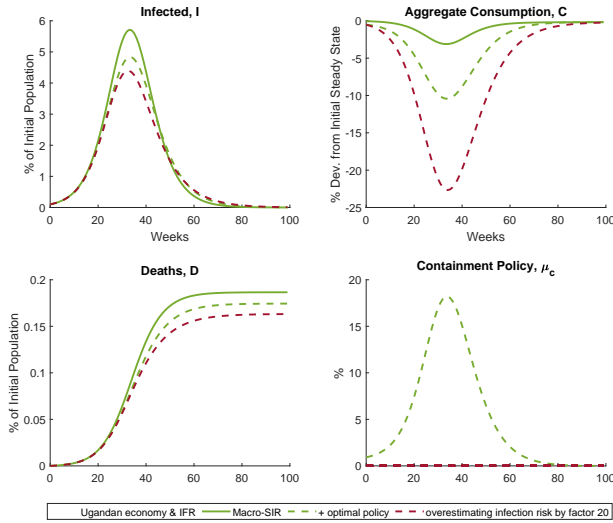
The figure shows the time path of epidemiological (left panels) and economic components (right panels) of the ERT model calibrated to Uganda (green). Solid line includes agents' voluntary adjustments. Dashed green line shows results from social planner problem maximizing overall utility. Dashed red line shows results when agents overestimate infection risk by factor 20.

medical risks. In this light, early and strict lockdowns may be effective in making containment easier later, as individuals perceive the danger as large and imminent.

4   Conclusion

We apply a standard SIR epidemiological model, and the recent extension with behavioral responses introduced by Eichenbaum et al. (2020), to compare optimal policy responses to the current pandemic for two countries, the United States and Uganda. We calibrate the model with country-specific distributions of age, comorbidities, and income, and extend the standard framework to allow for a subsistence constraint on consumption and a 'fear parameter' that may induce agents to overshoot in their adjustment given the true risks associated with the disease. We show that the optimal policy response to the pandemic, maximizing overall utility in our framework, is much more modest for Uganda than for the United States. The main reason is that reductions of consumption are more costly for poorer agents in general, and in particular for those close to the subsistence constraint. Furthermore, given that the demography of Uganda compared to the United States results in a substantially lower likelihood of a fatal outcome given infection, the health damage in a poorer country is predicted to be

lower.

These very different optimal policy responses stand in contrast to the relatively similar *actual* policy responses that we see across the world. Our results suggest that actual strict lockdown policies in Uganda and other countries with similar income levels and demographics may be too restrictive compared to optimal policies. This begs the question whether governments are optimizing as social planners and may have gotten it wrong, or whether their actions can be rationalized with considerations outside the model. One simple explanation would be that in the face of huge uncertainty, governments have adopted approaches from other countries which had already gained more experience with the epidemic, without adapting them to local conditions. As an alternative explanation, we explored the role of possible overestimation of the fatality risk among the population, leading to demand for stronger measures.

Finally, we reiterate that a central assumption in this exercise is that the disutility of death is equal to the foregone utility of living. While this assumption is common in macroeconomic research, there may well be different societal preferences underlying the choices taken by governments during this time. As Ghana's President Nana Akufo-Addo said in March explaining lockdown measures, "We know how to bring the economy back to life. What we do not know is how to bring people back to life. We will, therefore, protect people's lives, then their livelihoods." An interesting topic for future research would be to consider potential heterogeneities in country preferences that could rationalize the actual responses we observe.

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Optimal COVID-19 quarantine and testing policies[1]

Facundo Piguillem[2] and Liyan Shi[3]

Many countries are taking measures stopping productive activities to slow down the spread of COVID-19. At times these measures have been criticized as being excessive and too costly. In this paper we make an attempt to understand the optimal response to an infectious disease. We find that the observed policies are very close to a simple welfare maximization problem of a planner who tries to stop the diffusion of the disease. These extreme measures seem optimal in spite of the high output cost that it may have in the short run, and for various curvatures of the welfare function. The desire for cost smoothing makes more likely that either mitigation or no intervention strategies are optimal, but it does not greatly affect the optimal duration and intensity of the quarantines. We then study the possibility of either complementing or substituting the quarantine policy with random testing. We find that testing is a very close substitute of quarantine and can substantially reduce the need for indiscriminate quarantines.

1   Introduction

The arrival of COVID-19 at the beginning of 2020 took most of the world by surprise. It was quickly understood that even though related to SARS, its fatality rate was significantly lower. This drove many governments to deem it as a mild illness, resulting in very few initial measures to stop it.[1] However, soon after the outbreak it became clear that COVID-19 was substantially more contagious than SARS. This worried local and national officials because if the virus could spread freely the hospitals would not be able to treat the large inflow of potential patients: the health systems were facing a capacity constraint.

This per se would not be a daunting feature if it weren't because the fatality rate among untreated elderly (those above 60 years of age) was alarmingly high, with some studies estimating above 5% for patients between 60 and 70, and around 15%-20% for individuals above 70.[2] The combination of rapid diffusion and the need of Intensive Care Units (ICU) to prevent a high mortality rate resulted in many administrations taking aggressive measures to either stop the infection or, at the very least, slow down the diffusion, which is known as "flattening the curve."

The approach to deal with the treatment capacity problem has been heterogenous across countries. China took initial drastic measures stopping all economic activity in the most affected areas, while Japan and South Korea have implemented policies to slow down the diffusion without greatly affecting economic activities. Sweden minimized the intervention to the point that it is possible to name it a no-intervention policy.[3] As long as the number of affected individuals do not reach the treatment capacity constraint, the disease should be manageable. Other countries have taken intermediate approaches, but the common language appears to be to "flatten the curve", without necessarily eliminating the threat, mitigation rather than suppression.

Since any intervention that affects GDP is costly, and exponentially so as the intervention deepens, these different approaches raise many questions about the right policy:

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[1] One example of this is the fact that the Wuhan doctor who discovered the virus was initially disciplined for "spreading rumors" that could create paranoia. On the other hemisphere, President Trump in public appearances argued that it was no more than a seasonal flu.

[2] All available data shows that the fatality rate among individual under 40, without pre-existing conditions, is no different than a seasonal flu.

[3] The strategy of trying to eliminate the virus is also termed Suppression as in Ferguson et al. (2020), while flattening the curve is termed Mitigation.

should countries follow the China and New Zealand's approach taking drastic measures until the virus is extinct? Or is it better to do enough intervention to keep the affected population under the capacity constraint? If so, how much is enough? Could a no intervention policy be optimal? What should the role of testing be in this context?

In this paper we aim to provide a preliminary answer to the aforementioned questions and try to rationalize the diverse observed policies. To this end we build on Atkeson (2020) who incorporates a SEIR epidemiology model into well known economic setups.[4] In this environment there is an outbreak of an infectious disease which spreads out continuously over time. Some affected individuals are initially asymptomatic and engage in economic activities (meeting) with healthy, but susceptible, subjects who then contract the illness and pass it to others. Unlike Atkeson (2020) we assume that exposed individuals are also asymptomatic carriers who can transmit the virus to other susceptible agents. Once the subject is symptomatic and recognized as infected, it is contained and cannot transmit the illness. However, in this period she may need medical care. If she is not able to receive medical care, she dies with a higher probability than with proper care. We assume that the country has a capacity constraint on how many people can be treated at a given time. Once the capacity is exceeded, the average fatality rate in the economy starts to sharply rise. Furthermore, we follow Eichenbaum, Rebelo, and Trabandtz (2020) incorporating endogenous social distancing measures undertaken by each individual independently of any government measures.

In this context whether to choose suppression or mitigation depends on the possibility of eliminating the virus. Many epidemiologists argue that it is not possible to completely eliminate the virus, and that it would eventually be endemic. For instance, they argue that actions like those taken against the SARS in 2002 and Wuhan and New Zealand in 2020 are futile. Governments should only seek mitigation. To give a chance to the suppression strategy, we further assume that there could be a critical mass of 1 individual such that if at some point the number of contagious carriers is below that critical mass, the virus is completely eliminated. In addition, there is also the endogenous reaction of the population who knowing of the existence of the virus choose to be cautious and, thus, slow down the speed of the spread. If this reaction is sufficiently strong, the government may choose not to intervene with

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[4]In two contemporaneous paper Eichenbaum, Rebelo, and Trabandtz (2020) and Alvarez, Argente, and Lippi (2020) rely on the classical SIR model that does not distinguish between symptomatic and asymptomatic individuals.

additional restrictions.

We stress in this paper the three fundamental issues that we think should drive the optimal intervention. The first is the *capacity of the health system to deal with a large inflow of patients*. By many accounts COVID-19 does not seem to be an extremely deadly illness when the carriers are properly treated. Hence, the need to incorporate a hospital capacity constraint is a first order issue. Second, the government must internalize that the population would react anyway, so that the intervention, if any, only complements the private agents decisions. Third, but no less important, in the standard SIR model, the main (implicit) friction creating the need for indiscriminate quarantines, is the inability of the policy maker to distinguish the asymptomatic infected (exposed in the terminology of Atkeson (2020)) from the susceptible but still unaffected. If it could, the decision maker *would quarantine only the affected*, letting the unaffected population to continue with their normal activities. Even though this appears as a natural **information friction**, the technology available to test individuals, identify them and be able to impose personalized quarantines rather than indiscriminate ones, exists and could be a welfare improving substitute of what is nowadays termed lockdowns. Of course, testing the whole population at once would completely eliminate the problem, but it could be prohibitively expensive. But this is a cost-benefit analysis that should be properly addressed in the current state of affairs.

We analyze these issues in sequential order. First, we take as given the information friction, then we analyze policies that relax it. When the policy maker cannot separate an exposed, but asymptomatic, from a susceptible individual, it directly stops some or all of the economic activity to avoid the spread of the illness. By doing so, it prevents the realization of meetings that reproduce the virus. How much and for how long should production be restricted? In the current jargon, how strict and how long should the quarantine be?

We calibrate the model to the data arising from the outbreak in Italy. Since we believe that the official data for the number of cases is highly underestimating the actual number cases we target the number of fatalities. Still, the fatalities are also underestimated in the official data. Thus, we use the excess deaths per day published by the Istat. To discipline the endogenous reaction of the population we use the cellphone mobility index constructed by Durante, Guiso, and Gulino (2020). We find that depending on the curvature of the welfare function and the value of a life, three types of optimal policies arise: non-intervention, suppression and mitigation. How-

ever, conditional on following one of these strategies the intensity and duration of the indiscriminate quarantine (if any) is barely affected by either the curvature or the relative valuation of a life embedded in the welfare function. In turn, the critical mass plays a very important role shaping when each type of strategy is optimal.

First, when the critical mass is zero, in the sense that the virus cannot be eliminated, it is never optimal to follow a suppression strategy. In this case, for any curvature of the welfare function, if the value of a life is below 13 years of annual income, it is optimal not to intervene, *while if the value of life is larger, it is optimal to "flatten the curve" (mitigate)*. The mitigation strategy is a substantially milder than the observed interventions in many countries. It starts shutting down around 15% of the economic activities and slowly decreases for 90 days until only 10% of the economy is affected. After 91 days, the government stops intervening and only the individuals social distancing measures are left to control the spread of the virus. Two clarifications are worth mentioning. The fact that the government decides not to intervene does not mean that the virus can reproduce freely in an uncontrolled fashion.[5] This is done because the social distancing measures taken by the public are enough to set the curve in an "acceptable" path. Similarly, the mild intervention when is required, it is mild precisely because society is already socially distancing and, thus, the government only needs to complement the private agent's efforts. This type of policies seem to resemble the approaches taken by Japan and South Korea, among others.

When the critical mass is strictly positive, so that the virus can be eliminated, the suppression policy has a chance. As before, if the value of a life is below a 13 years of annual income threshold, it is optimal not to intervene. However, now as the as the cost of life surpasses that threshold, again mitigation becomes optimal. But now there is also a second threshold, this time increasing on the welfare function's IES, such that if the value of a life is larger than it, the government prefers to follow a suppression strategy. Again the optimal quarantine's shape is mostly unaffected by the welfare function's properties. As long as the government is following suppression its intensity and duration is determined by the virus' dynamic, not by the relative valuation of life and production. This type of quarantines shut down around 60% of the economic activity and lasts for around 6 weeks.

When comparing both policies with the observed quarantines, we find that the implemented quarantine in Italy is too "soft" to be optimal suppression and too "harsh"

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[5]This type of policy resembles the approach chosen by Sweden.

to be an optimal mitigation strategy. Italy appears to have followed an average of mitigation and suppression. Nevertheless, conditional on the information available at the time it is troublesome to deem it as suboptimal. Furthermore, we estimate that without any intervention there would be as many as $215,000$ fatalities.[6] With an optimal suppression policy, there are between $17,000$ fatalities, while with the optimal mitigation policy the number of fatalities is substantially larger, with at least 180.000.

Yet, these policies are drastic with large costs in terms of output, which can fall by more than 50% at the peak of the intervention. This brings about the possibility of complementing the quarantines with massive testing to simultaneously decrease the speed COVID-19's reproduction and be able to put to work a larger share of the population. To do so we take seriously that the main problem is an information friction. We consider the possibility that the government can initiate intense screening to identify the exposed individuals. Once identified as positive, the subject is required to endure a (personal) quarantine. This is done by randomly selecting individuals for which there is no information yet: those who have never tested positive before.[7]

Identifying a positive case has two beneficial effects. 1) It is possible to quarantine the individual, even in a stricter way than the rest of the population to slow down the reproduction of the virus. And, 2) once the individual is able to eliminate the virus from its biological system, she is immune and can be allowed to work without any restriction, helping to moderate the extent of the recession. This last contribution, is often overlooked and it could be of considerable relevance, see for instance Dewatripont et al. (2020) and Berger, Herkenhoff, and Mongey (2020), especially when many subjects could remain asymptomatic during the whole duration of the infection. Without the testing, we would quarantine many individuals that are immune and could be working.

We lack reliable data on the cost of a test. Thus, we assume that the marginal cost of the first unit is 1 day of daily output per worker and grows quadratically. The speed at which the marginal cost grows is chosen in such a way that it would be

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[6]This result is in contrast with the calculations by the panel of experts in Walker et al. (2020), who estimate around $645,000$ fatalities for Italy without any intervention. The difference arises because we allow for agents to react increasing social distancing. In a previous draft where we didn't consider social distancing we obtain similar results to this study.

[7]If a subject has been tested before but the results were always negative, it is still susceptible to the illness, and therefore is in the same situation as another who has never been tested. While those who have been affected and tested positive and recover, are from then on immune, so that there is no need to test them again.

economically infeasible to test the entire population at once. We find that **testing is intensively used as a substitute of indiscriminate quarantines** and generates substantial welfare gains. With the cost function that we assume, the output gains are so large that lockdowns could be completely avoided. In our favorite scenario, testing is used intensively, an average of 1% of the unidentified population is tested every day, for little less than two months. This policy is very costly, amounting to 1.9% of annual GDP. But this cost is easily compensated by rendering the indiscriminate quarantine substantially milder. With testing, instead of shutting down 60% of the economic activities it shuts down "only" 50%, and instead of doing it for 75 days, it does it for only 55. Last but not least, we find the Italian implemented quarantine closely resembles the optimal suppression quarantine with testing. Perhaps, with a quarantine that is slightly milder than optimal and a testing strategy that is not aggressive enough.

1.1   Literature review

The literature on epidemiology control dates back to the model proposed by Kermack and McKendrick (1927), also known as the SIR epidemiology model. However, to the best of our knowledge there has not been many applications to economics. With the recent outbreak of COVID-19, economic researchers have started to incorporate SIR models in economic environments to assess the potential economic implications of COVID-19.

Atkeson (2020) computes the projected paths of the disease and evaluates its economic impact. We build on his work deepening the information structure. In this work, it is implicitly assumed that only the symptomatically infected individuals are contagious. We instead assume that, as it happens in many countries, the symptomatically infected are isolated and therefore do not contribute to the speed of contagion. It is what we call exposed but asymptomatic individuals, potentially unidentified without testing, who actually fuel the spreading of the disease. This extension allows us 1) to better fit the dynamics of the disease and 2) to have a well-defined information friction calling for the need for testing. In addition, we optimize over the set of policies rather than focusing on some, yet interesting, paths.

Eichenbaum, Rebelo, and Trabandtz (2020) construct what they call a SIR-macro model with endogenous consumption and labor supply. The competitive equilibrium in

their model is suboptimal due to fact that agents do not fully internalize the externality of their economic interactions. They consider the optimal consumption tax policy that can correct the externality. Similarly, Farboodi, Jarosch, and Shimer (2020) consider a simpler model of economic decisions and analyze then optimal policy in that environment. We differ in many dimensions. First, as Atkeson (2020) both papers consider only the actively infected as potential carriers. Second, also both papers use a meeting technology that does not allow for congestion. Thus, the dynamics of how infection spreads doesn't feature our dilutive effect that kicks in later as immunity expands. Third, we consider policies that directly control economic activities, rather than altering marginal decisions. Nevertheless, Farboodi, Jarosch, and Shimer (2020), using location data, are able to quantify the endogenous reaction of economic agents to the presence of COVID. This allows them to generater a more meaningful estimation of the optimal policy. We similarly use the estimations from Durante, Guiso, and Gulino (2020) to quantify the population's reaction to threat posed by COVID.

As us, Alvarez, Argente, and Lippi (2020) also study the optimal lockdown policy. To this end they use a meeting technology similar to Eichenbaum, Rebelo, and Trabandtz (2020). They assume linear preferences, which weights output and the cost of disease. They also explicitly consider the possibility that in some countries the lockdown could be less effective or harder to implement. We differ from them in some dimensions. Our structure and meeting technology allow us to focus on the fundamental information friction in distinguishing types, which necessitates quarantines to stops the contagion or testing to overcome it. We consider also concave preferences, which generate a need to smooth the costs of the intervention, and show that is very relevant reducing the intensity and increasing the length. Similarly, to incorporate the hospital capacity problem, they assume an exogenous fatality rate linearly increasing in the number of infected. Instead, we model hospital capacity explicitly and calibrate it to the Italian situation. Finally, they solve the optimal control problem, without restricting the policy space, while we look for the optimal lockdown intensity in a restricted policy space. Alvarez, Argente, and Lippi (2020) do not incorporate the endogenous social distancing reactions of the population as Farboodi, Jarosch, and Shimer (2020) and Assenza et al. (2020) do.

Dewatripont et al. (2020) propose that testing, either prioritized or random, is essential to restart the economy. They argue that mass testing is technological feasible and a mere logistic issue of scaling up. Berger, Herkenhoff, and Mongey (2020) fix the

quarantine technology and estimate a SEIR model with testing. They show how testing is instrumental softening the economic effects of the quarantine and flattening further the curve. In this sense, like us the stress that testing is a substitute for quarantines. We instead do not take the quarantine policy as given, but rather study the joint determination of quarantine and testing. In the SIR framework, Chari, Kirpalani, and Phelan (2020) introduce a signal on whether an agent is infected and study targeted testing. They also conclude that testing, in particular targeted testing, is a more cost-effective policy than mere isolation.

2   A SEIR model of disease contagion

Time is continuous and runs indefinitely, $t \in [0, \infty)$. At time t the economy is inhabited by a population N_t with an initial mass of one: $N_0 = 1$. Since the spread of the illness is so fast that it can be measured by the day, we use the convention that one unit of time is one day. At any given time, each individual can be one of five types: susceptible, exposed, infected, identified recovered and unidentified recovered. We denote by S the number of individuals still unaffected but susceptible to the virus. There are two types of carriers of the virus: exposed asymptomatic E and infected symptomatic I. They are both infected and thus infectious. When an individual first becomes infected, it always starts in the group E, it may develop symptoms and become I, or it may never show any symptoms, in which case remains in E until it recovers.

When a subject recovers it becomes immune. Depending of the symptomatic history, R will denote the number of immune recovered agents that were previously symptomatically infected I, and R^u the also immune recovered subjects, but who where previously only symptomatic E. The first group has observable signals that make them identifiable by the government, while R^u are immune individuals that without additional information could remain unidentified. For this reason the distinction between R and R^u is important. Clearly, it must be the case that

$$N_t = S_t + E_t + I_t + R_t + R_t^u.$$

At $t = 0$, the economy is hit by a disease due to a deadly virus. If the exposed population is above a critical mass, $E > \underline{E} \geq 0$, then it starts to spread. Otherwise, it's

self-contained and all patients gradually recover. The virus spreads through meetings between exposed and unaffected individuals. To avoid this, the government can impose quarantines, which can be directed or indiscriminate. To impose indiscriminate quarantines the government simply resorts to shutting down a proportion q_t of the economic activity. All individuals involved on those activities must thus remain in their homes without interacting with others.

The government can also imposed directed quarantines, singling out a proportion of the carriers and force them to stay at home in isolation. Thus, a proportion q_t^I of infected individuals and a proportion q_t^E of exposed asymptomatic are forced into quarantines. We assume that symptomatic individuals, I_t infected agents, can be identified by their symptoms and are forced into a full quarantine, so that $q_t^I = 1$.[8] In this section we start by assuming that the government has no information about the identity of either E_t or R_t^u individuals, hence, it has no choice but setting $q_t^E = q_t^{R^u} = 0$.[9] Therefore, the virus spreads **only** through meetings between exposed asymptomatic and unaffected individuals.

Finally, those who are initially exposed after an incubation period become symptomatically infected. Those who already had it and are recovered become immune permanently.[10] The number of meetings in the economy depends on the intensity of *social distancing* attitude of the population $q_t^s \in [0, 1]$. When $q_t^s = 1$ individuals avoid every type of social interaction, so that there is no meetings at all; while when $q_t^s = 0$ individuals do not constraint themselves and any activity generates a social interaction. The number of infections depends on the number of individuals interacting adjusted by the intensity of the interaction: ι_t. Since identified recovered agents interact freely and the infected individuals are forced to remain isolated, the total adjusted number of possible interactions is:

$$\iota_t = (1 - q_t^s)(S_t + E_t + R_t^u) + R_t. \tag{1}$$

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[8]This assumption is in line with the preventive measures taken by all the governments as soon as they detect an infected subject.

[9]Alvarez, Argente, and Lippi (2020) assume that $q_t^I = 0$, as they merge all the carriers E_t and I_t into a single group I_t that is allowed to work as long as they are not subject to an indiscriminate quarantine.

[10]There is some debate as to how permanent is the immunity for recovered agents and as to whether there is immunity at all. There is consensus on the fact that most, but not necessarily all, individuals that recover from COVID-19 would be immune for at least the current year and most likely for the next two years.

The independent reaction of the population to the presence of the virus is a key element that the government must take into account when designing the optimal policy. There is ample evidence in many countries, including Italy that the population reacted taking precautionary measures when it was evident that COVID-19 was present and dangerous.[11] This reduces the need for government intervention and it could potentially imply that no intervention is optimal. Here we have written q_t^s as a function of only t, but in general it could depend on the state of the economy and the government intervention. In Section 2.1 we assume a functional form $q_t^s(q_t, I_t)$ and discipline it with available information. From now on we avoid to write down the explicit dependency of q_t^s on the state of the economy, but the reader should bear in mind that the dependency on t embodies it.

We denote by $\lambda m(\iota_t, E_t)$ the meeting function between carriers of the virus and the rest of the population. Potentially, the total number of carriers allowed to work is $(1 - q_t^I)I_t + (1 - q_t^E)E_t$. Because we are assuming that $q_t^I = 1$ and $q_t^E = 0$, the total number of carriers is just E_t, hence the second term in the meeting function rather than $I_t + E_t$.[12] Not all of these meetings generate an infection, since only $\frac{S_t}{\iota_t}$ of the workers are susceptible and individuals engage in social distancing, at every instant there are only $\lambda \frac{S_t(1 - q_t^s)}{\iota_t} m(\iota_t, E_t)$ meetings generating new affected (exposed) individuals.

Once exposed, an individual becomes symptomatically infected with intensity γ per unit of time, and can recover with intensity σ without ever being symptomatic.[13] Thus, the law of motion of the exposed type satisfies:

$$dE_t = \begin{cases} \left[\lambda \frac{S_t}{\iota_t} m(\iota_t, E_t(1 - q_t^s))(1 - q_t^s) - (\sigma + \gamma)E_t \right] dt, & \text{if } E_t \geq \underline{E} \\ -(\sigma + \gamma)E_t dt, & \text{if } E_t < \underline{E}. \end{cases} \tag{2}$$

We assume that the symptom appearance γ and the recovery σ are independent of time and the state of the economy. They just reflect the individual's strength to fight the virus inside their biological system. The same is true for the intensity of contagion λ, which is a scale parameter capturing the level of interactions among agents in their

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[11]See Section 3 for further details.

[12]In Atkeson (2020) only the infected individuals can transmit the virus, so that the infectious meetings in his economy are $m(L_t, I_t)$. He does not distinguish between symptomatic and asymptomatic carriers though. We borrow his notation and give it a different interpretation.

[13]The asymptomatic status prior to becoming symptomatically infected clarifies the effects in production, and it is instrumental in Section 5 when we analyze the information friction. Otherwise, we could merge them into a single type as in Alvarez, Argente, and Lippi (2020).

daily economic activity. The speed at which the illness spreads is clearly state depen-
dent, increasing in the number of exposed E_t and the share of the population which
are still susceptible. The function $m(\iota_t, E_t)$ could incorporate potential "congestion"
effects. For instance, one may think that when most of the population are already
affected, most meetings would be between individuals who are either immune or
already infected and thus would not generate new infections.

We want to emphasize that the presence of the minimum critical mass $\underline{E}$ could be very
important for the prescribed policy interventions. When $\underline{E} = 0$ the virus never dies,
it could be forced to affect a negligible number of people, but it would be always
around to re-surface and spread again. Instead, when $\underline{E} > 0$ it could be possible
to take drastic measures to force the affected population below the critical mass, so
that the virus disappears and the infection is definitively defeated. Instead, when
$\underline{E} = 0$, since the virus would eventually spread anyway, a policy maker could choose
to simply regulate the speed at which the number of exposed and infected subjects
arrive. This would be important when we bound the capacity of the health system to
treat the illness.[14]

Exposed subjects become symptomatically infected at rate γ. Once they are infected
they would require medical assistance and potential hospitalization. When treated
individuals recover at rate η and die at the rate Δ_t per unit of time. The law of motion
of (symptomatic) infected individuals satisfies:

$$dI_t = [\gamma E_t - (\eta + \Delta_t)I_t]dt.$$

As with γ and σ, here again η is independent of the economy's state. The process
by which the body is able to eliminate the virus from the system is not affected by
the health system, it only depends on the strength of the subject's immune system,
conditional on surviving. But notice that Δ_t does depend on the state of economy.
One may think that the way in which the illness affects a particular individual de-
pends only on her/his biological characteristics and therefore should be independent
of how other individuals are affected. However, here we assume that the death rate

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[14]Another way to think about $\underline{E}$ is as a way to prevent the modeling strategy from forcing policy
prescriptions. For instance, because growth is proportional, one we can divide a positive number
indefinitely by other positive number and it would always be strictly positive. In the context of our
model we could end up with less than a person infected, which is not physically possible, but it would
imply that the infection would reappear in the future. $\underline{E} > 0$ makes sure that, whenever fewer than a
minimum amount of person are infected, the disease would disappear.

depends on the capacity of the health system to treat patients.

Hospitals can optimally treat only H_t patients at a time. Once that capacity is exceeded the treatment received by each patient is diluted resulting in a suboptimal treatment. Those who are optimally treated die with intensity θ, while does who are treated in an overcrowded system die with intensity $\delta > \theta$. As a result, the average daily death intensity in the economy satisfies:

$$\Delta_t = \theta \underbrace{\min\left\{1, \frac{H_t}{I_t}\right\}}_{\text{fraction treated}} + \delta \underbrace{\max\left\{1 - \frac{H_t}{I_t}, 0\right\}}_{\text{fraction untreated}}. \tag{3}$$

Given the previous assumptions, the number of recovered patients and total population evolve according to:

$$dR_t^u = \sigma E_t dt, \tag{4}$$

$$dR_t = \eta I_t dt, \tag{5}$$

$$dN_t = -\Delta_t I_t dt. \tag{6}$$

From the previous structure it is straightforward, see Appendix A, to compute the average death rate from the illness and the duration of sickness. This of course would depend on whether the patients are treated or not. When all sick individuals are treated, a patient recovers in $\frac{\eta}{(\eta+\theta)^2}$ days, and on average a fraction $\frac{\theta}{(\eta+\theta)}$ of the patients die. When left untreated, the recovery happens in $\frac{\eta}{(\eta+\delta)^2}$ days, and the average death rate is $\frac{\delta}{(\eta+\delta)}$. These are moments that it is possible to match with the already available data. Note that due to selection, patients would appear to recover faster in countries with higher fatality rates.

We assume that indiscriminate quarantines q_t have a direct impact on economic activity while social distancing is less damaging, reducing production in a proportion $o(q_t^s) \leq 1 - q_t$. It is unclear how large if the effect of social distancing on production. One can think that social distancing q_t^s does not have an output cost. For instance, individuals still go shopping and buy the same value in goods, but now they do it less often and with less direct physical contacts, which would imply $o(q_t^s) = 0$. However, other economic activities could be affected. For example, agents could stop going to restaurants, even when they remain open.

For simplicity we assume that the production technology is linear. Each meeting produces one unit of output per individual involved in the meeting. Infected hospitalised individuals are unable to produce, since $q_t^I = 1$. In normal times the total production would be $Y_t = L_t = N_t$ per day. However, during the spreading of the virus, only the unaffected, fully recovered and those still undetected but yet exposed can produce, so that $L_t = S_t + E_t + R_t + R_t^u$. Hence, if the government allows for undistorted economic activity, i.e. $q_t = 0$, the total production would be $Y_t = S_t + E_t + R_t + R_t^u$. To prevent the spread of the virus the government bans certain activities. It does so by forcing quarantines among the population. Since the government is unable to distinguish S_t and R_t^u from E_t, it cannot condition the quarantine on each individual status, it simply ban a fraction $q_t \in [0, 1]$ of all economic activity. As result, the total production after a policy intervention is $Y_t = (1 - q_t)(S_t + E_t + R_t^u) + R_t$.[15]

We assume a closed economy. The only produced good is non-storable, and there is no possibility of borrowing or saving in financial assets. This implies that consumption is equal to production in every period: $C_t = Y_t$. All individuals, and therefore also society as whole, discount the future at rate $\rho > 0$. The government chooses a path $\{q_t\}_{t=0}^{\infty}$ to maximize society's welfare:

$$\max_{\{q_t : t \geq 0\}} \int_0^{\infty} e^{-\rho t} u\left((1 - q_t)(S_t + E_t + R_t^u) + R_t\right) dt; \qquad \text{(P1)}$$

subject to equations (1), (2), (5), and (6).

Notice that this setup allows for a variety of possibilities. A solution could be a forced quarantine for every individual for a limited period. For instance, we can think about Wuhan's **suppression** policy intervention as setting $q_t = 1$ for all $t \leq \bar{\tau}$ and $q_t = 0$ for all $t > \bar{\tau}$, for some $\bar{\tau} > 0$. In this case if in some point $E_t < \underline{E}$ the virus dies and never recovers. This problem would reduce to choosing the optimal length $\bar{\tau}$ of a complete lock down. Alternatively, one can think about policies that are more moderated, **mitigation** policies, with $q_t < 1$, but that last for a longer interval. For example, the government could try to maintain I_t below H_t at all t until most of the population becomes immune.

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[15]Notice that we are allowing the recovered subjects to return to work. This is clearly optimal and the recover status is fully observable. In spite of this, most, if not all, countries include inefficiently the recovered in the mandatory quarantines.

The choice of the welfare function is by no means trivial. In Problem (P1) we have purposely excluded the welfare lost due to fatalities. We have done so because it is, at the very least, highly controversial how to compare losses due to foregone consumption with welfare losses due to fatalities. What is the value of a life? If one believes that a human life is more important than everything else, then the correct welfare function should only minimize the number of fatalities. In this case, as long as $\theta > 0$ the solution to (P1) is almost trivial, setting $q_t = 1$ for as long as is needed to locate E_t below $\underline{E}$. If $\theta = 0$ and $\delta > 0$, then only policy paths that maintain $I_t \leq H_t$ will be part of the solution. Here the output cost becomes the relevant factor pinning down the optimal path.

However, (P1) is also problematic because current and past choices reveal that societies are willing to trade off human life for economic activity. For instance, the U.S. Center for Disease Control and Prevention (CDC) estimates that between 12.000 and 61.000 people die annually due to influenza. Yet, governments are not willing to stop the economic activity to prevent it. Similarly, in 2018 around 36.000 people died in car accidents in the U.S. But there has never been a discussion about banning circulation in motor vehicles. One can interpret these choices as balancing individual and collective responsibility. As long as the fatalities are not too large, society prefers to delegate the choice of the "acceptable risk" to the individual, while if the fatality rate is too high there maybe some frictions that prevent individuals from properly assessing the risk. Then, it becomes a collective responsibility and the government must intervene. For this reason we also consider and alternative problem where the policy maker trades off economic activity and lives:

$$\max_{\{q_t : t \geq 0\}} \int_0^\infty e^{-\rho t} \left[u \left((1 - q_t)(S_t + E_t + R_t^u) + R_t \right) - v \left(\Delta_t I_t \right) \right] dt; \qquad \text{(P2)}$$

subject to equations   (1), (2), (5), and (6).

Here the function $v(x)$ would be key in determining the number of acceptable deaths. Admittedly, it is hard to parameterize it, but we use data for alternative activities that generate fatalities to discipline its implications. In the sense that, if for instance, an activity is allowed when the fatalities are caused by influenza, it should also be allowed when caused by COVID-19.

2.1 Functional forms

One of the objectives of this paper is to analyze the implications of different curvatures in the welfare function. This determines the strength of the trade-off between reducing economic activity through q_t to decrease the speed at which the virus spreads. If the welfare function is linear, completely stoping the economy could be optimal if the cost can be compensated later once the virus no longer poses a threat. Instead, when the welfare function has a low Intertemporal Elasticity of Substitution (IES), it is more costly for the government to reduce current economic activity to reap future benefits. For this reason we assume that the welfare function is:

$$u(c) = \frac{c^{1-\epsilon} - 1}{1 - \epsilon}; \text{ if } \epsilon \neq 1 \text{ and } u(c) = \log(c); \text{ if } \epsilon = 1.$$

This functional form is mathematically tractable and meaningful in one dimension or another, allowing for a wide range of interpretations. In Section 4 we compute the optimal policy for a wide range of ϵ, starting at zero and reaching 4. We show there that particular value for ϵ is relevant to determine if the planner wants to follow a mitigation or suppression strategy, but once the strategy is chosen the intensity of the intervention is mostly unaffected.

The choice of $v(x)$ is less straightforward. One maybe think that a quadratic loss function $v(x) = \frac{d}{2}x^2$ would be appropriated, because the cost grows exponentially with the number of fatalities. However, it also has the potentially unappealing feature that the planner would be wiling to accept many fatalities if they are sufficiently spread out over time, while it wouldn't accept it if all fatalities happen in a concentrated interval of time. For instance, 1 dead today and 1 tomorrow is much better that 2 dead either today or tomorrow. An alternative is to use a linear function $v(x) = dx$, and choose d to reflect the statistical value of life. In this case, it does not matter when the deaths happen but the total number. As Alvarez, Argente, and Lippi (2020) and Farboodi, Jarosch, and Shimer (2020) we follow this approach, but instead of choosing a specific value for d we consider a wide range of values, ranging from 0 to 100 years of per capita output. We do this because society may value lives beyond it statistical value and may choose to preserve them even when is not "economically" efficient. Since it is not clear how to determine this additional value we leave it as a parameter.

We follow most of the epidemiology literature, and the current economic literature, assuming $m(\iota, E) = E$. Still, because we have the term $\frac{S}{\iota}$, our functional form allows

form some congestion, a feature that is absent in Alvarez, Argente, and Lippi (2020), Farboodi, Jarosch, and Shimer (2020) and Berger, Herkenhoff, and Mongey (2020) among many others.

Finally, we assume a linear function for the law of motion of social distancing. Taking into account the recent empirical literature on COVID-19, we allow for q_t^s to depend not only on the intensity of the government intervention, but also on the threat that the virus poses to society. The functional form is:

$$1 - q_t^s = 1 - \beta_0 q_t - \beta_1 I_t - \beta_2 \{\exists \, \text{COVID}\}_t. \tag{7}$$

There are three important coefficients in equation (7). The simplest to interpret is β_0, which captures the effectiveness of the government intervention. One could expect a number around 1, meaning that any intervention translates one-to-one into less social interactions. Nevertheless, it could be either smaller than 1, when the intervention substitutes other social interactions, or bigger than 1 when there are complementarities. The second coefficient, β_1 captures the continuous response of the population to the virus's spread. If there were no infections, the agents would not be concerned and would continue their normal activities, including social interactions. As the prevalence of the virus increases, the population becomes increasingly concerned and reduces the extend and intensity of their interactions.

Some recent empirical studies, e.g., Durante, Guiso, and Gulino (2020), have also found that the *awareness* of COVID-19 can cause a discontinuous and persistent change in habits. To allow for this possibility we introduce the indicator $\{\exists \, \text{COVID}\}_t$, which takes the value 1 if it is known that COVID-19 is present at day t, and zero otherwise. Thus, β_2 captures a sudden change in the behavior of the population when they found out about the outbreak. It is a permanent and constant increase in social distancing. As a result, absent any government intervention, social distancing would nevertheless increase by $\beta_1 I_t + \beta_2$ at day t. This component would play an important role in our no-intervention scenario and shaping the optimal policy.

3 Quantitative implications

3.1 Parametrization

There are several key parameters in the model. The parameters γ and σ determine how long an individual can be contagious without potentially showing any clear symptoms. The parameter γ is related to the incubation period, which is 6.5 days of generation time according to Ferguson et al. (2020), thus we set $1/\gamma = 7$. For η, which is the recovery rate of symptomatic subjects, there is a wide variate of information. In the initial work of Ferguson et al. (2020) they state that it takes an average of 9 days for a subject to recover. Alternatively, one can recover from the law of motion of active cases in Italy the analogous statistic and find that it takes an average of 48 days for an individual to recover. This last figure appears exaggerated, probably reflecting delays in the administrative process to "officially" declare a subject as recovered.[16] The experience for European outbreak shows that 9 days seems to be in the low end, with many studies considering values around 14 days (citation needed). For this reason we target an average duration recovery time of 17 days. The precise value for η would depend on the death rate which we discuses below.

For any average fatality rate d, the daily fatality rate θ and the average recovery rate η are jointly determined by the relationship show in the previous section. The relationship is:

$$\frac{\eta}{(\eta+\theta)^2} = Days; \quad \frac{\theta}{(\eta+\theta)} = d.$$

The solution to this system is:

$$\eta = \frac{(1-d)^2}{Days}; \quad \theta = \frac{d}{1-d}\eta,$$

where $Days$ is the average number of days until recovery and d is the average death rate. Thus, given any estimate for θ we can recover the implicit η that generates 17 days of recovery time using the last equation.

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[16]An individual is declared recovered after two consecutive tests with negative results. Thus, delays on any of the testings could generate a delay. Also, the information about patients is provided by the regions with some of them taking more time than others to process the paper work and the information.

There are 4 parameters for which there is ample uncertainty: θ, σ, λ and the date of the first infection. θ is related the expected number of deaths for a given number of infected agents. The second, determines for how long an asymptomatic agent can be contagious and therefore is important for determining the dynamics. λ has been the subject of considerable debate since it determines the reproduction factor of the virus R_0. One may think that σ is a fundamental property of the virus, in the sense that it should be the same across countries. However, both θ and λ can be very specific to each country. For instance, the age structure of the population can affect the average death rates, while the nature of the social interactions would determine λ.

To address these issues we estimate these four parameters to match the observed dynamics of COVID-19 in Italy. Ideally one should fit the dynamics of infected cases and compute the implied death rate with the number of fatalities. The problem with this approach is that the information for "cases" only reflects the number of individuals who have been tested and generated a positive result. There are many reasons to believe that this measure would not reflect the real state of the country in terms of infected individuals. First, those who are asymptomatic are unlikely tested and therefore are not recorded. Second, it is widely known that initially there was a scarcity of test kits, which forced the authorities to tested only subjects that were likely to be infected or vulnerable. Thus, many mildly symptomatic individuals were left untested. Finally, initially the tests were imprecise which delivered many false negatives.

To avoid this problem we target instead the path of fatalities. Given the parameters of the model, there is a one to one mapping from the number of infected to the number of fatalities. Still, even the number of fatalities is controversial. Since many fatalities, especially at the peak of the infection, maybe have been reported as non-COVID related, the fatality rate could be underestimated. To deal with this additional complication we use the information from the Italian Istituto Nazionale di Statistica, that computes the excess daily fatalities in Italy relative to the average of the same day in the previous 5 years.[17] In Figure 1, Panel a), we show the total reported excess number of deaths in Italy during 2020 (until April 15th) and the reported deaths by COVID the same day. Since the number of deaths in January is relatively smaller than the previous years, we normalized the series such that the average for January is zero.

It is evident from the figure that at the end of February there is an steep increase in the reported excess deaths that is not reflected in reported deaths by COVID. This

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[17]The information for every month can be found on https://www.istat.it/it/archivio/240401.

pattern remains for most of March until the beginning of April where both series seem to coincide. For this reason we construct our own measure of COVID deaths using the excess deaths from March 1st until April 7th, and from then on we use the reported COVID deaths.

Figure 1: **Calibrated moments**

Panel a): Fatalities   Panel b): Mobility
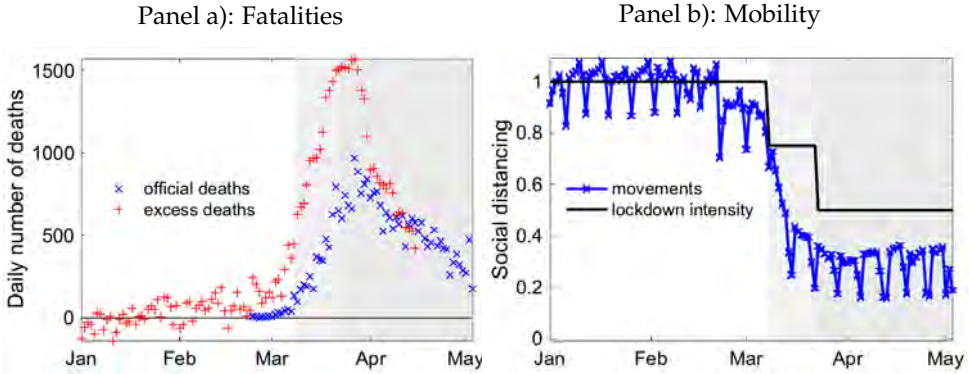
To be precise we target the daily fatalities' path from March 1st to May 3rd. We exclude the last week of February (the first reported COVID death was in February 22nd) because the relevance of COVID in the excess deaths for that week is lower. We are confident, although, that most (or all) the excess deaths in March are COVID related. With this data we construct a loss function:

$$Lo = -\sum_{t=t_0}^{t^{end}} \left(\frac{D_t - deaths_t}{deaths_t} \right)^2,$$

where D_t are fatalities generate by the model. As result, θ, σ, λ and the date of the first infection minimize Lo. Loosely speaking the initial fatalities between March 1st and March 8th are mainly determined by the initial time of the outbreak and λ, which controls the number of meetings generating infections. The outcomes after the consecutive government interventions and the reaction of the population shed light on the number of asymptomatic agents, determined by σ and the fatality rate θ.[18]

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[18]Here is important that most of the symptomatic agents are in individual quarantines. If there were no asymptomatic $\sigma = \infty$ the infection would died out rapidly, while with many asymptomatic $\sigma = 0$, the infection would keep spreading quickly. Similarly, the changes in the number of fatalities would

To implement this strategy we need three additional pieces of information. First, for a given number of initially recorded fatalities there are many combinations of initial mass and outbreak date that are consistent with the observation. To avoid this ambiguity we assume that $e_0 = 2/60.000.000$. That is, there were initially only two exposed individuals.[19]

Second, as we show in equation (7) the effect of the intervention depends on their intensities, which is controlled not only by the economic activity but also by the additional reaction of the population. Following Durante, Guiso, and Gulino (2020) and Farboodi, Jarosch, and Shimer (2020) we incorporate the endogenous reaction of the population due to the outbreak of COVID beyond the economic measures undertaken by the government. We do this by using the mobility index constructed by Durante, Guiso, and Gulino (2020), based on the cell phones information. It is clear that part of the change in mobility is related to the economic lockdown ordered by the government. Thus, we appeal to some estimates of the effect on the economic additivity using information provided by Guiso and Terlizzese (2020). They estimate that the initial intervention on March 8th affected 16% of the sectors and the second one on March 22th reached 40% of sectors. We adjust these values upwards because these estimations do not consider the effect of school closing. As stated by Barrot, Grassi, and Sauvagnat (2020), the fact that workers must remain home taking care of their children had an important impact on GDP. Thus, we assume that the initial intervention was $q = 1/4$ and the second $q = 1/2$.

The observed pattern for mobility is shown in Panel b) of Figure 1 depicted with the blue curve. For the sake of comparison, the black line represents q, the proportion of economic activity that was shutdown after successive interventions.[20] A couple of features are worth mentioning. First, it is evident that society started to react reducing mobility before the government ordered any restrictions. The endogenous reaction is measured by the distance between the blue and black lines before March 8th. This feature is also documented by Farboodi, Jarosch, and Shimer (2020) for the U.S. economy. Second, the economic restrictions do have an additional impact reducing mobility. The initial mild lockdown in March 8th is accompany by a sizable

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be larger the larger is θ.

[19]The initial reports in Italy estimated that there were two independent outbreaks named as the "Lombardia" and "Venetto" clusters.

[20]The series is normalized such that the average mobility previous to the arrival of COVID is 1. For further details see Durante, Guiso, and Gulino (2020).

additional reduction in mobility, while the later increased intensity is followed by a lower decrease in mobility. To calibrate the model we directly use the blue line as our measure of social distancing. From this viewpoint the reason why social distancing is changing is inconsequential. However, for the next sections, where we present some counterfactuals and the optimal policy q^*, it is important to determine how government interventions affect social distancing and to which extend society reacts endogenously beyond, or independently, of the general restrictions to the economic activity. To this end, we estimate equation (7) using the following empirical model:

$$1 - q_t^s = \alpha + \beta_0 q_t + \beta_1 Deaths_t + \beta_2 Awareness_t + \sum_{i=1}^{6} \beta_{2+i} \, day_t^i, \qquad (8)$$

where $1 - q_t^s$ is the observed mobility, $Deaths_t$ is the observed number of fatalities in day t, $Awarness_t$ is an indicator function that takes the value 1 if in day t it is widely known that virus is in the country and day_t^i captures the day effect from Monday to Saturday. As discussed in Section 2 there are three important coefficients in equation (8). First, β_2 captures a sudden change in the behavior of the population when they found out about the outbreak. It is a permanent and constant increase in social distancing while the virus is present. We follow Durante, Guiso, and Gulino (2020) and set the initial "awareness" day as February 20th. The parameter β_1 captures the additional reaction of the population as the virus spread. Thus, absent any government intervention, mobility will reduce by $\beta_1 Deaths_t + \beta_2$ at day t. Finally, β_0 captures the effectiveness of the government intervention. One could expect a number around 1, but it could be smaller, when it substitute other social interactions, or bigger than 1 where there is complementarity.

Table 1 shows the estimation of equation (8). All the coefficients have the expected sign and highly significative. The awareness coefficient is -0.24, meaning that as soon as people understand that there is an infectious disease, they reduce mobility by almost 25%. On top of this effect, individuals take additional precautions as the number of deaths increases. For instance, 1.000 daily deaths reduce mobility by an extra 11%. This means that even if the government does not take any measure, mobility and social interactions are drastically reduced. The indiscriminate quarantine seems to be very effective, its coefficient of -1.22 implies that the quarantine has an effect beyond the reduction in production. One can think about complementarities. For instance, the enforcement of the policy could increase the reaction of the popula-

Table 1: Mobility equation

Variable	Coefficient	t-Stat	St. Deviation
β_0: government policy q	-1.2248	-14.89	0.082
β_1: reaction to deaths	-0.00011	-3.29	0.00003
β_2: awareness	-0.2456	-7.87	0.031
Intercept	0.8588	28.19	0.030
Monday	0.1492	3.79	0.0394
Tuesday	0.1670	4.24	0.0394
Wednesday	0.1618	4.11	0.0393
Thursday	0.1722	4.37	0.0390
Friday	0.1950	5.02	0.0388
Saturday	0.1149	2.96	0.0388

tion that feels it as a "civic duty," as most of society is enduring the same problems. It could also be changes in habits. Instead of going to the supermarket everyday to buy a few items, individuals may prefer to reduce the number of trips and buy more items in each trip.

Finally, we assume that hospital capacity was binding as soon as February 24th and continue so until March 31st. When the capacity is binding $\delta = 2.4 \times \theta$. In Appendix C we describe in detail why we make this assumption. This implies that initially the number of fatalities were larger because some patients were untreated.

In our model we do not distinguish between patients who require critical care versus those who don't. For this reason we need to scale the observed capacity to the number of infected. At the time of the outbreak in Italy there were $5,343$ beds for intensive care and a population of $60,000,000$ people.[21] Since only $0.3 \times 4.4\% = 1.32\%$ of the infected need critical care, the country can treat no more than $5,343/0.0132$ infected individuals at a time. Thus, the country is prepared to treat only $100 \times (5,343/0.0132)/60,000,000 = 0.67\%$ of the population. To capture the increase in capacity we assume a quadratic function for the ratio H_t/I_t such that $H_t < I_t$ before February 24th and after March 31st, with the series reaching a minimum on March 14th (largest excess demand of beds). This choice makes sure that the excess capacity pastes smoothly in the corners and, because it is quadratic, the three dates exactly pin dow the three parameters of function. These three dates are chosen to match the

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[21]Source: President Conte's national speech on March 24th, 2020. He also mentioned that due to the outbreak the numbers of beds increased to 8,370.

Table 2: Parameter values

Parameter	Symbol	Value	Moment
Contagion rate	λ	44.00%	Fit fatality's path
Exposed to infected rate	γ	14.29%	7 days incubation period
Recovery rate	η	5.75%	17 days to recovery for I
Recovery rate	σ	6.50%	Fit fatality's path
Daily death rate if treated	θ	0.07%	Fit fatality's path
Daily death rate if untreated	δ	0.16%	Fit fatality's path
Hospital capacity	h	0.00674	5,343 ICUs for 60 million population
Initial exposed	E_0	2/60mn	Two individuals in population
Critical mass	$\underline{E}$	E_0	Minimum possible number
Daily discount rate	ρ	0.05/365	interest rate

sharp increase in deaths during March and the subsequent fall (see Panel a) of Figure 1). Given I_t we can recover the implicity series for H_t, which we then use in the following sections to compute the optimal policy.

The resulting parameter values are shown in Table 2. We obtain $\lambda = 0.44$, $\theta = 0.07\%$, $\eta = 0.0575$, $\sigma = 0.065$ and the day of the outbreak is January 7th. A few comments are worth mentioning. First, the calibrated initial reproduction factor is $R_0 = 2.2$, which is within the range of other estimates that situate it between 2 and 2.5. Thus, the fact that σ is very close to η plays an important role. Second, it implies that there is roughly one asymptomatic individual for each symptomatic. Third, because they recover very slowly, the quarantines can take some time until it has an effect. It is precisely the large drop in cases after the successive interventions what identifies the value of σ. Last but not least, the estimated daily death rate implies an average fatality rate of 1.0% of the infected individuals. This rate seems to consistent with many studies that warn about using initial data to recover the true death probability.

The implied path of fatalities by the model and the realized one in Italy can be seen in Figure 2. In Panel a) we show the cumulative numbers, while in Panel b) we present the daily numbers. In both panels the observed path of **reported** COVID fatalities is depicted with the blue "+" mark. Each mark corresponding to one observation. The red dashed line corresponds to the model prediction using the observed mobility data. We assumed that $q_t = 0.1$ to project mobility after May 3rd. **In both panels the scale is logarithmic.** There are clear distances between the model's predicted

Figure 2: **Calibrated paths**

Panel a): Cumulative   Panel b): Daily
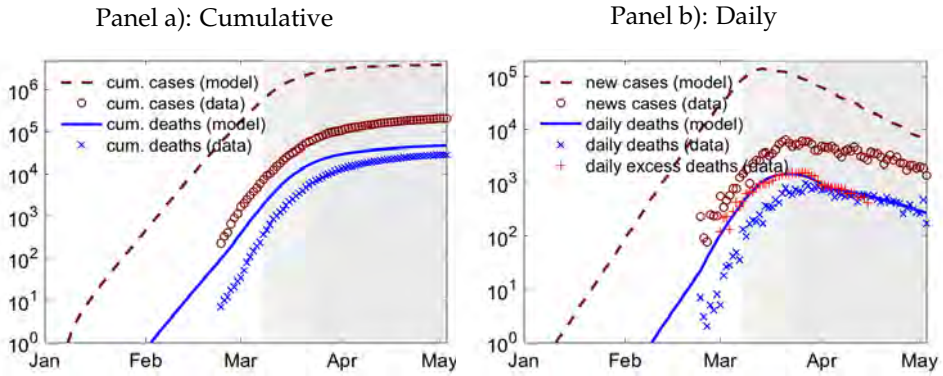
fatalities and cases and the analogous measures in the data. The difference in fatalities is due to inclusion on our calibration of the excess deaths each day but not counted as COVID. This difference is prominent at the beginning but then it stabilizes at the of the time series. On May 3 the cumulative number of fatalities seems to be twice the officially reported. Regarding the cases, the discrepancy is more pronounced. The model estimates that by May 3rd there were more than 2 million individuals that have or have had the virus, while the official reported cases are around 300 thousands.

In Panel b) of Figure 2 we show the implied **daily** paths by the model, this time including the model infected individuals. The actual "measured" infected cases are plotted with the red circles. There are two important takeaways from this figure. The daily predictions are fairly good. The model predicts that there is at least one more month in which the daily fatalities would be above 100 individuals. As with the cumulative data, the model implied cases are substantially above the actual measured cases (recall that the scale is logarithmic). To put it in a context, at the peak of its reproduction the "measured" increased in infected individuals was around $6,550$ new cases, while the model states that the same day there were $29,000$ new infections.

3.2   Simulated paths without intervention

With these parameter values we can estimate what would be the evolution of the illness, and its economic impact, if it were without any government intervention, i.e.,

with $q_t = 0$ for all t. In Figure 3 we show the dynamics of the main variables. In the top panel we show the endogenous social distancing measures. Even without intervention social distancing is still reduced with q_t^s falling sharply. This is the blue curve vs. the observed red $*$ data points. Mobility reduces by more than 50% even without a quarantine. This happens because β_2 is large, -0.24, but also because $\beta_1 < 0$, without an indiscriminate quarantine there are more infected, which in turn strengthens the individual reactions.

In the second panel we plot the proportion of infected and exposed subjects and the hospital capacity at each day. The economy starts with an initial mass of $\frac{2}{60.000.00}\%$ of exposed individuals and 0 infected. Initially the exposed move around and engaged in economic activities without necessarily knowing that they are carriers. Soon after, some "confirmed" infected start to arise, but still those numbers are very small, and definitively smaller than the number of exposed individuals. In this period, the growth rate of the infection is large, around 100% per day, but the quantities do not seem alarming due to the still small number of affected individuals. After 45 days, the number of infected are about the same as the number of exposed. At this point, if a policy maker takes a picture of the situation, it can only see the type i individuals, but the number of carriers is $2 \times i$.

Nevertheless, the number of infected cases is still small, although growing over time. The initial slope is steep, with the growth in the number of total cases in an apparent explosive path. The situation deteriorates after around 40 days when the hospital capacity is reached. The fatality rate that was low at the beginning starts to rise due to the infected that are either untreated or badly treated (third panel). After 90 days the number of infected is at its maximum, with around 5% of the population symptomatically infected and 4% have been affected, but do not show symptoms yet.

At this point, the growth rate of the infected starts to decrease. The main reason for this is that the number of susceptible people reached a point, such that the reproduction rate of the virus $\lambda(S/N)$ is smaller than its death rate, given by $\eta + \Delta_t$. After that, the virus starts to die by itself. The cost in lives is large, without intervention 0.36% of the population dies, with the analogous effect on total production and consumption.

There are two important takeaways from these simulations. First, the virus needs unaffected individuals to reproduce. As the infection spreads, the number of susceptible unaffected people decreases. More and more meetings start to happen between ex-

Figure 3: **Potential path: no intervention scenario**
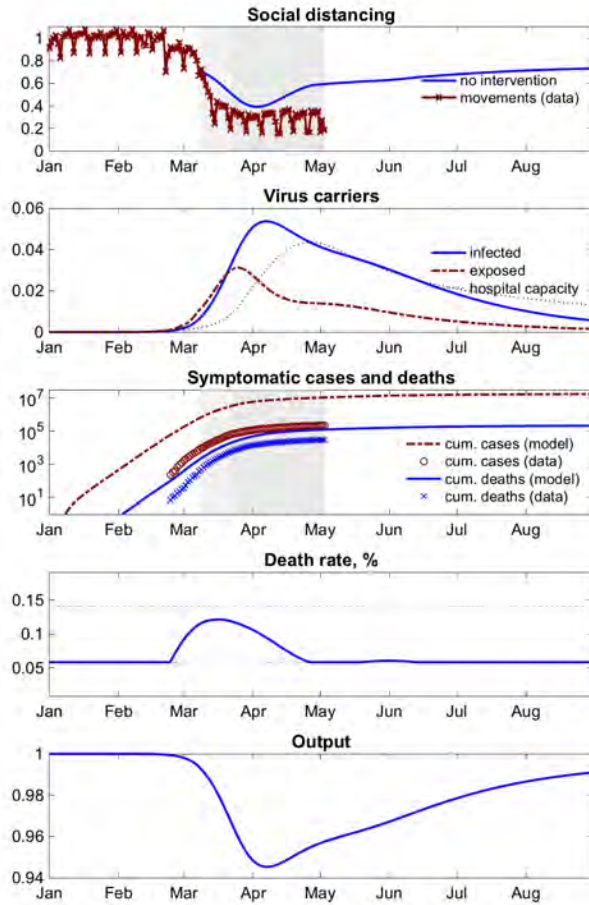
posed and already immune individuals. It is true that still some new subjects become infected, but every period fewer individuals are becoming infected than the people who are either recovering or dying. In addition, the population changes its behavior. As the prevalence explodes, agents start to adjust their behavior which significantly slows down the reproduction of the virus. This additional uncoordinated social reaction is key element determining the necessity of further public intervention.

4 Optimal intervention

4.1 Simple quarantines

In most countries affected by COVID-19 the approach has been to impose quarantines for a determined period of time. Moreover, the intensity of the quarantine has been changing over time and it is expected to continue decreasing over time to a point at which all restrictions would cease to exist. The response of the intervention has been mainly driven by the information about the number of infected cases and the status of the health system. Since all indicators are highly related we assume that the optimal policy depends on exceeded capacity of the health system. We can think about it as restricting the set of policies q_t to be a three-parameter step function such that, for some $\tilde{q} \in [0, 1]$, $b \in \mathbb{R}$ and $\tau \geq 0$, the government intervention satisfies:

$$q_t = \begin{cases} \tilde{q} + b \times H_t, & \text{if } t \leq \tau \\ 0, & \text{if } t > \tau. \end{cases} \quad (9)$$

For instance, a complete shutdown of all economic activities for two weeks would be represented by $\tilde{q} = 1$, $b = 0$ and $\tau = 15$, and any fixed intensity intervention would be characterized by the set of policies with $b = 0$. The parameter b would capture the time varying intensity component.[22] Here we are assuming that q_t depends only on H_t, why not to make it depend on other state variables? Because of the structure of the model, all variables are deterministically linked, thus all state variables contained the same information. However, different state variables are potentially shaped in different ways, which could help to better approximate the optimal unrestricted policy.

---

[22]We have run experiments with q_t functions that depend directly on t and allow time changing shapes. We found that the optimal policy is initially increasing and then decreasing. This drives us to believe that the shape embodied in I_t, H_t and E_t are not overly restrictive.

To understand this potential concern we have estimated the optimal policy assuming the dependency of q_t on E_t, I_t and $\Delta_t I_t$, we found that the policy depending on H_t as in (9) generates the highest welfare.

One important determinant of the optimal policy is the existence of the critical mass $\underline{E}$. As long as $\underline{E} = 0$ the suppression policy has little chances, no matter how small is the exposed population, as long as it remains positive there would be new waves of contagion. The only long term solution is to build a mass of immune individuals to prevent the reproduction of the virus. However, when $\underline{E} > 0$ the intervention could aim to completely eliminate the virus without building a large stock of immune subjects and still preventing further waves. To assess these two very different strategies we assume that the critical mass is $\underline{E} = \frac{1}{60\text{million}}$. This means that if the government manages to reduced the number of exposed to less than one individual in the population the virus disappears.

The main results are shown in Table 3 and Figure 4. We assume that the quarantine is implemented in day 48, which corresponds to March 8th in the calendar of our calibration: the day in which the Italian government decided the first intervention. We present two results, in column (2) of Table 3 is the optimal quarantine if the intended outcome is to **suppress** the virus, which is always feasible when $\underline{E} > 0$. The results, in column (3), show the optimal quarantine if the intervention only seeks to **mitigate** the spread. This corresponds to the "flattening the curve" strategy. Finally, column (1) shows some analogous statistics for the scenario without intervention. An important consideration when reading these results is that neither the value of life $v(\cdot)$ nor the curvature of the welfare function are important in shaping the dynamics of the optimal q_t. As we show in Figure 4 different combinations of d and ϵ determine whether the planner wants to follow a no-intervention, suppression or mitigation strategy, But once this general strategy is chosen, the optimal q_t is barely affected by the particular shape of the welfare function.

Column (1) shows the relevance of the individual responses. Absent a quarantine policy the model predicts $215k$ fatalities, around a third of the projection by the panel of experts in Walker et al. (2020), who estimate around $645k$ fatalities for Italy without intervention. In a previous draft of this paper we abstracted from social distancing (assuming $\beta_1 = \beta_2 = 0$), and estimated a number of fatalities in the no intervention scenario ranging from $600k$ to $780k$, in line with Walker et al. (2020).

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Figure 4: **Optimal quarantines**
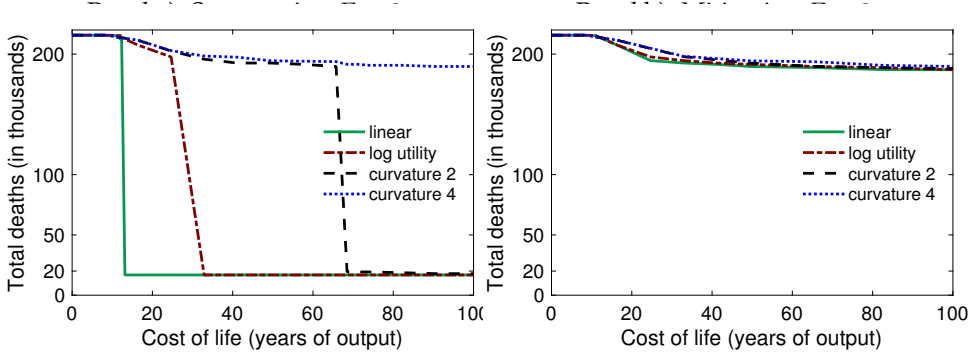
There are many interesting results worth mentioning. First, suppose that $\underline{E} > 0$ and the policy is intended to suppress the virus. Then, the optimal intervention takes the form of a fixed intensity for a determined time span. In column (2) we show that it is optimal to implement a wide spread quarantine for two months and half (exactly 75 days), which resembles the implemented policy in many countries. This policy is extremely effective in reducing the number of symptomatic total cases from 29% to 2% of the population, reducing also the total fatalities from 0.36% to 0.028% of the population.

In panel a) of Figure 4 we show how the number of fatalities change with the curvature of the welfare function and the value of a life. First, consider the area with a cost of life smaller than 1. For any curvature of the welfare function the government chooses not to intervene and let the population to freely adjust to the situation. As the cost of life increases the government chooses to intervene. Here the curvature of the welfare function plays a role determining the type of the intervention. If the welfare function is linear, the policy jumps to suppression. If the welfare function is logarithmic, the government chooses mitigation for cost of life between 15 and 25, but after that it jumps to suppression. Interestingly, the suppression policy overlaps the one with linear welfare function. When the curvature is 2, there is a larger area where is mitigation is optimal, but after suppression is chosen (cost of life larger than 65), the policy almost the same as the one generated by the linear and logarithmic welfare functions. If the curvature is large enough, the government may never choose a suppression policy for any reasonable value of a life.

Table 3: Optimal fixed intensity quarantine

	No Intervention (1)	Suppression (2)	Mitigation (3)
Quarantine:			
Initial day	-	Mar 8	Mar 8
Duration	-	75	64
Maximum q	-	0.61	0.19
Average q	-	0.60	0.12
Symptomatic rate (per pers.)	29%	2%	29%
Symptomatic ppl. (number)	17.4mn	1.2mn	17.4mn
Immunity rate (per pers.)	41.2%	2.8%	41.4%
Immune ppl. (number)	24.7mn	1.7mn	24.8mn
Death rate (per pers.)	0.36%	0.028%	0.31%
Total fatalities	215k	17k	185k
Welfare gain (cons. equiv.)	-	1.4%	0.2%

In panel (a) of Figure 5 we plot the optimal suppression policy and compare it with the calibrated intensity of the observed quarantine. A simple inspection reveals that the implemented quarantine is not enough to generate suppression. Nevertheless, Figure 6 shows that the paths of deaths and cases resulting from the optimal suppression and implemented quarantines tend to converge, with the implemented quarantine decreasing a slower pace. This suggests that the quarantine in Italy is less intense and probably would last longer than what the optimal policy prescribes.

To avoid the high cost in output, or when $\underline{E} = 0$, the optimal intervention could aim to mitigate the spread of the virus. This possibility is shown in column (3) and panels (b) of Figures 4 and 5. Again, it is not very important whether there is a concern for cost of smoothing. For any curvature of the welfare function the optimal policy starts "strongly" with values around $q_t = 0.19$ and it slowly reduced until all the restriction are lifted after two months. Overall the intervention lasts between 64 days with an average intensity of 0.12. This policy has a large cost in terms of both lives and output. The number of fatalities are slightly below of those without intervention, $187k$ vs. $215k$, but there is a large build up of immune individuals, around 25 millions, that prevent the arrival of future waves. The desire for cost smoothing only makes the quarantine slightly shorter keeping more or less the same intensity. The optimal policy with mitigation depends on the implicit dynamics of the model rather than on

Figure 5: **Optimal quarantines**

Panel a): Suppression   Panel b): Mitigation
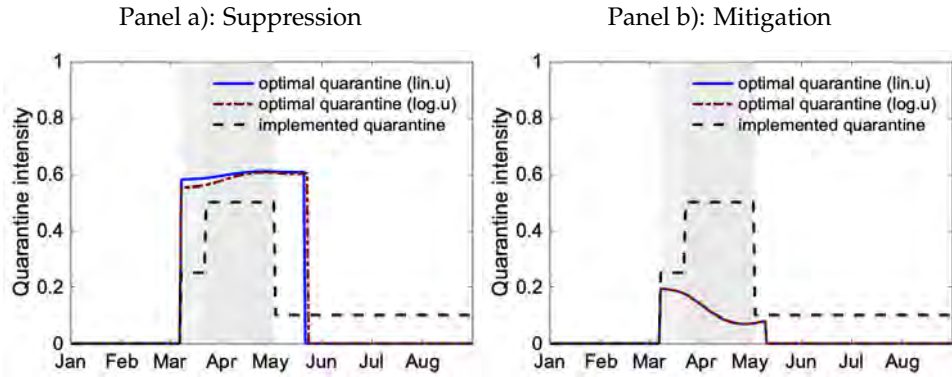

the structure of the welfare function.

When comparing both suppression and mitigation with the observed policy, it is clear that the observed policy is too strong to be a mitigation policy and too soft to be a suppression policy, with both having similar durations. Loosely speaking the implemented quarantine appears to be an average of the optimal mitigation and suppression policies. This could be due to the fact that when the Italian government had to decide on the optimal intervention it was uncertain about the endogenous reaction of the population (embodied in q_t^s) and/or the precise dynamics of the virus. It appears that it started with an optimal mitigation policy (flattening the curve) but ex-post switched to a suppression policy.

The takeaway from these results is that the shape and duration of the interventions are not determined by the perceived cost of human life vs output, but instead by the dynamics of the virus. This does not mean that welfare function is irrelevant: it is the main driver of the **type** of intervention. Once the type of intervention is decided, the duration and intensity easily follow. This could explain why there is large observed heterogeneity in the approaches decided by different countries, but not so much when these different approaches are grouped into the three potential characteristics: no-intervention, mitigation and suppression.

In Figures 6 and 7 we plot the effect of the optimal interventions described in Table 3 over output, Panel a), number of cases, Panel b) and Fatalities, Panel c). All the pat-

terns are fairly intuitive. The optimal suppression generates a large drop in output, but also quickly reduces the number of cases and fatalities. In contrast, the mitigation policy has a smaller impact on production, but accumulates more infected cases and generates more fatalities, it does achieve the goal of delaying the number of cases and fatalities until the hospital capacity is increased.
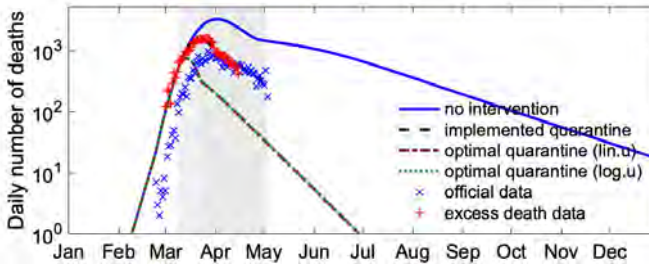
Figure 6: **Intervention and effects: suppression**
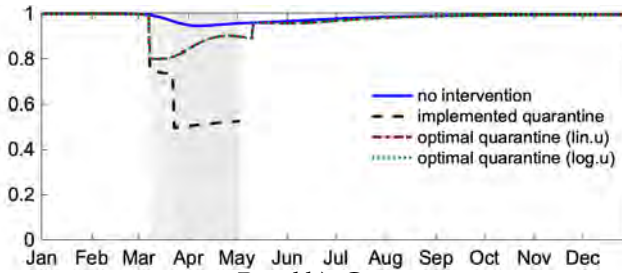Panel a): Output
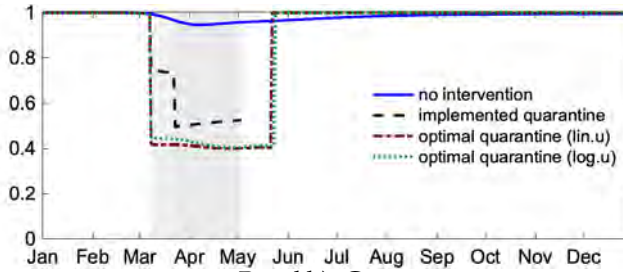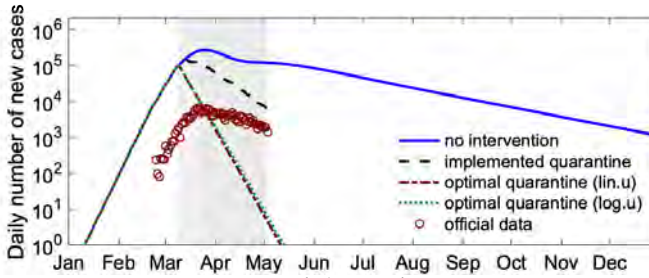
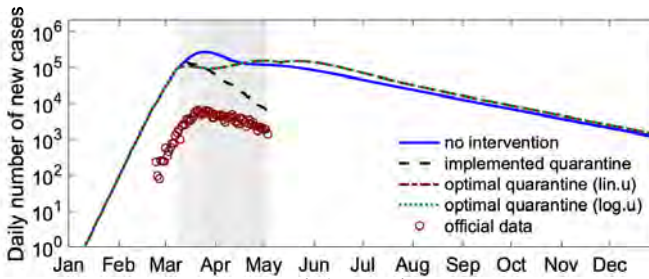
Panel b): Cases

Panel c): Fatalities

Figure 7: **Intervention and effects: mitigation**

Panel a): Output

Panel b): Cases

Panel c): Fatalities
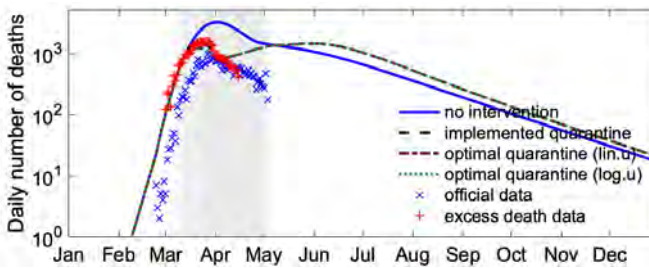
5   Combining testing and quarantines

The main assumption generating the necessity of an indiscriminate quarantine policy, is the inability of the policy maker to distinguish the exposed subjects from those that are susceptible, but have not been affected yet. If the government knew at each time who are the virus' carriers, it could simply quarantine the exposed subjects and allow everyone else to work to avoid the output cost. The technology to do so is certainly

available, but it could be prohibitively costly to undertake such an approach over a vast proportion of the population. However, since the immediate output cost of the quarantine appears to be also very large, it is worth evaluating how much the planner would be willing to spend on testing to reduce the cost of the quarantine.[23]

To deal with this problem we divide the population of exposed individuals in two groups: the unidentified exposed and the exposed population that has been designated as a *positive* carrier of the virus. We maintain the notation E_t for those subjects that carry the virus, but do not know it. These individuals are indistinguishable from those in the group S_t and therefore the government must still set $q_t^E = q_t$. The same rule must also apply to individuals who where previously E_t and recovered without ever exhibiting symptoms. To separate them, the government can test randomly a subset of individuals in the set $S_t + E_t + R_t^u$. If the test result is positive, it means that the subject carries the virus, it is identified with the new group E_t^p, and it is forced into mandatory quarantine, as the group I_t, until she fully recovers, i.e., the group E_t^p is assigned a quarantine measure q_t^I. This group of individuals maybe asymptomatic and they may remain so until they are fully recovered or develop symptoms. Notice that we assuming that the testing technology cannot detect antibodies, for all practical purposes when an individual test negative it could be either S_t or R_t^u, which remains unknown to the tester. Now the total population is:

$$N_t = \underbrace{S_t + E_t + R_t^u}_{\text{unidentified}} + \underbrace{E_t^p + I_t + R_t}_{\text{identified}}.$$

To understand the relevance of testing it is useful to first present the new law of motion for E_t. Suppose the government randomly screens α_t of the individuals in the group $S_t + E_t + R_t^u$, it can identify $\alpha_t E_t$ individuals as positive carriers. Then, the new law of motion for E_t is:[24]

$$dE_t = \begin{cases} \left(\lambda \frac{S_t}{\iota_t} \left(1 - q_t^s\right)^2 - (\gamma + \sigma + \alpha_t) \right) E_t dt, & \text{if } E_t \geq \underline{E} \\ - (\gamma + \sigma + \alpha_t) E_t dt, & \text{if } E_t < \underline{E}. \end{cases} \tag{10}$$

Equation (10) shows the first positive contribution of testing to welfare. Recall that

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[23]Note that we are abstracting from antibodies testing. This technology is available and in use in many countries. Since this kind of testing is not fundamental to stop the initial spread of a virus we leave it for future research.

[24]Here we assume for $m(\cdot)$ the functional form described in Section 2.1.

only the group E_t can spread the disease, so the smaller the group, the smaller the contagion rate. Comparing (10) with (2) is evident that testing adds a downwards drift α_t to the population of asymptomatic individuals. Before the group was reducing only when they were either becoming actively infected at rate γ or recovering at rate σ, but now some individuals are also exiting the group because some are identified, at rate α_t, as positive carriers and, hence, cannot infect anyone else.

As the unidentified exposed, the positively identified subjects can eventually become symptomatic and join the group of infected at rate γ, or recover, at the same rate σ as the E. Unlike the E subjects, when an E^p recovers she joins the group of recovered R_t rather than R_t^u, and therefore she is allowed to work. The law of motion for E_t^p and the new law of motion for R_t satisfy:

$$dE_t^p = \alpha_t E_t dt - (\gamma + \sigma) E_t^p dt \tag{11}$$

$$dR_t = (\eta I_t + \sigma E_t^p)\, dt \tag{12}$$

$$dR_t^u = \sigma E_t dt. \tag{13}$$

Comparing equation (12) to (5) we can see the second important contribution of testing. Since the recovered are immune and allowed to work, as they recover they rejoin the labor force at rate σ, which is useful in reducing the output costs of the quarantine. In short, the group of positively tested individuals generate a bulk that reduces the speed of contagion and increases the available resources to get by the quarantine times. This is especially important when the exposed may never be symptomatic. Without testing, they would never be sick, and therefore they would always be treated as susceptible population subject to quarantines. In this new environment the law of motion of infected is slightly modified to:

$$dI_t = [\gamma (E_t + E_t^p) - (\eta + \Delta_t) I_t]\, dt. \tag{14}$$

The only difference with the previous section is the inflow of positively-tested exposed subjects which happens at rate γ. The population's law of motion remains exactly the same $dN_t = -\Delta_t I_t dt$, since the infection only affects the population by the death rate; and to die a subject must show symptoms first, which only happens if they previously were part of the I_t group. Finally, the production feasibility set remains the same as before, with the mass $E_t + S_t + R_t^u$ subject to quarantines but the R_t allowed to work. We only subtract the cost of the tests.

Suppose the government test x_t individuals at each instant, then the flow cost is governed by the convex cost function $\Phi(x)$, with $\Phi(0) = 0$, $\Phi'(x) > 0$ and $\Phi''(x) > 0$. Given the previous description that the government screens the population with intensity α_t, the number of tests at each instant are $x_t = \alpha_t(S_t + E_t + R_t^u)$. As a result, the feasibility constraint becomes:

$$Y_t = (1 - q_t)(S_t + E_t + R_t^u) - \Phi(\alpha_t(S_t + E_t + R_t^u)) + R_t.$$

We maintain the previous parametrization, see Table 2. We maintain the assumption that q_t satisfies equation (9) and we assume a similar structure for the testing function:

$$\alpha_t = \begin{cases} \tilde{\alpha} + b_\alpha \times I_t, & \text{if } t \leq \tau \\ 0, & \text{if } t > \tau. \end{cases} \tag{15}$$

We do not have information about the cost of each test. We start by assuming that the cost function is quadratic: $\Phi(x) = x + 5x^2$, so that the initial marginal cost of testing one person is one day of per capita output. The factor 5 multiplying the quadratic term makes sure that the marginal cost grows quickly and that testing the whole population is not economically feasible when $q = 1$.

In Table 4 we present the optimal policies. We compare the optimal combination of quarantine and testing policies in columns (3), (4) and (5) with the optimal policy that uses only indiscriminate quarantines, in columns (1) and (2). As opposed to the optimal policy without testing now the curvature of the welfare function is relevant shaping the optimal policy, but only when the government intends to suppress the virus. Conditional on the mitigation strategy, the optimal policy is still invariant to the properties of the welfare function. For this reason we have included two alternative computation for the optimal suppression with testing in columns (3) and (4).

The first thing to notice is that testing is used intensively, the entire unidentified population is tested every day, for a week, when the utility is linear. Instead, when the utility is logarithmic an average of 9% of the unidentified are tested every day for two months if suppression is intended, and an average of 5% of the unidentified are tested every day for 45 days, if mitigation is intended. These numbers, are far larger than the observed testing strategies. Also, in both cases there are welfare improvements. With the logarithmic utility the consumption equivalent gain ranges from 5% to 600%

Table 4: Optimal quarantine and testing policies

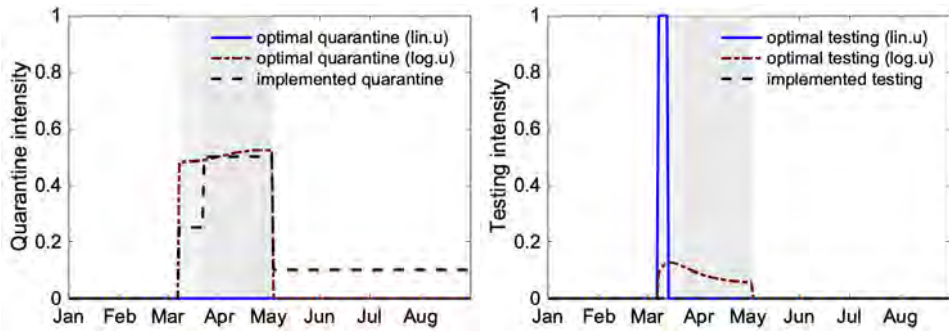|	Quarantine Only		Quarantine & Testing		
	Suppression	Mitigation	Suppression		Mitigation
			Lin. Util	Log. Util	
	(1)	(2)	(3)	(4)	(5)
Intervention:					
Initial day	Mar 8	Mar 8	Mar 8	Mar 8	Mar 8
Duration	75	64	6	57	44
Quarantine:					
Maximum q	0.61	0.19	0	0.52	0.1
Average q	0.60	0.12	0	0.50	0.08
Testing:					
Maximum α	-	-	1	0.13	0.05
Average α	-	-	1	0.09	0.05
Total cost (% of GDP)	-	-	9.5%	1.9%	0.7%
Symptomatic rate (per pers.)	2%	29%	1%	1.6%	27.6%
Symptomatic ppl. (number)	1.2mn	17.4mn	0.6mn	1mn	16.6mn
Asymptomatic rate (per pers.)	0	0	0.36%	0.18%	0.6%
Asymptomatic ppl. (number)	0	0	0.2mn	0.1mn	0.4mn
Immunity rate (per pers.)	2.8%	41.4%	2.6%	2.9%	41.3%
Immune ppl. (number)	1.7mn	24.8mn	1.6mn	1.7mn	24.8mn
Death rate (per pers.)	0.028%	0.31%	0.025%	0.028%	0.31%
Total fatalities	17k	185k	15k	17k	185k
Welfare gain (cons. equiv.)	1.4%	0.2%	2%	1.3%	0.21%

Notes: Column (1) reports the welfare gain for linear utility. With log utility, the welfare gain is 1.2%.

above the value of the policy without testing. The important takeaway from this re-
sult is that *testing is a substitute rather than a complement of quarantines.* Looking
at the fatality numbers and the total infected cases is evident that these numbers are
very similar to those in which testing is not allowed. *The main difference lies on the
path for output, which is what generates the welfare gains.*

Since testing is costly, there are important differences depending on the curvature
of the utility function. When the utility is linear, so that the concern is more about
productive efficiency, testing completely replaces the quarantine. Rather than doing
indiscriminate and inefficient quarantines, it is optimal to test the whole unidentified
population for about a week, keeping production unaffected and letting the individual
social distancing measures to control the spread of the virus. The time path for
this testing policy can be seen in the blue line of Figure 8, panel b). Testing spikes for

a week, then it is reduced to zero from then on. In panel a) we plot the simultaneous quarantine intervention in the blue line. Now, there is no indiscriminate quarantine. Clearly, this testing is costly, with our calibration it amounts to 9.5% of GDP, by no means small, but definitively smaller than reducing daily production by 60% for 75 days, which around 10% of annual GDP, as the optimal suppression strategy prescribes.

Figure 8: **Optimal quarantine and testing: suppression**

Panel a): Quarantine   Panel b): Testing

As we mentioned before, when smoothing is a concern the optimal quarantine and testing strategy depends on whether the government is following suppression or mitigation. In this section we focus on the suppression strategy and we delay for Appendix D the description of the effects on the mitigation strategy. When there is suppression the optimal policy generates both a shorter duration and a lower intensity of the quarantine respect to the one without testing, but with a slowly decreasing testing policy. The indiscriminate quarantine has a similar shape as when testing is not possible (compare with Figure 5), and now is remarkably closer to the quarantine implemented by the Italian government. In this sense, once could interpret the Italian quarantine in a broader sense as a combination of indiscriminate quarantine and testing, even though both policies seem to be short of what is optimal. The milder quarantine is replaced with a continuous testing policy that entails to 5% of the unidentified population every day.[25]

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[25]We want to emphasize that the percentage is with respect to the unidentified $S_t + E_t$, not with

Again, the optimal testing policy is expensive, at the end it amounts to around 1.9% of annual GDP. Since we are assuming random testing, a planner could do it better using additional information, such as the likelihood that an individual has been exposed or the relevance of the subject in the production network. These considerations would only tilt our result more in favor of testing rather than indiscriminate quarantines. In any case, notice that the optimal testing policy follows the path of potentially exposed individuals. The larger the fraction of exposed, the more likely that a test is successful at identifying a positive case.

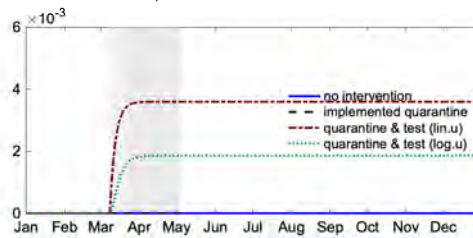Figure 9: **Output with testing**

Panel a): Output
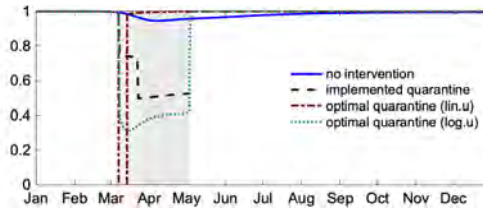
Panel b): Unidentified exposed
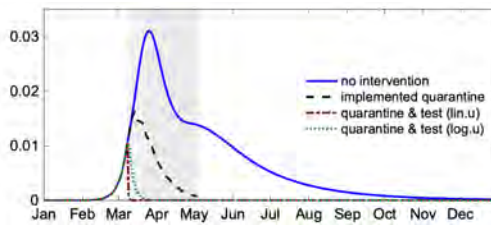
Panel c): Identified Recovered

respect to the entire population. So that the number of tests is continuously decreasing over time.

The implied output and number of unidentified asymptomatic individuals by the optimal testing strategy can be seen in Panels a) and b) of Figure 9, respectively. Panel c) presents an additional measure that only exist with testing: the asymptomatic individuals what were previously identified as positive and then recovered. Because now it is know that they are immune, they are allowed to work. This measure becomes particularly relevant with the long quarantines. After three months, it amounts to almost 2% of the labor force.

6 Conclusions

In this paper we have extended the standard epidemiologic SIR model allowing for asymptomatic subjects to be tested and considered the trade-off with output losses. We show that if the government has no means to identify the carriers of the virus, the observed mandatory quarantines around the world seem to be close to what it can be considered optimal.

However, if the government can increase the intensity of testing over subjects, that is a far superior strategy. We acknowledge that ultimately this statement depends on the cost of actually performing those tests. The results of this paper indicate that carefully analyzing and assessing this possibility should be a priority.

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Appendix

A   Model calculations

Mapping to data moments: If untreated, the density function for dying after s units of time is

$$f^u(s) = \delta e^{-(\eta+\delta)s}$$

The death rate is

$$\int_0^\infty f^u(s)\,ds = \int_0^\infty \delta e^{-(\eta+\delta)t}ds = \frac{\delta}{\eta+\delta}.$$

The density function for recovering after s units of time is

$$g^u(s) = \eta e^{-(\eta+\delta)s}.$$

The average recovery duration is

$$\int_0^\infty g^u(s)\,s\,ds = \int_0^\infty \eta e^{-(\eta+\delta)s}s\,ds = \frac{\eta}{(\eta+\delta)^2}.$$

Similarly, if treated, the death rate is $\frac{\theta}{\eta+\theta}$. The average recovery duration is $\frac{\eta}{(\eta+\theta)^2}$.

B   Death rate data

Table 5: Fatality rates South Korea and Italy

Classification		Cases		Fatal cases		Weight	Cases		Deaths		Lethality	Weight
						South Korea					Italy	
		Number	(%)	Number	(%)	Rate (%)	age group	Number	(%)	Number	(%)	(%)	age group
All		9,137	100	126	100	1.38	1	35,731	100	3,047	100	8.5	1
Age	Above 80	406	4.4	55	43.65	13.55	0.0342	5,352	15	1,243	50.2	23.2	0.0717
	70–79	611	6.7	39	30.95	6.38	0.0672	7,121	19.9	1,090	35.8	15.3	0.0988
	60–69	1154	12.6	20	15.87	1.73	0.1198	6,337	17.7	312	10.2	4.9	0.1216
	50–59	1724	18.9	10	7.94	0.58	0.1648	6,834	19.1	83	2.7	1.2	0.1549
	40–49	1246	13.6	1	0.79	0.08	0.1626	4,396	12.3	25	0.8	0.6	0.1531
	30–39	943	10.3	1	0.79	0.11	0.1405	2,525	7.1	9	0.3	0.4	0.1172
	20–29	2473	27.1	0	0	0	0.1327	1,374	3.8	0	0	0	0.1027
	10–19	475	5.2	0	0	0	0.0954	270	0.8	0	0	0	0.0956
	0–9	105	1.2	0	0	0	0.0828	205	0.6	0	0	0	0.0843

C   Estimating fatality rates

There is much controversy about the "true" value of the fatality rate, especially when all the available data is too raw to provide a concrete answer. Most studies tend to

state that on average 1% of the infected die. However, this value could significantly change with the demographic structure of the population. In particular, the fatality rate appears to sharply increase with age and the lack of proper treatment. Since we are focusing on the Italian case, both factors are first order issues for our estimations. The study by Ferguson et al. (2020) estimates that the average fatality rate in Wuhan is around 0.99%. The same paper states that around 4.4% of the infected subjects require hospitalization. They also estimate that 30% of the hospitalised cases require critical care; and even when the patient receives proper critical care she dies with 0.5 probability. If we assumed that without critical care the subject dies with certainty, that implies that the fatality rate for the untreated is twice the analogous for the treated. This indicates that $\delta \approx 2 \times \theta$, providing a first support to our calibration.

Another calculation to determine the difference between θ and δ is to compare the fatality rates in a country that didn't reached the health capacity with another that did. A candidate for the first is South Korea, while Italy is a clear candidate for a country in which the health system was overwhelmed. In Appendix B we present the information for the fatality rates by age for both countries. To obtain the average fatality rate, we multiply each age-specific rate by the relative weight of that age group in the population. We obtain that the average rate for South Korea is 1.22%, while for Italy is significantly larger at 4.09%. But, how much of this total difference is due to the different age distributions and how much due to the difference in the health systems? We made an intermediate calculation where we recompute the average death rate for South Korea, but using the population weights of Italy, which delivers 1.92%. We interpret the difference $1.92\% - 1.22\% = 0.7\%$ as the pure age composition effect. This number is by itself substantial and informative about the significant risk that COVID-19 represents for an "old" country as Italy. It is striking that only the age adjustment generates a death rate almost identical to the calibration using the virus dynamic's information.

Still, the observed fatality rate in Italy is, so far, more than 4% and, if our adjustment is correct, the additional two percentage points are not explained by the age composition. If we attribute the difference to the lack of proper medical attention, we obtain again that $\delta \approx 2 \times \theta$. Since these two independent sources deliver consistent estimations, we calibrate our model with $\delta = 2 \times \theta$.

D   Testing with mitigation

Figure 10: **Optimal quarantine and testing: mitigation**
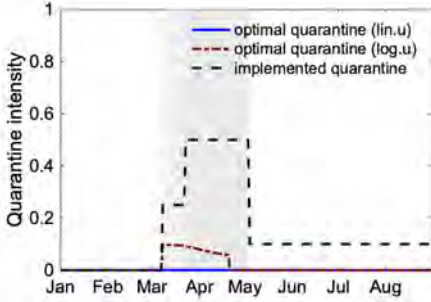
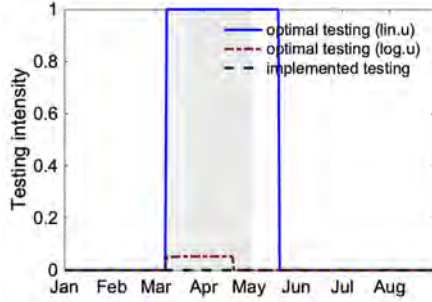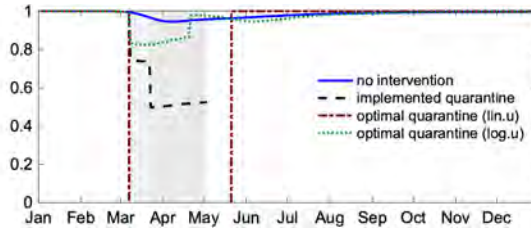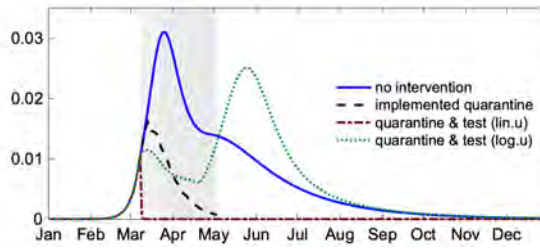Panel a): Quarantine   Panel b): Testing

Figure 11: **Output with testing**

Panel a): Output

Panel b): Unidentified exposed

Panel c): Identified Recovered