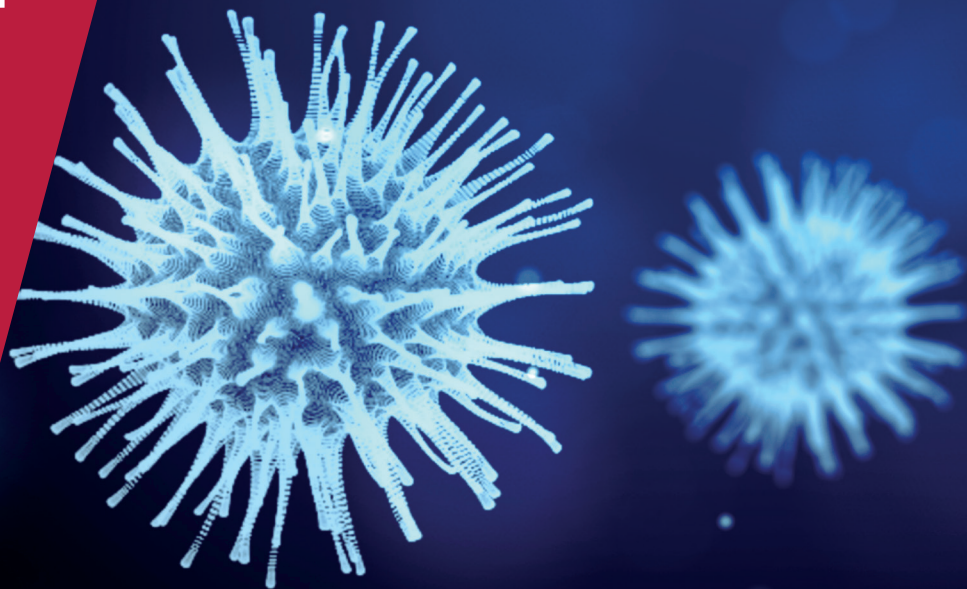


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COVID ECONOMICS
VETTED AND REAL-TIME PAPERS

ISSUE 29
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POLICY COMMUNICATION

Olivier Coibion, Yuriy Gorodnichenko
and Michael Weber

MONEY MARKET FUNDS

Lei Li, Yi Li, Marco Macchiavelli
and Xing (Alex) Zhou

FISCAL POLICY

Christian Bredemeier, Falko Juessen
and Roland Winkler

CRIMINALITY AND LOCKDOWNS

Rubén Poblete-Cazenave

THE LABOUR MARKET

Jake Bradley, Alessandro Ruggieri and
Adam H. Spencer

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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Contact: Submissions should be made at <https://portal.cepr.org/call-papers-covid-economics>. Other queries should be sent to covidecon@cepr.org.

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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.

<i>American Economic Review</i>	<i>Journal of Econometrics</i> *
<i>American Economic Review, Applied Economics</i>	<i>Journal of Economic Growth</i>
<i>American Economic Review, Insights</i>	<i>Journal of Economic Theory</i>
<i>American Economic Review, Economic Policy</i>	<i>Journal of the European Economic Association</i> *
<i>American Economic Review, Macroeconomics</i>	<i>Journal of Finance</i>
<i>American Economic Review, Microeconomics</i>	<i>Journal of Financial Economics</i>
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<i>Journal of Development Economics</i>	<i>Journal of Population Economics</i>
	<i>Quarterly Journal of Economics</i> *
	<i>Review of Economics and Statistics</i>
	<i>Review of Economic Studies</i> *
	<i>Review of Financial Studies</i>

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

Covid Economics

Vetted and Real-Time Papers

Issue 29, 16 June 2020

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Does policy communication during COVID work?¹

Olivier Coibion,² Yuriy Gorodnichenko³ and Michael Weber⁴

Date submitted: 11 June 2020; Date accepted: 12 June 2020

Using a large-scale survey of U.S. households during the Covid-19 pandemic, we study how new information about fiscal and monetary policy responses to the crisis affects households' expectations. We provide random subsets of participants in the Nielsen Homescan panel with different combinations of information about the severity of the pandemic, recent actions by the Federal Reserve, stimulus measures, as well as recommendations from health officials. This experiment allows us to assess to what extent these policy announcements alter the beliefs and spending plans of households. In short, they do not, contrary to the powerful effects they have in standard macroeconomic models.

- 1 We thank the National Science Foundation for financial support in conducting the surveys. We also thank Shannon Hazlett and Victoria Stevens at Nielsen for their assistance with the collection of the PanelViews Survey. Results in this article are calculated based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data is available at <http://research.chicagobooth.edu/nielsen>. The randomized control trial is registered at the AER RCT Registry (#AEARCTR- 0005989).
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“The single biggest problem in communication is the illusion that it has taken place.” – George Bernard Shaw.

“[for monetary policy to be most effective] not only do expectations about policy matter, but, at least under current conditions, very little else matters.” Woodford (2005)

I. Introduction

Monetary and fiscal policies affect the economy (Romer and Romer 2004, 2009) but how they operate remains a point of contention. A common thread across many macroeconomic models is the role of expectations: policies have powerful effects in modern mainstream models in large part because firms and households incorporate these announcements into their decision plans. In real business cycle models, for example, an announcement of higher government spending should make households feel poorer (since they will have to pay for this spending via higher taxes now or in the future) which induces them to work more. Forward guidance on the part of monetary policy-makers is predicted to have large effects in New Keynesian models because the promise of future lower interest rates by the central bank should induce households to anticipate higher inflation in the future which in turn should lead them to consume more today before those price increases materialize.

How powerful are these mechanisms in practice? Recent research should give one pause: there is a growing body of evidence documenting that, in advanced economies, inattention to macroeconomic policy and the broader economic environment is pervasive among households and firms. Announcements by monetary and fiscal policy-makers are rarely found to have large effects on the expectations of economic agents other than those participating directly in financial markets, suggesting that these expectational forces may in fact be quite weak. Still, one might expect a strengthening of these forces in a crisis, as a worried population turns its attention to its leaders for guidance and support.

Using a large-scale survey of U.S. households during the COVID-19 pandemic, we study how new information about policy responses affects the expectations and decisions of respondents. Specifically, we provide random subsets of participants with different combinations of information about the severity of the pandemic, recent actions by the Federal Reserve, stimulus measures implemented by Congress, as well as recommendations from the U.S. Center for Disease Control (CDC). We then characterize how their economic expectations and spending plans respond to these information treatments. This allows us to assess to what extent these policy announcements alter the beliefs and plans of economic agents.

By and large, we find very little effect of these information treatments on the economic expectations of agents for income, mortgage rates, inflation or the unemployment rate nor do we find an effect on their planned decisions, contrary to the powerful effects they have in standard macroeconomic models. Why might agents’ economic beliefs not respond to this information? One possible explanation is that they were already aware of the information provided in the treatments. While we do not have the prior beliefs of

agents for all information treatments, those for which we do suggest that this is not a likely explanation. For example, households' prior beliefs about the transmission rate of COVID-19 or its recovery rate were wildly misinformed prior to the information treatments. Furthermore, previous work has documented how uninformed households tend to be about most monetary and fiscal policies and how even large policy announcements do not make their way into households' aggregate expectations, even in the midst of a crisis (e.g., Coibion et al. 2020). Furthermore, Binder (2020) documents that even after the historic policy actions of the Federal Reserve in response to the COVID-19 crisis, only a third of U.S. households had heard about these policy actions. A second possible explanation is if households are skeptical of the information that we provide. Again, we view this as very unlikely because other information treatments in identical settings have previously been found to lead to dramatic revisions in households' views about the economy (e.g., Coibion, Gorodnichenko and Weber 2019). A third possible explanation rests on the idea that, because of cognitive constraints, many households might not directly understand the implications of complex policies for their optimal savings and consumption decisions (e.g., D'Acunto et al. 2020a,b). The fourth, and in our view most likely, explanation is that households do not believe that the policy responses described in the treatments are effective: i.e., the multipliers they associate with the described policy responses are close to zero. Note that zero multipliers may be observed because so-called information effects (i.e., policy actions reveal a bad state of the economy) offset any positive effects of a policy action.

Our paper builds on a recent but growing literature in macroeconomics that relies on surveys to measure expectations and randomized information treatments to establish causality (e.g., Cavallo et al. 2017, Coibion, Gorodnichenko and Kumar 2018, Armona et al. 2019). We depart from previous work along several dimensions. First, we use a large-scale survey of U.S. households participating in the Nielsen Homescan panel, providing us with a sample size that is an order of magnitude larger than in commonly available surveys. Second, our survey was run in April 2020 in the midst of the COVID epidemic, so we are able to study the dramatic policy actions taken specifically in response to the outbreak. In addition, we are able to provide new insight about how informed households were about both the deadliness of the disease and how it spreads across the population. There has been a surge of research on the corona virus in recent months, much of it relying on surveys. We build on this growing body of work by utilizing randomized control trials (RCT) to study the effects of economic policy responses to the crisis. Third, we combine treatments about the severity of the disease with treatments not only about economic policy responses (e.g. fiscal and monetary) but also about health policies (recommendations from the CDC). This allows us to speak about the relative benefits of very different types of policy responses within a common framework.

Previous work has documented extensively how inattentive households (and firms) tend to be to macroeconomic conditions (Bachmann, Berg, and Sims (2015), Coibion, Gorodnichenko, and Kumar (2018), Coibion et al. (2019), D'Acunto et al. (2019)). We find the same qualitative patterns hold during

the COVID crisis but also document that this lack of understanding extends to information about the coronavirus. For example, when we ask households what they think the recovery rate is once infected with COVID, they report an average answer of 73%, far lower than the 97% reported by the World Health Organization (WHO). Similarly, when we ask them how many people tend to be infected by someone carrying the COVID virus, their average answer is 21, far higher than the actual rate of around 2 estimated by the WHO. This suggests that information treatments that provide factual information about transmission and recovery rates could potentially have important effects on households' expectations about the economy.

Despite this, we find very small effects of providing information about the deadliness and ease of spread of the disease on households' expectations. When respondents are treated with information that, on average, the disease is harder to spread and less deadly than they had originally thought, their views about future inflation, mortgage rates and unemployment are effectively unchanged. They reduce their reported expected future income on average but the change is economically insignificant. Their perceptions about whether now is a good or bad time to buy durables are also effectively unchanged. The one exception is for unemployed workers who are asked about the likelihood of finding a job: those who are treated with information about the disease raise their likelihood of finding a job by about twenty percentage points. These results suggest that the large changes in expectations during the COVID-19 pandemic for income, the stock market, or mortgage rates are less likely driven by direct concerns about the virus but more likely a response to the lockdowns imposed by local authorities in line with findings in Coibion, Gorodnichenko, and Weber (2020).

Information treatments about fiscal, monetary or health policies similarly do very little to the expectations of households, both about the aggregate economy or about their own income. And when they do, those effects are not necessarily positive. For example, among the unemployed who become more optimistic about their future job prospects when they are told that COVID-19 spreads less easily and is less deadly than they thought, providing additional information about the responses of policy-makers fully offsets the effect of the information about the disease. This is consistent with the presence of an information effect to policies: finding out that fiscal, monetary or health policy-makers are implementing large policy changes makes the unemployed less optimistic about their job prospects, but only when done in conjunction with information about the disease. Information treatments that are only about policy changes have effectively no effect on most agents' macroeconomic or individual expectations. These results are consistent with recent findings documenting an information effects of monetary policy which suggest that large policy moves might reveal information about the state of the economy which is called Delphic in the context of forward guidance (see, e.g., Campbell et al. 2012)

By studying the effect of policy actions on households' macroeconomic expectations through RCTs, our paper is closest to Andre et al. (2019). They present specific scenarios of both fiscal and monetary shocks to households (as well as experts) to assess how they believe these shocks will affect the economy. They find

that households' views about fiscal shocks are similar to those of experts, but their perceptions of how monetary shocks affect the economy differ significantly from those in standard models or those perceived by experts. One important difference is that Andre et al. (2019) present respondents with hypothetical exogenous shocks to either fiscal or monetary policy whereas we present households with information about clearly endogenous policy responses. Our results therefore speak directly to the effects of *systematic* policy changes whereas theirs are focused on exogenous policy. Our findings suggest that these systematic policy responses have little effect on households' expectations, either because they believe they are ineffective or because policy responses induce an information effect (in which households interpret the sheer fact of a policy response as indicative of a weaker economy) that effectively offsets the effect of the policy change.

Our work is also closely related to Binder (2020) and Fetzer et al. (2020) that assess how randomized provision of COVID19 health facts influences concerns (about personal financial situation and about aggregate economy) of households participating in online surveys.¹ Apart from the fact that we are using a survey that is an order-of-magnitude larger in size (and hence more precise estimates of treatment effects), we also study how the provision of health facts and/or policy responses shapes expectations.

Our research also relates to a broader literature on the effect of monetary policy on household expectations. That literature has documented that monetary policy decisions and announcements have little to no effect on household inflation expectations (e.g., Lamla and Vinogradov 2019, Coibion et al. 2020). This result is generally interpreted as indicating that households are unaware of the policy actions. Our results suggest an additional possible mechanism underlying these results: even when households are made aware of these policy decisions, they do not view them as having meaningful effects on the aggregate economy. Hence, it is not only important to reach households with communication but also to design and implement policies that are easy and simple to grasp for non-expert households and to explain the implications of policies for optimal consumption, savings, and investment decisions (D'Acunto, Hoang, and Weber, 2020a).

II. Survey Description

In this section, we describe the implementation of the survey as well as the information treatments. We build on our earlier work (Coibion, Gorodnichenko, and Weber 2019, Coibion, Gorodnichenko, Georgarakos, and Weber 2020, and D'Acunto et al. 2020c,d) using the Nielsen Homescan panel to study expectations and spending decisions.

A The Survey

¹ Binder (2020) also uses a difference-in-difference approach to study how informing households about the Fed's policy rate cut changes expectations.

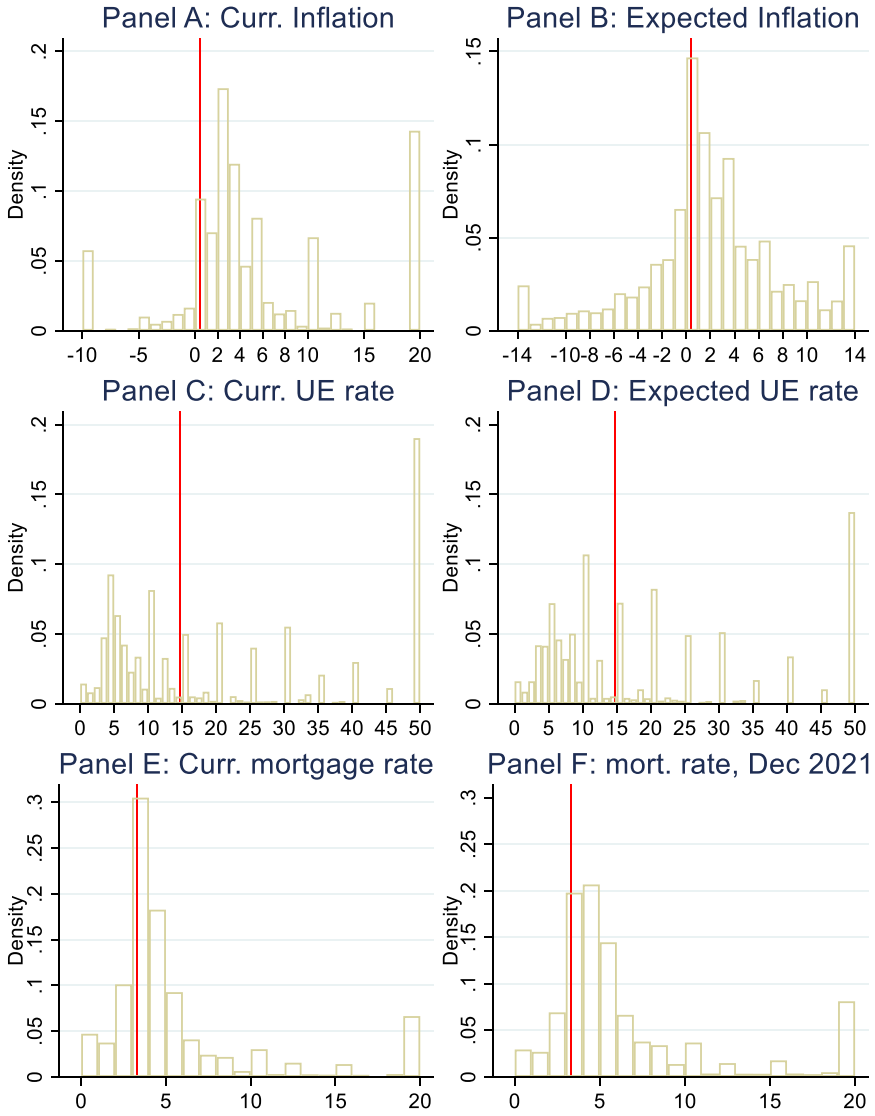
Our survey was run in April 2020 on the Nielsen Homescan panel of households. This panel consists of 80-90,000 households who track their spending daily for A.C. Nielsen. Following Coibion, Gorodnichenko and Weber (2019) and Coibion et al. (2020), we ran a survey on these households that included various information treatments that we provided in a randomized fashion. The survey consisted of an initial set of questions designed to measure the prior beliefs and plans of households, followed by a randomized information treatment, and concluding with a final set of questions meant to assess how/whether treatments affected the expectations and plans of participants. 13,771 individuals responded to the survey, yielding a response rate of 27%. The response rate compares favorably to the average response rates of surveys on Qualtrics which is the most commonly used survey platform for online surveys that estimates a response rate between 5% to 10%. Survey questions are provided in the Appendix.

Nielsen attempts to balance the panel on nine dimensions: household size, income, age of household head, education of female household head, education of male household head, presence of children, race/ethnicity, and occupation of the household head. Panelists are recruited online, but the panel is balanced using Nielsen's traditional mailing methodology. Nielsen checks the sample characteristics on a weekly basis and performs adjustments when necessary. Nielsen provides sampling weights to correct for possible imbalances in the composition of respondents in our survey. All of our reported results use sampling weights.

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

Table 1 reports moments of initial beliefs and expectations reported by households. We present both raw moments as well as "robust" moments controlling for outliers using Huber (1964) robust methods, and we focus on the latter in our discussions. On average, households in April 2020 perceived an inflation rate of 2.6% and expected a lower inflation rate of 1.7% over the next twelve months, significantly lower than in other comparable survey waves of Nielsen panelists (e.g., Coibion, Gorodnichenko and Weber 2019, Coibion et al., 2020). Inflation expectations and perceptions exhibit significant cross-sectional dispersion, with a standard deviation of close to 3%. This dispersion can also be seen in Figure 1, which plots the distribution of answers as well as the current value of the variable at the time of the survey (red, vertical line). Unlike in

Figure 1. Perceptions and expectations



Notes: Each panel plots the distribution of pre-treatment beliefs in the Nielsen household panel. The red, vertical line shows the current value of the corresponding variable at the time of the survey. Panels A, C, and E report perceptions of current values. Panels B, D, and F report one-year ahead forecasts.

Table 1. Descriptive statistics.

	Huber robust moments		Raw moments		
	Mean	St. Dev	Mean	Median	St. Dev
	(1)	(2)	(3)	(4)	(5)
Pre-treatment data					
Perceived inflation, previous 12 months	2.61	2.47	4.67	3.00	10.00
Expected inflation, implied mean, 12-month ahead	1.66	3.26	1.70	1.29	5.81
Perceived unemployment rate, current	9.79	6.77	12.66	10.00	9.58
Expected unemployment rate, 12-month ahead	10.64	6.53	13.10	10.00	9.04
Expected unemployment rate, in 3-5 years	6.08	3.54	9.50	6.00	7.93
Expected household income growth, 12-month ahead	-	-	-2.36	0.00	14.39
Perceived and expected mortgage rate for a “person like you”					
Current	3.57	1.08	5.46	3.80	5.64
End of 2020	3.55	1.38	5.79	4.00	6.11
End of 2021	4.09	1.42	6.24	4.00	6.00
Next 5-10 years	4.61	1.56	7.25	5.00	7.98
Post-treatment data					
Expected inflation, point prediction, 12-month ahead	3.93	3.68	6.64	4.00	9.57
Expected unemployment rate, end of 2020	10.61	6.54	13.20	10.00	9.18
Expected unemployment rate, next 3-5 years	5.32	2.88	8.93	5.00	7.93
Expected household income growth, 12-month ahead	0.52	1.71	1.04	0.00	17.77
Perceived and expected mortgage rate for a “person with excellent credit”					
Current	3.63	1.21	5.62	4.00	5.97
End of 2020	3.72	1.47	5.96	4.00	6.16
End of 2021	4.16	1.41	6.32	4.00	6.10
Next 5-10 years	4.57	1.53	6.57	5.00	5.93

Notes: pre-treatment expected inflation (12 months ahead) is computed as mean implied from the reported probability distribution over a range of bins. All other measures of inflation are reported as point predictions. Perceived and expected mortgage rates are elicited for “a person like you” at the pre-treatment stage and for “someone with excellent credit” at the post-treatment stage. Moments in columns (1) and (2) are computed using the Huber-robust method. Because many households report zero changes in household income, the Huber method to compute moments robust to outliers does not converge and hence robust moments are not available for pre-treatment expectations for household income growth.

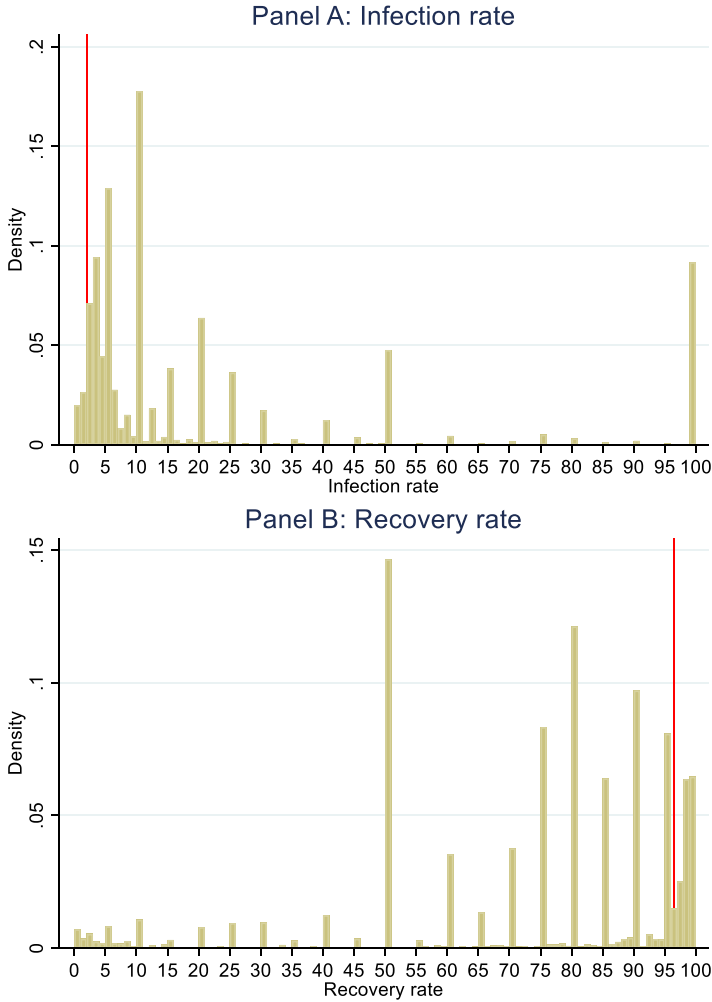
previous waves, households believed that the unemployment rate was nearly 10% in April and expected an even higher rate of unemployment twelve months later (nearly 11%). Disagreement about both current and future unemployment was also pervasive, as illustrated in Panels C and D of Figure 1. Table 1 also reports households' perceptions of the current mortgage interest rate as well as their expectations for this interest rate at the end of 2020, 2021 as well as over longer horizon of 3-5 years. The average belief about the current mortgage rate was 3.6%, close to the average value of 3.3% on March 26 2020, with households anticipating a very gradual increase in mortgage rates over the next 3-5 years.² As illustrated in Panels E-F of Figure 1, however, there is significant disagreement across households about the path of future interest rates.

Respondents were also asked questions about COVID-19. First, we asked them about the infection rate, i.e. how many uninfected people might be expected to be infected by one person carrying the virus. As Panel A of Figure 2 documents, households reported a wide range of answers with many answering 100 or more. Very few gave answers close to the WHO's estimate of an infection rate of 2, suggesting that most households significantly over-estimated how contagious the virus actually is. Second, they were asked about how lethal the virus is. Specifically, we asked them how likely a person was to survive after having been infected with the virus, i.e. the recovery rate. We plot responses to this question in Panel B of Figure 2. Again, the range of answers provided by households is enormous, with a recovery rate of 50% being the most commonly provided answer, nowhere near the answer of 96-97% provided by the WHO. We conclude that, consistent with Binder (2020) and Fetzer et al. (2020), households were very uninformed about the actual contagiousness and danger of the disease, with most households being far more pessimistic about the disease than health authorities.

Finally, respondents were also asked about expectations about their own economic situation. For example, we asked them to report how they expected their income to change over the next twelve months. As reported in Table 1, the raw average was -2.4%, again masking significant variation (cross-sectional standard deviation of 14 percentage points). In addition, we asked respondents to tell us whether they were currently employed. Those reporting being employed were then asked about the probability of losing their jobs over the next 12 months. Panel B of Figure 3 plots the resulting distribution of answers. Most respondents report a probability very close to or equal to 0%, indicating limited concerns about losing their jobs. For those reporting that they were not currently employed but are looking for a job (approximately 7% of respondents), we asked them about the probability of finding a job over the next 12 months. As illustrated in Panel A of Figure 3, answers were extremely dispersed. While some report probabilities of finding a job close to 100%, almost as many report a probability of just 50% and 32% report a probability of 10% or less.

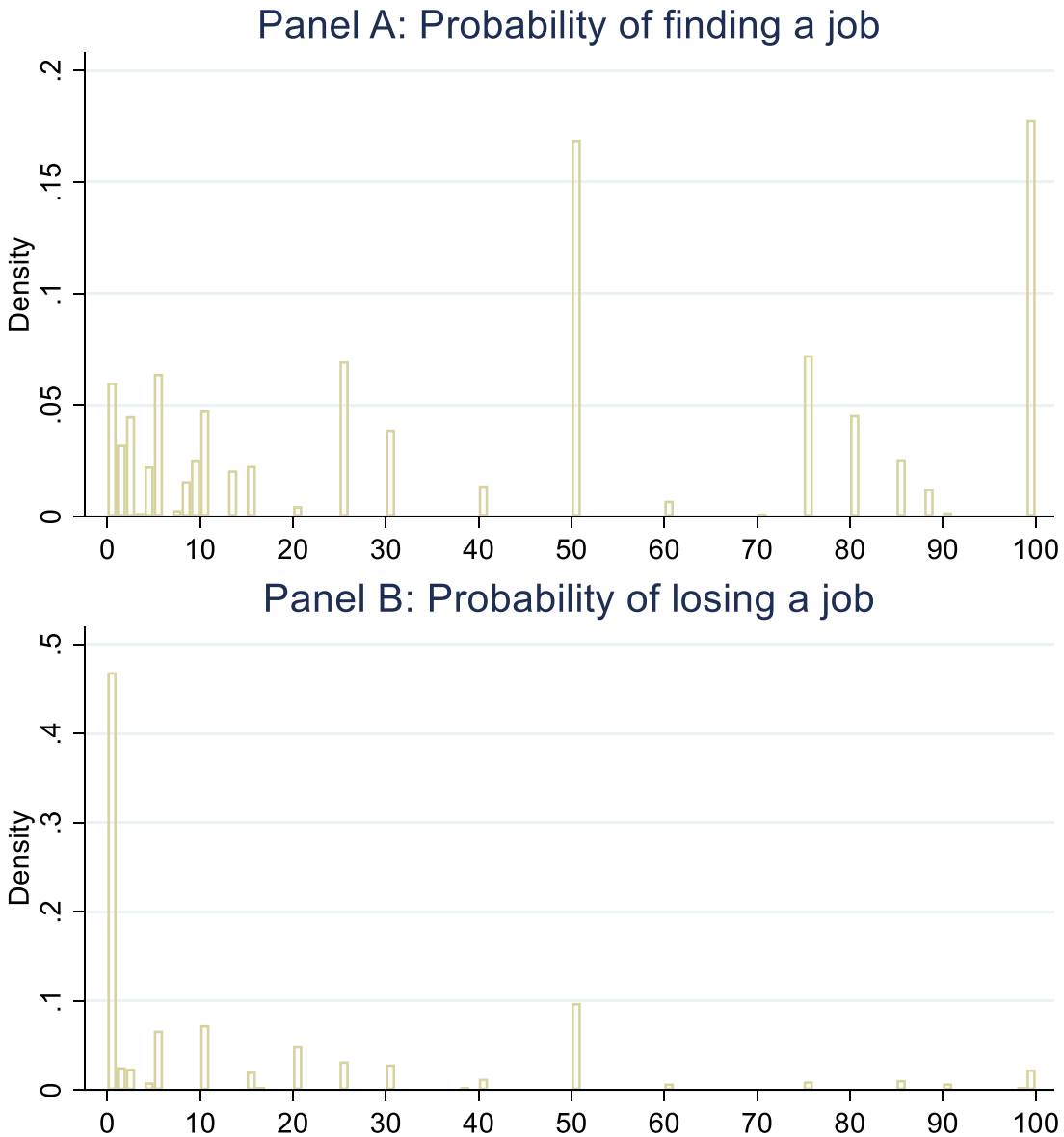
² The survey is conducted over mortgage lenders originating loans in the U.S. See FRED, Federal Reserve Bank of St. Louis: <https://fred.stlouisfed.org/series/MORTGAGE30US>

Figure 2. Distribution of beliefs about how contagious and fatal the COVID19 virus is.



Notes: Panel A: Infection rate is measured as the response to the following question, “Think of a person who has the coronavirus. How many non-infected people do you think will catch the virus from this person?”. The response is winsorized at 100. Panel B: the recovery rate is measured as the response to the following question, “If a person contracts coronavirus, what do you think is the probability that this person recovers from the virus? Please enter a number between 0 (Do not recover) and 100 (Recover for sure)”. In each panel, the red, vertical line shows the estimates provided by the World Health Organization.

Figure 3. Subjective probabilities for labor market transitions.



Notes: The histograms plot distribution of perceived probabilities to find a job (Panel A) and to lose a job (Panel B). Both panels report data for the control group only. Panel A is only for people who are unemployed (don't have a job and look for a job). Panel B is only for people who have a job.

B Treatments

After being asked this initial set of questions, respondents were then randomly assigned to one of multiple treatments groups. The first group is the control group, which gets no information provided to them. However, they still receive the same set of follow-up questions which allow us to measure any change in their expectations for comparison to treatment groups. Even though they are not provided with information, we may still observe changes in expectations because the wording of questions pre- and post-treatment is generally different, a strategy we employ to avoid respondents leaving the survey if they are being asked the same questions twice. For example, inflation expectations are initially measured using a distributional question while posterior beliefs are measured by respondents being asked to provide a point estimate. Because the wording of questions can lead to some differences in answers, having the control group answering both sets of questions allows us to control for any effect that different wording may induce.

Respondents not assigned to the control group were randomly placed in one of nine groups, as summarized in Table 2. These nine groups differ first in terms of whether they received information about the COVID-19 virus, and second in terms of whether they were provided with additional information about fiscal, monetary or health policies of the government. With respect to the information about the virus, approximately half of non-control group participants received the information about the virus (treatment groups 6-10), while the other half did not (treatment groups 2-5). The specific wording used in providing the WHO information about the virus to treatment groups 6-10 was:

“According to official estimates of the World Health Organization for these rates: The recovery rate from the corona virus is approximately 96-97 percent (that is, there is 96-97 in 100 chance to recover). Approximately 2 non-infected people will catch the coronavirus from a person who has the coronavirus.”

In addition to the possibility of being treated with information about the severity of the COVID epidemic, households could also randomly be treated with information about the fiscal policy response (treatment groups T3 and T8), the monetary policy response (treatment groups T2 and T7), both (treatment groups T4 and T9), neither (control group T1 and treatment group T6), or the recommendations from health officials (treatment groups T5 and T10). For each type of policy treatment, we therefore have two treatment groups: one that also received the information treatment vis-a-vis the severity of the disease and one that only received the policy treatment. The objective of this exercise is to measure the effectiveness of policy communication when background information is also provided. This feature of our survey is a key innovation relative to previous research that studies the effects of information provision on expectations

Table 2. Summary of treatments

Treatment	Health information is provided (basic COVID-19 facts about recovery and contagion rates)	Policy response is provided
T1 (control)	No	No
T2	No	Fed actions
T3	No	Congress actions
T4	No	Fed and Congress actions
T5	No	Health officials (CDC recommendations and the prevalence of shelter-in-place orders)
T6	Yes	No
T7	Yes	Fed actions
T8	Yes	Congress actions
T9	Yes	Fed and Congress actions
T10	Yes	Health officials (CDC recommendations and the prevalence of shelter-in-place orders)

such as Coibion et al. (2020) that treat households with forward guidance by the Federal Reserve. Treatments about the path of future interest rates as in Coibion et al. (2020) allows clean identification of treatments on revisions of expectations but possibly does not provide all necessary information to policy-makers that are interested in the response of households to *endogenous* policy actions. In the context of forward guidance for example, one might want to study the effect of providing information on future interest rates with conditional statements typically used by the Federal Reserve such as ‘until the unemployment rate falls below x%’. We build on this work by providing real-world information treatments that explicitly identify endogenous policy actions.

The specific, truthful policy treatments that we consider are as follows. The monetary policy treatment is given by the following quote:

“In response to the COVID-19 crisis, the Federal Reserve reduced short-term interest rates to zero and implemented additional measures similar to what it did during the last recession.”

The fiscal policy treatment is given by:

“In response to the COVID-19 crisis, the Congress approved a \$2 trillion package to stimulate the economy, including one-time \$1,200 check per person (plus another \$500 per child) to persons

with annual income less than \$75,000. Couples who filed jointly and made less than \$150,000 will get a one-time \$2,400 check (plus another \$500 per child).”

The joint monetary and fiscal treatment is:

“In response to the COVID-19 crisis, the Federal Reserve reduced short-term interest rates to zero and implemented additional measures similar to what it did during the last recession. In addition, the Congress approved a \$2 trillion package to stimulate the economy, including one-time \$1,200 check per person (plus another \$500 per child) to persons households with annual income less than \$75,000. Couples who filed jointly and made less than \$150,000 will get a one-time \$2,400 check (plus another \$500 per child).

While the health recommendation treatment is:

“The U.S. government health officials encourage social distancing, avoiding discretionary travel, and working remotely. Three in four Americans are in areas with local governments declaring “shelter in place” (lockdown).”

If provided, these information bits about policy responses appear immediately after the WHO health facts. Note that both the fiscal and monetary treatments (as well as the joint monetary-fiscal treatments) explicitly tie the policy response to the COVID-19 crisis, indicating that these are *endogenous* policy responses unlike the *exogenous* shocks proposed to households in Andre et al. (2019). Consistent with random assignment of treatments, we find (Appendix Table 1) that treatment status is not predicted by personal/household characteristics.

III. Econometric framework

To measure the effect of policy communications on households’ beliefs and plans, we use the following specification as a baseline:

$$E_i^{post}(X) - E_i^{prior}(X) = \sum_{s=1}^S \beta_s \times Treatment_{s,i} + error, \quad (1)$$

where i indexes respondents, X is an outcome variable, $E_i^{post}(\cdot)$ and $E_i^{prior}(\cdot)$ are post-treatment (“posterior”) and pre-treatment (“prior”) beliefs of respondent i about variable X , $Treatment_{s,i}$ is an indicator variable equal to one if respondent i received treatment s and zero otherwise. The β_s coefficients provide an estimate of the average effect of each treatment on the revision in beliefs. Although one may expect that β for the control group is equal to zero, differences in the wording of the pre- and post-treatment

questions, mean reversion in the responses, and the like can generate non-zero belief revision for the control group. We will therefore report $\hat{\beta}$ for a treatment group relative to $\hat{\beta}$ for the control group.

While specification (1) provides a useful summary of information treatments on the beliefs, it may give an incomplete picture of how treatments influence beliefs if the provided signals happen to be in the middle of the distribution for prior beliefs. For example, if households believe on average that inflation will be 2 percent, treating households with a 2-percent inflation projection prepared by professional forecasters will not move the average belief in the treatment group but it should make the posterior distribution more concentrated on 2 percent by moving beliefs of those who initially predicted inflation other than 2 percent closer to 2 percent after the treatment. While our treatments do not have a numeric forecast and so it is hard to assess whether provided information is in the middle or tail of prior distributions, we can nonetheless utilize an alternative specification to measure this more subtle adjustment of beliefs:

$$E_i^{post}(X) = \sum_{s=1}^S \beta_s \times Treatment_{s,i} + \sum_{s=1}^S \gamma_s \times Treatment_{s,i} \times E_i^{prior}(X) + error. \quad (2)$$

In this specification, β_s and γ_s measure “level” and “slope” effects of treatments respectively. If a signal happens to be above (below) the average pre-treatment belief, β should be positive (negative). As discussed in e.g. Coibion et al. (2020), estimated slopes should be smaller for treated groups relative to the control group if respondents are Bayesian learners. If there is no difference in slopes between control and treatment groups, then the provided message is not informative for households. We will report $\hat{\beta}$ and $\hat{\gamma}$ for a treatment group relative to $\hat{\beta}$ and $\hat{\gamma}$ for the control group.

Specifications (1) and (2) utilize pre-treatment and post-treatment beliefs but some survey responses are available only at the post-treatment stage. For these responses, we employ the following specification:

$$E_i^{post}(X) = \sum_{s=1}^S \beta_s \times Treatment_{s,i} + error. \quad (3)$$

Given that treatment assignment is random, specifications (1)-(3) do not require controls to account for respondents’ heterogeneity to estimate treatment effects. Including controls only reduces standard errors and does not make material impact on our estimates (results are available upon request). To keep our analysis simple, we thus do not include controls in the reported results. To attenuate the adverse effects of extreme survey responses and, more generally, influential observations on our estimates, we winsorize data at the bottom and top 1 percent, drop implausible values (e.g., mortgage rates greater than 40 percent), and estimate specifications (1)-(3) using Huber (1964) robust regressions. Huber-robust regressions differ from using winsorized data in standard regressions because they also take correlations across variables into account.

IV. Results

Using these empirical specifications, we now turn to how treatments affect households' beliefs and plans. We discuss each of these in turn.

A. Macroeconomic expectations

Modern macroeconomic theory emphasizes the central role of expectations and the power of communicating policy actions to economic agents. Indeed, credible announcements about current or future policy are predicted to have large effects on perceptions and expectations about macroeconomic variables and thus influence firms' and households' choices. We now examine whether informing households about COVID-19 facts as well as policy actions taken in response by various government bodies can move households' expectations.

Error! Reference source not found. reports results for specification (1). We generally find that the average size of belief revisions in the control group is economically small with the only exception being inflation expectations (column 1). The large revision for inflation expectations reflects the fact that the pre-treatment expectations are elicited via a distribution question with pre-set upper and lower bounds at +/- 12% similar to the wording in the New York Fed Survey of Consumer Expectations, while post-treatment expectations are collected as point predictions.

We find that informing households about COVID-19 recovery (opposite of fatality) and contagion rates (treatment T6) generally has no material effect on expectations for inflation (column 1), the unemployment rate (columns 2 and 3), mortgage rates (columns 4-7) or households' expected income growth. Note that the vast majority of households is overly skeptical about the COVID-19 recovery and contagion rates and therefore this treatment presents a clear, one-sided surprise for households. While the estimated coefficients are statistically significant for the current mortgage rate and expected household income growth, the economic significance of these effects is very small. For example, this information treatment lowers households' expected income growth by 0.094 percentage point, which is small relative to the standard deviation of the belief revision in the control group (0.906 percent point; column 8, bottom row, **Error! Reference source not found.**) by an order of magnitude. Our results are line with the findings in Binder (2020) and Fetzer et al. (2020) who also document that randomized provision of COVID-19 health facts has at most a very modest (if any) effect on economic (personal or aggregate) expectations. These results are consistent with two views. One is that households are unable to interpret health facts in a macroeconomic context, that is, they cannot draw a connection between the severity of COVID-19 and macroeconomic outcomes. The second viewpoint is that households believe that COVID-19 does not influence economic outcomes. This alternative view is unlikely to be empirically relevant. For example, Coibion, Gorodnichenko and Weber (2020) document that households attribute pervasive, large losses in

their income and wealth to the COVID-19 outbreak and that they are highly concerned about their financial situation because of the COVID-19 pandemic. Thus, we interpret this result as implying that households are unable to quickly draw connections between the severity of the disease and macroeconomic outcomes. One implication of this is that policy responses which focus on communicating about the disease and its health consequences cannot be expected to significantly affect households' economic expectations. Health communications cannot be a substitute for economic communications unless it is clearly communicated how these health facts are relevant for individuals and the broader economy.

Appraising households of the Federal Reserve's actions (treatment T2) *lowers* inflation expectations by 0.7 percentage point. While one might have expected to see an increase in households' inflation expectations in response to this policy, our finding is consistent with Coibion et al. (2020) documenting a positive comovement of inflation and interest rate expectations unconditionally and in response to treatments with numeric inflation/interest rate information. Specifically, when the Fed lowers interest rates, households lower their inflation expectations, which could capture an "information effect" of policy announcements. Also in agreement with Coibion et al. (2020), our estimates suggest that households do not believe in the ability of the Fed to influence the unemployment rate: treatment T2 has no discernable effect on the expected unemployment rate in either the short- or long-run (columns 2 and 3 in **Error! Reference source not found.** respectively). Nor do we find any economic effect on the mortgage rate expectations: the estimated coefficients are close to zero. This result suggests that, given how low mortgage rates were by historical standards before the COVID-19 crisis, households may view the Fed's power to lower mortgage rate even further as limited. Finally, households do not observe a connection between monetary policy and their income growth. This latter results suggests that indirect effects of monetary policy on income expectations are weak in household surveys contrary to theoretical predictions in Heterogeneous Agent New Keynesian (HANK) models.

In contrast, informing households about the fiscal policy response ("Congress actions"; treatment T3) raises inflation expectations modestly by 0.3 percentage points. Interestingly, this treatment also raises short-run expectations for the unemployment rate (column 2) by a similar magnitude. This positive comovement of inflation and unemployment ("stagflation") is consistent with Kamdar (2018): households tend to view high inflation as positively associated with high unemployment. It is also in line with the simple affective heuristic proposed in Andre et al. (2019). However, this fiscal policy action does not move households' longer-run expectations for the unemployment rate (column 3) or mortgage rate expectations (columns 4-7). Strikingly, although the fiscal policy involves a direct transfer to households (which we provide in the treatment) and the vast majority of households participating in the survey qualify for these transfers, households do not view this policy as having a materially important effect on their expected

income growth. In fact, the estimated coefficient is negative (column 8), again suggesting a potential information effect.

Table 3. Macroeconomic and household-level expectations.

Treatment	Health info is provided	Policy response is provided	Inflation	Unemployment rate		Mortgage rate			Household income growth	
				Short-run	Long-run	Current	End of 2020	End of 2021		In 3-5 years
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1	No	No (Control group)	2.442*** (0.138)	-0.024 (0.101)	-0.300*** (0.044)	0.003* (0.002)	0.131*** (0.017)	0.064*** (0.020)	-0.007 (0.017)	0.124*** (0.023)
		<i>Relative to control group</i>								
T2	No	Fed actions	-0.691*** (0.190)	0.166 (0.140)	-0.034 (0.064)	-0.003 (0.002)	-0.084*** (0.025)	0.032 (0.029)	0.019 (0.024)	0.011 (0.033)
T3	No	Congress actions	0.360* (0.194)	0.348** (0.141)	0.089 (0.063)	-0.003 (0.002)	-0.032 (0.024)	0.025 (0.028)	-0.002 (0.023)	-0.076** (0.031)
T4	No	Fed and Congress actions	-0.291 (0.191)	0.396*** (0.140)	-0.064 (0.062)	-0.005** (0.002)	-0.074*** (0.024)	0.023 (0.029)	-0.003 (0.024)	-0.006 (0.033)
T5	No	Health officials	0.179 (0.195)	0.280** (0.138)	0.016 (0.063)	-0.005** (0.002)	-0.008 (0.025)	0.013 (0.029)	0.008 (0.023)	-0.043 (0.033)
T6	Yes	No	-0.183 (0.190)	-0.056 (0.138)	0.061 (0.060)	-0.006*** (0.002)	-0.004 (0.024)	0.032 (0.028)	-0.004 (0.023)	-0.094*** (0.030)
T7	Yes	Fed actions	-0.137 (0.196)	0.250* (0.142)	-0.081 (0.063)	-0.002 (0.002)	-0.062** (0.025)	-0.056* (0.029)	-0.031 (0.025)	0.020 (0.034)
T8	Yes	Congress actions	-0.253 (0.190)	-0.021 (0.139)	-0.060 (0.065)	-0.006*** (0.002)	0.042* (0.025)	0.053* (0.029)	0.020 (0.023)	-0.106*** (0.032)
T9	Yes	Fed and Congress actions	-0.000 (0.192)	0.050 (0.142)	-0.182*** (0.063)	-0.004* (0.002)	-0.068*** (0.024)	-0.016 (0.029)	-0.038 (0.024)	0.033 (0.034)
T10	Yes	Health officials	-0.371** (0.186)	-0.035 (0.142)	-0.022 (0.063)	-0.001 (0.002)	-0.027 (0.024)	-0.002 (0.029)	-0.010 (0.024)	-0.014 (0.033)
Observations			12,248	11,716	11,412	8,433	11,389	11,639	11,302	9,351
R-squared			0.003	0.002	0.002	0.001	0.003	0.002	0.001	0.003
St.Dev. of dep. variable in control group			4.912	3.869	1.687	0.0720	0.645	0.743	0.640	0.906

Notes: The table reports Huber-robust estimation of specification (1) for macroeconomic expectations. All dependent variables are measured in percent. Revisions in inflation expectations are measured as post-treatment inflation forecast prediction minus pre-treatment implied-mean inflation forecast. Inflation expectations is at the one-year horizon. Revisions in short-run unemployment expectations are measured as post-treatment unemployment rate expected at the end of 2020 minus pre-treatment one-year-ahead forecast of the unemployment rate. Revisions in long-run unemployment expectations are measured as post-treatment unemployment rate expected at the next 3-5 years minus pre-treatment unemployment rate expected in the 3-5 years. Revisions in mortgage rate expectations (perceptions) are measured as post-treatment expected mortgage rate for "a person with excellent credit" minus pre-treatment expected mortgage rate for "a person like you". Revision in household expected income is measured as post-treatment expectations (one year ahead; "How much higher or lower do you think your household's total net income will be over the next twelve months compared to the last twelve months? Please provide an answer in percentage terms.") minus pre-treatment expectations (one year ahead; "How much higher or lower do you think your household's total after-tax (i.e., 'take home') income will be over the next twelve months compared to the last twelve months? Please provide an answer in percentage terms."). Robust standard errors are in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Table 4. Macroeconomic and household-level expectations (slope specification).

Health info is provided	Policy response is provided	Unemployment rate			Mortgage rate			Household inc. growth	
		Inflation	Unemployment rate		Current	End of 2020	End of 2021		In 3-5 years
		(1)	Short-run (2)	Long-run (3)	(4)	(5)	(6)		(7)
No	No (Control group); T1	3.944*** (0.122)	1.496*** (0.157)	0.372*** (0.074)	0.002 (0.001)	0.252*** (0.028)	0.176*** (0.034)	0.104*** (0.032)	0.144*** (0.027)
<i>Relative to control group</i>									
No	Fed actions; T2	-0.668*** (0.165)	-0.311 (0.207)	0.173* (0.102)	-0.003 (0.002)	-0.083*** (0.040)	-0.005 (0.045)	-0.021 (0.041)	0.020 (0.038)
No	Congress actions; T3	-0.018 (0.173)	-0.375* (0.211)	-0.217** (0.102)	-0.002 (0.002)	-0.069* (0.038)	0.010 (0.045)	-0.046 (0.040)	0.112*** (0.043)
No	Fed and Congress actions; T4	-0.445*** (0.168)	-0.265 (0.213)	0.445*** (0.101)	-0.003 (0.002)	-0.145*** (0.037)	0.017 (0.047)	-0.059 (0.041)	-0.007 (0.038)
No	Health officials; T5	-0.104 (0.174)	-0.246 (0.213)	0.549*** (0.103)	-0.004** (0.002)	-0.046 (0.039)	-0.008 (0.046)	0.015 (0.044)	-0.051 (0.038)
Yes	No; T6	-0.483*** (0.167)	-0.363* (0.208)	-0.364*** (0.096)	-0.005** (0.002)	-0.098*** (0.036)	-0.038 (0.043)	-0.068* (0.039)	-0.110*** (0.036)
Yes	Fed actions; T7	-0.300* (0.172)	0.005 (0.215)	0.642*** (0.102)	0.000 (0.002)	-0.097** (0.039)	-0.095** (0.045)	-0.054 (0.044)	0.105** (0.044)
Yes	Congress actions; T8	-0.640*** (0.166)	-0.209 (0.214)	0.496*** (0.106)	-0.005*** (0.002)	-0.005 (0.038)	0.033 (0.045)	-0.008 (0.041)	-0.127*** (0.038)
Yes	Fed and Congress actions; T9	-0.652*** (0.168)	-0.156 (0.219)	-0.183* (0.104)	-0.003 (0.002)	-0.103*** (0.038)	-0.059 (0.044)	-0.054 (0.042)	0.031 (0.039)
Yes	Health officials; T10	-0.617*** (0.171)	0.046 (0.223)	0.762*** (0.096)	-0.000 (0.002)	-0.068* (0.037)	0.058 (0.051)	-0.043 (0.043)	-0.015 (0.039)
No	No (Control group); T1	0.300*** (0.024)	0.849*** (0.013)	0.887*** (0.011)	1.000*** (0.000)	0.970*** (0.005)	0.975*** (0.006)	0.977*** (0.006)	1.000*** (0.002)
<i>Relative to control group</i>									
No	Fed actions; T2	-0.124*** (0.032)	0.043** (0.017)	-0.042*** (0.015)	0.000 (0.000)	0.001 (0.008)	0.009 (0.008)	0.010 (0.007)	-0.003 (0.003)
No	Congress actions; T3	0.033 (0.034)	0.073*** (0.018)	0.058*** (0.014)	0.000 (0.000)	0.008 (0.008)	0.003 (0.008)	0.010 (0.007)	-0.484*** (0.008)
No	Fed and Congress actions; T4	-0.046 (0.033)	0.062*** (0.017)	-0.095*** (0.014)	0.000 (0.000)	0.018*** (0.006)	0.001 (0.009)	0.013** (0.007)	-0.001 (0.003)
No	Health officials; T5	0.016 (0.036)	0.051*** (0.018)	-0.116*** (0.015)	0.000* (0.000)	0.008 (0.008)	0.005 (0.008)	-0.000 (0.008)	-0.003 (0.003)
Yes	No; T6	-0.007 (0.033)	0.030* (0.018)	0.075*** (0.013)	0.000 (0.000)	0.023*** (0.006)	0.017** (0.007)	0.014** (0.006)	-0.003 (0.003)
Yes	Fed actions; T7	-0.102*** (0.033)	0.020 (0.018)	-0.149*** (0.015)	0.000 (0.000)	0.009 (0.007)	0.009 (0.008)	0.005 (0.008)	-0.369*** (0.008)
Yes	Congress actions; T8	0.077** (0.033)	0.038** (0.018)	-0.114*** (0.015)	0.000* (0.000)	0.013* (0.007)	0.005 (0.008)	0.008 (0.007)	-0.004 (0.003)
Yes	Fed and Congress actions; T9	0.009 (0.034)	0.016 (0.018)	0.005 (0.015)	0.000 (0.000)	0.008 (0.007)	0.011 (0.008)	0.005 (0.007)	-0.006* (0.003)
Yes	Health officials; T10	0.085** (0.034)	-0.024 (0.019)	-0.165*** (0.013)	0.000 (0.000)	0.012* (0.006)	-0.012 (0.009)	0.008 (0.007)	-0.002 (0.003)
Observations		12,048	10,012	11,186	7,977	11,314	11,504	11,173	9,598
R-squared		0.147	0.866	0.913	1.000	0.976	0.969	0.977	0.982
St.Dev. of dep. variable in control group		4.344	8.554	5.739	4.102	3.619	3.856	3.264	9.185

Notes: The table reports Huber-robust estimation of specification (2) for macroeconomic expectations. All dependent variables are measured in percent. See notes to Table 3 for definitions of variables. Robust standard errors are in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

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When we tell households about the fiscal *and* monetary policy response (treatment T4), the estimated responses are roughly a mix of responses to treatments T2 and T3. We do not observe any evidence suggesting that the policies reinforce each other. Similar to T2 and T3, treatment T4 does not generate economically large responses of macroeconomic expectations. This finding is particularly remarkable given that policy responses are enormous by historical standards and yet the American public treats these as largely irrelevant for the economy.

Treating people with information about good practices and the share of people under shelter-in-place orders (treatment T5) similarly has no noticeable effect on macroeconomic expectations. One might expect this treatment to have a pronounced effect on macroeconomic expectations if a) households were not fully aware of how nationally pervasive lockdown orders were at the time and b) if households believed that lockdowns significantly affected economic activity. While we do not observe individuals' prior beliefs about the share of the U.S. population under lockdown at the time and therefore cannot test a) directly, the fact that households were so uninformed about the recovery rates and transmission rates of the disease suggests that they were unlikely to be significantly more informed about lockdown policies. Thus, we interpret our finding of no effect from the health policy information treatment on households' macroeconomic expectations as indicative that they did not perceive lockdowns as very costly in economic terms.

One might anticipate that combining information on policy responses with health information on the severity of COVID-19 (treatments T7-T10) could alter how households translate policy responses into macroeconomic expectations. While we fail to find any marked difference in the responses of expectations for unemployment, mortgage rates, and income growth, we do observe several interesting facts for inflation expectations. First, the effect of the Fed's actions is considerably mitigated: when households were informed about the Fed policy response, they lowered their inflation expectations but when households are also informed that COVID-19 is not as bad as they thought, the deflationary effect of the Fed policy response is largely gone (and is similar to the effect in response to information about only the recovery and contagion rates of COVID-19). Second, while the fiscal policy response ("Congress actions") raised inflation expectations, combining this response with health information lowers inflation expectations (although the effect is not statistically significant). Finally, providing information about COVID-19 recovery/contagion rate and information about CDC recommendations and the share of people under lockdown orders *lowers* inflation expectations. These results suggest that the broader context is important for inflation but other macroeconomic expectations are largely insensitive to information about health facts or policy responses.

To further explore the effect of treatments on macroeconomic expectations, we report estimated effects for specification (2) in **Error! Reference source not found.** and visualize the distribution of post- and pre-treatment beliefs in Appendix Figures 1-7. Column (1) of the table shows the results for inflation

expectations. Note that the slope for the control group is 0.3 (rather than approximately 1) and the average revision (intercept) is 3.9 (rather than 0) because of the differences in the pre-treatment and post-treatment questions eliciting inflation expectations (distribution vs. point prediction). Relative to this benchmark, we find that the estimated “level” effects (i.e., coefficients β in specification (2)) tend to be negative. These results suggest that the received signals are interpreted by households as providing information that is below the average initial beliefs of households. At the same time, the slope effects tend to be close to zero in economic terms although some coefficients are statistically different from zero. Therefore, the treatments generally shift the distribution of inflation expectations to the left without a discernable change in the cross-sectional variation in expectations. Interestingly, while some information treatment may be conceived as disinflationary, the monetary and fiscal policies that employed a wide arsenal of tools to fight the COVID-19 crisis are hardly disinflationary by themselves. This reaction to treatments thus appears to be consistent with significant information effects, that is, households could interpret strong policy responses as signaling a confirmation of an economic catastrophe.

Short-term unemployment rate expectations (column (2) of **Error! Reference source not found.**) show little “level” or “slope” reaction to the treatments. In contrast, longer-term expectations (column (3)) have some variation in the “level” effect ranging from 0.762 percentage point increase for treatment T10 (COVID facts and health information) to -0.364 percentage point decrease for treatment T5 (COVID facts only). The slope effects are generally negative suggesting some compression in the post-treatment disagreement across respondents. Consistent with the results in **Error! Reference source not found.**, we find no material “level” or “slope” response in expectations for mortgage rates (columns (4)-(7) of **Error! Reference source not found.**). Similarly, there is generally little variation in response to treatments for households’ income growth (column (8) of **Error! Reference source not found.**).

In summary, our results suggest that while inflation expectations have some limited sensitivity to information treatments, other macroeconomic expectations (especially, expectations for mortgage rates) do not exhibit any discernable reaction to the provided information. Given that households are (on average) poorly informed about macroeconomic policies or health facts and that the benefits of having access to information about the enormous policy responses as well as health facts are predicted to be high by mainstream macroeconomic theory, this weak (if any) reaction to the information treatments is indeed striking.

B. Labor market expectations

We now consider how these treatments affect households’ expectations for their labor market outcomes, specifically the probability of keeping their job if employed and the probability of finding a job if unemployed. Because we do not have pre-treatment measures of these subjective probabilities, we use specification (3) to estimate the effect of information treatments on perceived labor market outcomes. We

find (**Error! Reference source not found.**) that information treatments do not have a materially important effect on the subjective probability of losing a job (column (1)): the estimated coefficients are small (fractions of a percentage point) and generally not significant statistically. In contrast, when it comes to how the unemployed perceive the probability of finding a job, the provision of COVID-19 facts (treatment T6) raises this perceived probability by 20 percentage points, a large effect. Interestingly, any other treatment, including treatments where information about COVID-19 facts is combined with information on policy responses, generate no statistically significant effect on the perceived probability of finding a job. This pattern appears to suggest two conclusions. First, households do not view policy responses as having an important effect on their labor market outcome. Second, providing basic COVID-19 facts appears to be helpful in making unemployed households less pessimistic about their labor market prospects—thus suggesting some role for information campaigns highlighting public health implications of the COVID-19 outbreak—but the information effect in the policy response seems to offset this positive effect.

Table 5. Probability of losing a job or finding a job.

Treatment	Health info is provided	Policy response is provided	Probability to	Probability to
			lose a job	find a job
			(1)	(2)
T1	No	No (Control group)	0.961*** (0.088)	45.853*** (3.909)
		<i>Relative to control group</i>		
T2	No	Fed actions	0.245* (0.135)	2.638 (5.575)
T3	No	Congress actions	0.086 (0.130)	-2.978 (5.791)
T4	No	Fed and Congress actions	-0.188 (0.115)	6.957 (5.444)
T5	No	Health officials	-0.071 (0.121)	-2.930 (5.934)
T6	Yes	No	0.015 (0.125)	20.138*** (6.125)
T7	Yes	Fed actions	0.011 (0.126)	-1.574 (5.678)
T8	Yes	Congress actions	-0.030 (0.125)	2.962 (5.691)
T9	Yes	Fed and Congress actions	0.149 (0.132)	6.608 (5.971)
T10	Yes	Health officials	0.129 (0.131)	7.017 (5.943)
	Observations		5,084	894
	R-squared		0.002	0.031
	St.Dev. of dep. variable in control group		2.414	34.98

Notes: The table reports Huber-robust estimation of specification (3) for expected labor market outcomes. All dependent variables are measured in percent ranging from 0 to 100. The sample for column (3) includes only employed (at the time of the survey) people. The sample for column (2) includes only unemployed (don't have a job and look for a job at the time of the survey) people. Robust standard errors are in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

C. Planned consumer spending

Coibion, Gorodnichenko and Weber (2020) and Dietrich et al. (2020) document that, during the COVID-19 crisis, households significantly downgraded their plans to buy durable goods such as houses/apartments, cars, and large appliances. In part, the policy response to the crisis was aimed to make households more enthusiastic about purchases of durable goods. For example, policy interest rates were cut down to zero and new rounds of quantitative easing reduced mortgage rates thus making the financial cost of durable purchases more enticing. However, it remains unclear to what extent these policies turned the tide of pessimism and encouraged purchases of new goods.³ To gauge the influence of these policies on consumer spending, we asked respondents at the post-treatment stage to report whether it is a good time to buy a durable good. Specifically, respondents can report their beliefs on a 1 (very good time) to 5 (very bad time) scale.

Using specification (3), we find (**Error! Reference source not found.**) that information treatments generally make households more positive about buying a house (the coefficients are negative) but the magnitude of the response is quite small. The largest responses are approximately -0.1 to -0.15 while the scale varies from 1 to 5 and the standard deviation of scores in the control group is approximately one. The views for car or appliance purchases in response to the treatments are more mixed with some treatments resulting in less positive views and some treatment resulting in more positive views. However, the economic magnitudes remain rather small. These results suggest that although informing households about policies or health facts is somewhat helpful in improving consumer sentiment, the effects are modest at best, thus again pointing to limited effectiveness of information provision on economic outcomes.

D. Policy approval

While consumers seem to not understand the economic implications of the policy responses, they may still appreciate the reaction of various government bodies to the crisis. To measure this potential effect, we ask respondents to rate the actions of the President, the Congress, the Federal Reserve, and U.S. health officials by answering the following question on a scale running from 0 (not helpful at all) to 10 (extremely helpful): "How much do you trust the actions taken by [GOVERNMENT BODY] will be helpful for you? And the

³ At the same time, historically low rates did generate a wave of mortgage refinances. According to information from the Mortgage Bankers Association, refinances increased to \$1.5 trillion as of early May, a 51% jump compared to 2019.

overall American population?” Note that we ask households to assess the value of the actions for them personally and for the country as a whole so that we can get a metric—however imperfect—about the ability of households to grasp partial equilibrium and general equilibrium effects.

For the control group, U.S. health officials have the highest scores (the averages are 6.3 for the country and 6.1 for the respondent) followed by the Fed (5.6 for the country and 5.0 for the respondent), the President (4.9 for the country and 4.6 for the respondent), and then Congress (4.5 for the country and 4.3 for the respondent). Households consistently perceive policy institutions as being better for the country than for them personally. At the same time, we observe a high correlation (ranging from 0.7 for the Fed to 0.9 for the President) between responses for personal and country-level implications and much weaker correlation between assessment for various government bodies (e.g., the correlation between personal effect from the President’s actions and the Fed’s actions is 0.3), thus suggesting that households differentiate actions of various government branches during the crisis.

Table 6. Good time to buy a durable good

Treatment	Health info is provided	Policy response is provided	House	Car	Appliance
			(1)	(2)	(3)
T1	No	No (Control group)	3.023*** (0.029)	3.019*** (0.028)	3.031*** (0.016)
		<i>Relative to control group</i>			
T2	No	Fed actions	-0.003 (0.040)	0.074* (0.040)	-0.023 (0.024)
T3	No	Congress actions	0.076* (0.040)	0.138*** (0.040)	0.041* (0.024)
T4	No	Fed and Congress actions	-0.106*** (0.040)	0.076* (0.040)	-0.008 (0.024)
T5	No	Health officials	-0.112*** (0.040)	-0.119*** (0.040)	-0.096*** (0.024)
T6	Yes	No	0.016 (0.040)	0.014 (0.040)	-0.063*** (0.023)
T7	Yes	Fed actions	0.002 (0.040)	0.047 (0.040)	-0.019 (0.023)
T8	Yes	Congress actions	-0.144*** (0.040)	0.016 (0.040)	-0.006 (0.024)
T9	Yes	Fed and Congress actions	0.053 (0.040)	0.081** (0.040)	0.018 (0.023)
T10	Yes	Health officials	-0.054 (0.040)	0.088** (0.040)	0.005 (0.023)
Observations			13,761	13,761	13,210
R-squared			0.005	0.004	0.003
St.Dev. of dep. variable in control group			1.021	1.022	0.664

Notes: The table reports Huber-robust estimation of specification (3) for whether it is a good time to buy a durable. All dependent variables are measured on the scale ranging from 1 (very good time) to 5 (very bad

time). Robust standard errors are in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

Information treatments have highly heterogeneous effects on these scores. Using specification (3), we find (columns (1) and (2) of **Error! Reference source not found.**) that information about actual policies does not improve approval of the President's actions. If anything, treatments T2 (monetary policy) and T4 (monetary and fiscal policy) reduce the approval of the President's actions. These results are consistent with the view that respondents generally have strong priors about the President. In contrast, *every* treatment raises the appreciation of Congress. This includes treating households with information about monetary policy which is not controlled (at least directly) by the Congress. The Federal Reserve is viewed less positively when households are informed about monetary policy (treatment T2) but the Fed gets some credit for fiscal policy. The views on the actions of U.S. health officials are weakly improved by the treatments when respondents are informed about basic COVID-19 facts. The latter observation suggests that when households are told that COVID-19 is not as contagious and fatal as they think initially, they tend to credit U.S. health officials.

While treatment effects are statistically significant, the economic significance of the effects varies. For example, treatments can materially improve the image of Congress while views on the President's actions appear to be rather unresponsive to the provided information. Thus, similar to the responses of macroeconomic expectations, consumer expenditure plans, and labor market expectations, the perceptions of policy effectiveness show some reaction to information treatments but the effects range from zero to modest. This is again consistent with the notion that the general public is rather confused about the responsibilities of various government bodies as well as implications of the bodies' actions. Specifically, fiscal and monetary policies get fairly little credit.

V. Discussion and Concluding Remarks

Understanding the way in which policy actions affect the economy has long been a challenge for macroeconomists. Standard models imply that households' expectations play a large role in driving these effects, as households incorporate the announcements into their expectations and their decisions. Our results challenge this key mechanism: we find little evidence that even large policy decisions have much of an effect on households' economic expectations or their planned actions. This result obtains for both monetary and fiscal policies during the COVID-19 crisis, and extends to some of the health recommendations made by the federal government as well.

This result is in the same spirit as recent work documenting pervasive inattention on the part of households and firms to monetary policy actions and announcements. However, it goes beyond inattention

because we directly inform participants about recent and dramatic policy decisions, yet even this directly provided information has essentially no effect on household beliefs. Perhaps, cognitive constraints as modeled in Gabaix (2019), Woodford (2018), Farhi and Werning (2019), and Angeletos and Lian (2018) and the singular nature of COVID-19 limit the ability of households to reason through the implications of the pandemic and policy responses (see e.g. Iovino and Sergeyev (2020) for an application of this notion to quantitative easing) and, as a result, inattention and cognitive constraints reinforce each other in dampening the response of beliefs and hence economic outcomes to policy announcements.

Our results are also distinct from and complementary to Andre et al. (2019) who study how households respond to *exogenous* fiscal and monetary policy actions: we explicitly describe the policy treatments as an *endogenous* response to the COVID19 crisis. Taken together, these results point toward a world in which policy shocks have non-trivial effects on household expectations and actions while systematic policy decisions have much smaller (if any) effects, which is the complete opposite of what we tend to observe in standard macroeconomic models in which systematic policy is close to all-powerful while policy shocks have much smaller effects. We view this as a fundamental challenge to workhorse models used by macroeconomists in which the rapid and endogenous adjustment of household expectations is a key driver of macroeconomic outcomes.

Table 7. Policy evaluation.

Treatment	Health info	Policy info	How much do you trust the actions taken by the [Government Bank] will be helpful for {you, U.S.}?							
			President		Congress		Federal Reserve		Health officials	
			you	U.S.	you	U.S.	you	U.S.	you	U.S.
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1	No	No (Control group)	4.522***	4.875***	4.241***	4.641***	5.184***	5.798***	6.390***	6.645***
		<i>Relative to control group</i>	(0.103)	(0.100)	(0.059)	(0.055)	(0.049)	(0.048)	(0.056)	(0.053)
T2	No	Fed actions	-0.263*	-0.294**	0.179**	0.258***	-0.212***	-0.004	0.001	-0.070
			(0.146)	(0.143)	(0.082)	(0.076)	(0.069)	(0.068)	(0.081)	(0.077)
T3	No	Congress actions	0.059	-0.016	0.216***	0.165**	0.160**	0.066	0.035	-0.001
			(0.147)	(0.142)	(0.083)	(0.078)	(0.069)	(0.069)	(0.081)	(0.077)
T4	No	Fed and Congress actions	-0.311**	-0.417***	0.279***	0.274***	-0.127*	0.084	-0.047	0.059
			(0.147)	(0.143)	(0.083)	(0.077)	(0.070)	(0.069)	(0.080)	(0.076)
T5	No	Health officials	-0.169	-0.229	0.172**	0.168**	-0.044	-0.203***	0.073	0.041
			(0.147)	(0.143)	(0.082)	(0.077)	(0.069)	(0.066)	(0.080)	(0.076)
T6	Yes	No	-0.038	-0.069	0.180**	0.075	0.007	-0.006	0.100	0.118
			(0.147)	(0.143)	(0.081)	(0.076)	(0.068)	(0.068)	(0.079)	(0.075)
T7	Yes	Fed actions	0.184	0.173	0.200**	0.336***	-0.071	0.167**	0.106	0.127*
			(0.145)	(0.142)	(0.083)	(0.078)	(0.069)	(0.069)	(0.080)	(0.076)
T8	Yes	Congress actions	-0.064	-0.097	0.495***	0.405***	0.209***	0.191***	0.361***	0.279***
			(0.147)	(0.143)	(0.082)	(0.076)	(0.069)	(0.068)	(0.080)	(0.076)
T9	Yes	Fed and Congress actions	0.003	-0.003	0.570***	0.570***	0.213***	0.293***	0.115	0.073
			(0.145)	(0.141)	(0.082)	(0.078)	(0.068)	(0.069)	(0.080)	(0.076)
T10	Yes	Health officials	-0.045	-0.088	0.050	0.130*	-0.000	0.050	0.175**	0.164**
			(0.147)	(0.143)	(0.083)	(0.078)	(0.070)	(0.068)	(0.080)	(0.076)
		Observations	13,521	13,521	13,473	13,467	13,346	13,299	13,423	13,376
		R-squared	0.002	0.002	0.006	0.006	0.005	0.005	0.003	0.002
		St.Dev. of dep. variable in control group	3.391	3.336	2.152	2.069	1.882	1.767	1.986	1.872

Notes: The table reports Huber-robust estimation of specification (3) for political approval of policies implemented by various government bodies. All dependent variables are measured on the scale ranging from 0 (not helpful at all) to 10 (extremely helpful). Robust standard errors are in parentheses. ***, **, * denote statistical significance at 1, 5, and 10 percent levels.

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Online Appendix

Appendix 1: Survey Questions

1. What is your date of birth? (Please select the month, day, and year in a dropdown menu)
2. What is your gender?
 - Male
 - Female
3. What is your first name? (Please type it in)
4. Which of the following goods and services have you spent money on over the last three months? (Select all that apply)
 - Debt payments (mortgages, auto loans, student loans, etc.)
 - Housing (including rent, maintenance and home owner/renter insurance, housekeeping and cleaning service, but not including mortgage payments)
 - Utilities (including water, sewer, electricity, gas, heating oil, phone, cable, internet)
 - Food (including groceries, dining out, take-out food, and beverages)
 - Clothing, footwear, and personal care
 - Gasoline
 - Other regular transportation costs (including public transportation fares and car maintenance)
 - Medical care (including health insurance, out-of-pocket medical bills and prescription drugs)
 - Travel, recreation, and entertainment
 - Education and child care
 - Furniture, jewelry, small appliances and other small durable goods
 - Other (including gifts, child support or alimony, charitable giving, and other miscellaneous)
5. Over the last three months on average, how much did your household spend (per month) on goods and services in total and for each of the individual components listed below?
Please enter a number between 1 and 10,000 for each category. The sum of the expenditures for the individual categories should add up to the total amount.

Total monthly spending	\$ _____
Debt payments (mortgages, auto loans, student loans, etc.)	\$ _____
Housing (including rent, maintenance and home owner/renter insurance, housekeeping and cleaning service, but not including mortgage payments)	\$ _____
Utilities (including water, sewer, electricity, gas, heating oil, phone, cable, internet)	\$ _____
Food (including groceries, dining out, take-out food, and beverages)	\$ _____
Clothing, footwear, and personal care	\$ _____
Gasoline	\$ _____
Other regular transportation costs (including public transportation fares and car maintenance)	\$ _____
Medical care (including health insurance, out-of-pocket medical bills and prescription drugs)	\$ _____
Travel, recreation, and entertainment	\$ _____
Education and child care	\$ _____
Furniture, jewelry, small appliances and other small durable goods	\$ _____
Other (including gifts, child support or alimony, charitable giving, and other miscellaneous)	\$ _____
	\$ Total _____

[TOTAL ANSWERS FROM ABOVE]

6. Suppose that you had to make an unexpected payment equal to one month of your after-tax income, would you have sufficient financial resources (access to credit, savings, loans from relatives or friends, etc.) to pay for the entire amount?
 - Yes
 - No
 - Don't know/prefer not to answer
7. Which of the following best characterizes your household:
 - Own our house/apartment without a mortgage
 - Own our house/apartment and have a fixed-rate mortgage
 - Own our house/apartment and have a variable-rate mortgage
 - Rent our house/apartment
 - Other
8. Does your household have total financial investments (excluding housing) worth more than one month of combined household income?
 - Yes
 - No

ASK IF: Q8=YES

9. What percent of your financial wealth (excluding housing) do you invest in the following categories? Put "0" if you do not invest in a given category.

Wealth Investment Allotment

- | | |
|---|---------------|
| ▪ Checking and Savings Account, Certificate of deposits | _____ percent |
| ▪ Cash | _____ percent |
| ▪ US Bonds | _____ percent |
| ▪ US Stocks | _____ percent |
| ▪ Foreign Stocks and Bonds | _____ percent |
| ▪ Gold and precious metals | _____ percent |
| ▪ Bitcoin and other cryptocurrencies | _____ percent |
| ▪ Other | _____ percent |
| ▪ % Total [TOTAL ANSWERS FROM ABOVE – MUST SUM TO 100%] | _____ |

10. Over the last 6 months, did you buy a new home, car, or other major big-ticket item (fridge, TV, furniture, etc.)?
 - Yes
 - No

ASK IF: Q10=YES

11. Which of the following did you purchase in the last 6 months? Please select all that apply.
 - A house/apartment
 - A car or other vehicle
 - A large home appliance or electronics
 - None of the above

ASK IF: Q11=YES

12. How much did you spend on the following?

- A house/apartment _____
- A car or other vehicle _____
- A large home appliance or electronics _____

13. Do you currently plan to buy a new home, car, or other major big-ticket item (fridge, TV, furniture, etc.) in the next 12 months?

- Yes
- No

ASK IF: Q13=YES

14. Which of the following do you plan to purchase in the next 12 months? Please select all that apply.

- A house/apartment
- A car or other vehicle
- A large home appliance or electronics
- None of the above

ASK IF: Q10=YES

15. How much do you plan to spend on the following?

- A house/apartment _____
- A car or other vehicle _____
- A large home appliance or electronics _____

We would like to ask you some questions about the overall economy and in particular about the rate of inflation/deflation (Note: inflation is the percentage rise in overall prices in the economy, most commonly measured by the Consumer Price Index and deflation corresponds to when prices are falling).

16. In THIS question, you will be asked about the probability (PERCENT CHANCE) of something happening. The percent chance must be a number between 0 and 100 and the sum of your answers must add up to 100.

What do you think is the percent chance that, over the next 12 months...

Percentage Chance

- the rate of inflation will be 12% or more _____
- the rate of inflation will be between 8% and 12% _____
- the rate of inflation will be between 4% and 8% _____
- the rate of inflation will be between 2% and 4% _____
- the rate of inflation will be between 0% and 2% _____
- the rate of deflation (opposite of inflation) will be between 0% and 2% _____
- the rate of deflation (opposite of inflation) will be between 2% and 4% _____
- the rate of deflation (opposite of inflation) will be between 4% and 8% _____
- the rate of deflation (opposite of inflation) will be between 8% and 12% _____
- the rate of deflation (opposite of inflation) will be 12% or more _____
- % Total _____

17. Do you have a paid job?

- Yes

- No
18. In your current job, do you...
Please select all that apply.
- Supervise 1 to 10 other people
 - Supervise 11 to 50 other people
 - Supervise more than 50 other people
 - Make decisions about hiring/firing workers
 - Make decisions about what prices to set
 - Make decisions about capital expenditures
 - Make decisions about wages/salaries
 - Make decisions about marketing or sales
 - None of the above >EXCLUSIVE

ASK IF: Q19=YES

19. How much do you make before taxes and other deductions at your [main/current] job, on an annual basis? Please include any bonuses, overtime pay, tips or commissions.
- _____ dollars per year
- Prefer not to answer

ASK IF: Q19=YES

20. How many total hours per week do you work in a typical week?
_____ Hours/week [RANGE: 0-168, ONE DECIMAL]

ASK IF Q19=YES

RANDOMIZE

21. Please check relevant options that characterize your job:
- I have to come to an office, factory, etc. to perform my work duties
 - I can work remotely from home
 - I travel to meet my clients
 - My job has fixed hours.
 - My hours vary depending on business intensity but the expectation is that I work 20 or 40 hours per week on average.
 - I can work as few or as many hours as I want.
 - My hours are determined by my supervisor.

ASK IF: Q17=NO

22. Are you actively looking for a job? (Select one)
- Yes
 - No

ASK IF: Q17=NO

23. Here are a number of possible reasons why people who are not working choose not to look for work. Please select all that apply to you.
- Homemaker
 - Raising children
 - Student

- Retiree
 - Disabled, health issues
 - Couldn't find a job
 - On break
 - No financial need
 - Other
24. How much higher or lower do you think your household's total after-tax (i.e., 'take home') income will be over the next twelve months compared to the last twelve months? Please provide an answer in percentage terms.
- My after-tax income will rise by _____% [RANGE: 0-300, ONE DECIMAL]
 - My after-tax income will stay the same
 - My after-tax income will fall by _____% [RANGE: 0-300, ONE DECIMAL]
25. What is your best guess about what the current unemployment rate in the US is, what it will be in 12 months and over the next 3-5 years?
- Current unemployment rate: _____% [RANGE: 0-100, ONE DECIMAL]
 - Unemployment rate in 12 months: _____% [RANGE: 0-100, ONE DECIMAL]
 - Over the next 3-5 years? _____% [RANGE: 0-100, ONE DECIMAL]
26. What do you think is the current interest rate on a fixed-rate 30-year mortgage for someone with excellent credit and what do you think it will be in the future?
- Current rate? _____% per year [RANGE: 0-100, ONE DECIMAL]
 - At the end of 2020? _____% per year [RANGE: 0-100, ONE DECIMAL]
 - At the end of 2021? _____% per year [RANGE: 0-100, ONE DECIMAL]
 - In the next 5-10 years? _____% per year [RANGE: 0-100, ONE DECIMAL]
27. Have you seen or heard anything in the news about COVID-19 or the Coronavirus?
- Yes
 - No
 - Don't know
28. How concerned are you about the effects that the coronavirus might have on the financial situation of your household? Slider from 0 (Not at all concerned) to 10 (Extremely concerned)

ASK IF: 17=YES

29. Have you lost earnings due to coronavirus concerns?

- Yes
- No

ASK IF: 29=YES

30. Could you provide an estimate of lost income? (Please round to the nearest dollar)

\$ _____

ASK IF: Q8=YES

31. Have you lost any financial wealth due to coronavirus concerns?
- Yes
 - No

ASK IF: Q31=YES

32. Could you provide an estimate of lost wealth? (Please round to the nearest dollar)
- \$ _____

33. Are you currently under lockdown in your location?
- Yes
 - No

ASK IF Q26=YES

34. How long do you think the lockdown in your location will last?
- Months: _____
- Days: _____

35. How long do you think it will be before conditions return to normal in your location?
- Months: _____
- Days: _____

36. If a person contracts coronavirus, what do you think is the probability that this person recovers from the virus?
Please enter a number between 0 (Do not recover) and 100 (Recover for sure)
- Please enter a number: _____

37. Think of a person who has the coronavirus. How many non-infected people do you think will catch the virus from this person?
- Please enter a number: _____

38. How would you rate the following government bodies in handling the current situation? Please assign a score ranging from 1 (Poor job) to 10 (Excellent job)
- President _____ score [Don't know box]
 - Congress _____ score [Don't know box]
 - US Treasury _____ score [Don't know box]
 - US Federal Reserve _____ score [Don't know box]
 - US Center for Disease Control (CDC) _____ score [Don't know box]

Now we come to the final part of this survey but before you proceed, we would like you to know the following.

Option 1: No information (control group)

Option 2: You indicated that you believe that a person infected with the coronavirus has a [RESPONSE IN QXX]% chance of recovering from the virus.

According to official estimates of the World Health Organization for these rates:

- The recovery rate from the corona virus is approximately 96-97 percent (that is, there is 96-97 in 100 chance to recover).
- Approximately 2 non-infected people will catch the coronavirus from a person who has the coronavirus.

COMBINE OPTIONS A OR B OR C OR D OR E WITH THE OPTION CHOSEN ABOVE. SO PEOPLE SHOULD SEE ONE OF THESE OPTIONS AT RANDOM BEFORE GOING TO Q46; #1.A, #1.B, #1.C, #1.D, #1E, #2.A, #2B, #2C, #2D, #2E.

OPTION 1A SHOULD HAVE QUOTA 10% OF THE TIME, THE REMAINING OPTIONS ARE EQUALLY RANDOMLY DISTRIBUTED OVER THE REMAINING 90% OF RESPONDENTS

Option A. No information is provided.

Option B. In response to the COVID-19 crisis, the Federal Reserve reduced short-term interest rates to zero and implemented additional measures similar to what it did during the last recession.

Option C. In Response to the COVID-19 crisis, the Congress approved a \$2 trillion package to stimulate the economy, including one-time \$1,200 check per person (plus another \$500 per child) to persons households with annual income less than \$75,000. Couples who filed jointly and made less than \$150,000 will get a one-time \$2,400 check (plus another \$500 per child).

Option D. In response to the COVID-19 crisis, the Federal Reserve reduced short-term interest rates to zero and Implemented additional measures similar to what it did during the last recession. In addition, the Congress approved a \$2 trillion package to stimulate the economy, including one-time \$1,200 check per person (plus another \$500 per child) to persons households with annual income less than \$75,000. Couples who filed jointly and made less than \$150,000 will get a one-time \$2,400 check (plus another \$500 per child).

Option E: The U.S. government health officials encourage social distancing, avoiding discretionary travel, and working remotely. At least one in Three in four Americans are in areas with local governments declaring “shelter in place” (lockdown). [<https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html>]

39. What do you think the inflation rate (as measured by the Consumer Price Index) is going to be over the next 12 months? Please provide an answer as a percentage change from current prices.

..... % [RANGE: -100-100, ONE DECIMAL]

If you think there was inflation, please enter a positive number. If you think there was deflation, please enter a negative number. If you think there was neither inflation nor deflation, please enter zero.

40. How much higher or lower do you think **your household’s total net income** will be over the next twelve months compared to the last twelve months? Please provide an answer in percentage terms.

Please provide an answer in percentage terms. If you think that your household’s total net income will decrease, please fill in a negative percentage (insert a minus sign for the number). If you think that your household’s total net income will increase, please fill in a positive percentage. If you think that your household’s total net income will not change, please fill in 0 (zero).

..... % [RANGE: -100-100, ONE DECIMAL]

41. What is your best guess about what the current unemployment rate in the US is, what it will be in 12 months and over the next 3-5 years?

- Current unemployment rate: _____ % [RANGE: 0-100, ONE DECIMAL]

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- Unemployment rate in 12 months: _____% [RANGE: 0-100, ONE DECIMAL]
- Over the next 3-5 years? _____% [RANGE: 0-100, ONE DECIMAL]

ASK IF: QXX=YES

42. What do you think is the percent chance that you will lose your job during the next 12 months?
 _____% [RANGE: -100-100, ONE DECIMAL]

ASK IF: XX=YES

43. What do you think is the percent chance that you will find a job during the next 12 months?
 _____% [RANGE: -100-100, ONE DECIMAL]

44. What do you think is the current interest rate on a fixed-rate 30-year mortgage for someone with excellent credit and what do you think it will be in the future?

- Current rate? _____% per year [RANGE: 0-100, ONE DECIMAL]
- At the end of 2020? _____% per year [RANGE: 0-100, ONE DECIMAL]
- At the end of 2021? _____% per year [RANGE: 0-100, ONE DECIMAL]
- In the next 5-10 years? _____% per year [RANGE: 0-100, ONE DECIMAL]

RANDOMIZE ORDER

45. Generally speaking, do you think that now is a good time or a bad time **to buy**...

A house or apartment	<input type="radio"/> Very good
A car or other vehicle	<input type="radio"/> Good
Large appliances, furniture, electronics (incl. gadgets)	<input type="radio"/> Neither good nor bad
	<input type="radio"/> Bad
	<input type="radio"/> Very bad

ASK IF: Q43AA=YES

46. How much do you trust the actions taken by the Federal Reserve will be helpful for you? And the overall American population? Please choose from 0 (Not helpful at all) to 10 (Extremely helpful)
 Two sliders from 1 to 10

ASK IF: Q43AA=YES

47. How much do you trust the actions taken by the public health officials will be helpful for you? And the overall American population? Please choose from 0 (Not helpful at all) to 10 (Extremely helpful)
 Two sliders from 1 to 10

ASK IF: Q43AA=YES

48. How much do you trust the actions taken by President Trump will be helpful for you? And the overall American population? Please choose from 0 (Not helpful at all) to 10 (Extremely helpful)
 Two sliders from 1 to 10

ASK IF: Q43AA=YES

49. How much do you trust the actions taken by the Congress will be helpful for you? And the overall American population? Please choose from 0 (Not helpful at all) to 10 (Extremely helpful)

Two sliders from 1 to 10

This is the last question.

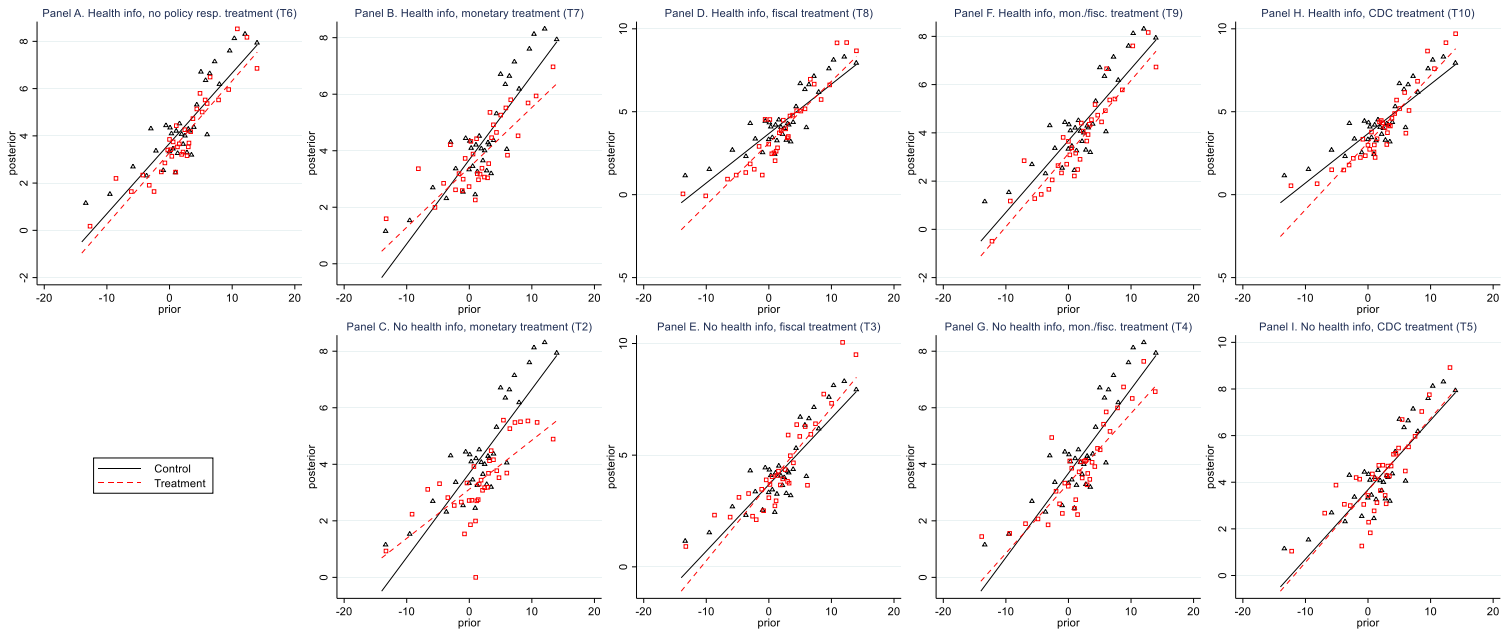
50. If the chance of winning a lottery is 10 percent, how many people out of 1,000 would be expected to win the lottery? Enter a number here _____.

Appendix Table 1. Predictability of treatment status.

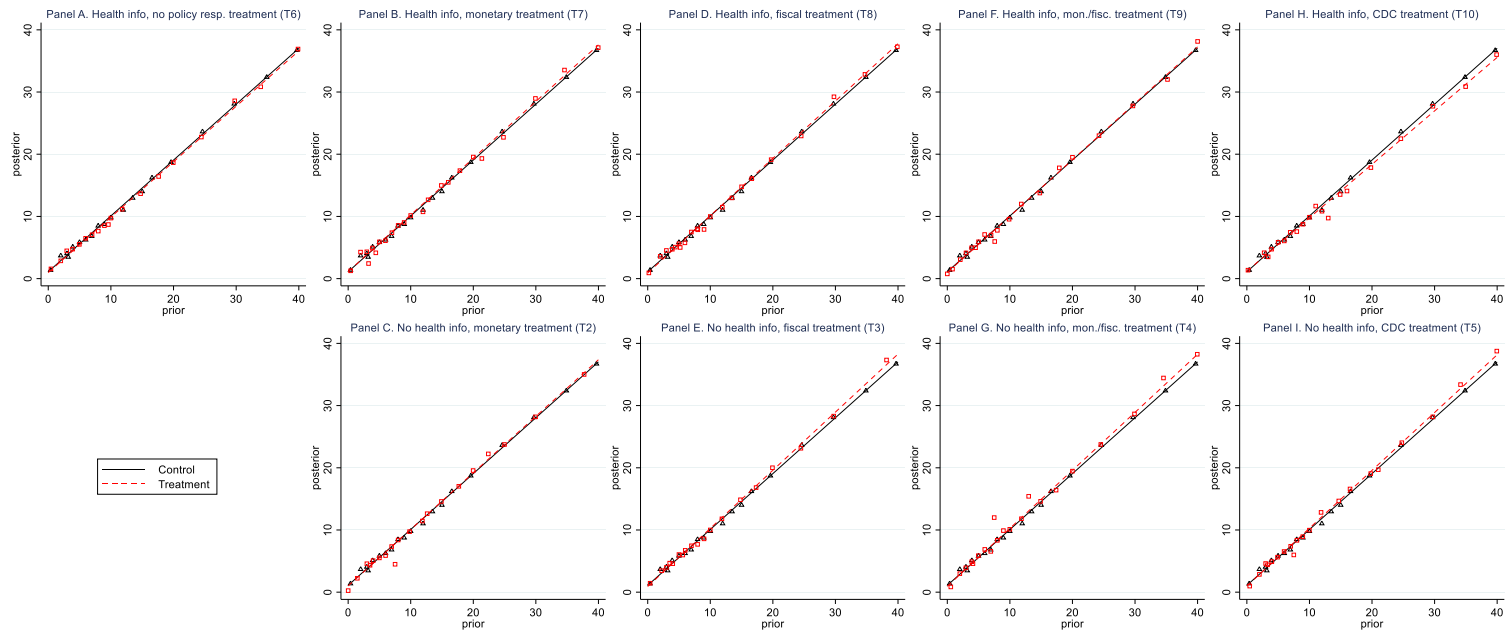
Treatment	F-statistic	p-value
T1 (control)	1.11	0.29
T2	1.08	0.33
T3	1.13	0.26
T4	0.57	0.99
T5	1.51	0.02
T6	1.13	0.26
T7	1.19	0.19
T8	0.81	0.81
T9	0.83	0.76
T10	0.79	0.83

Notes: The table reports results for estimating the following linear-probability regression for each treatment k separately: $Treatment_i^{(k)} = X_i b^{(k)} + error$ where i indexes respondents, $Treatment_i^{(k)}$ is a dummy variable equal to one if household i is provided with treatment k and zero otherwise, X is a vector of household/individual characteristics. Individual characteristics are gender, age, age squared, employed indicator, unemployment indicator, and race. Household characteristics are household income (binned; indicator variable for each bin), household size (indicator variable for each size), census region (indicator variable for each region), male head education (indicator variable for each group), female head education (indicator variable for each group). The table reports F-statistic for the joint statistical significance of b .

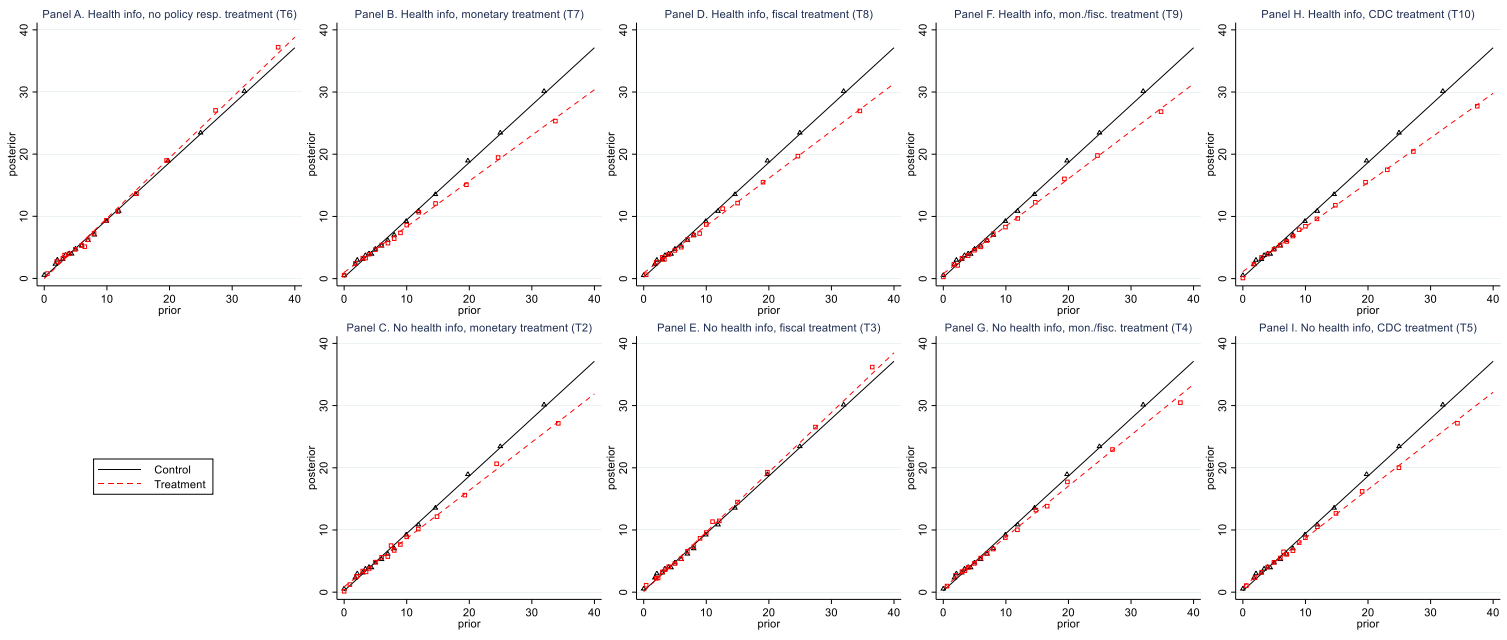
Appendix Figure 1. Treatment effect on inflation expectations by treatment, restrict the sample to have responses [-40,40].



Appendix Figure 2. Treatment effect on unemployment expectations (1-year ahead) by treatment, restrict the sample to have responses [0,40].

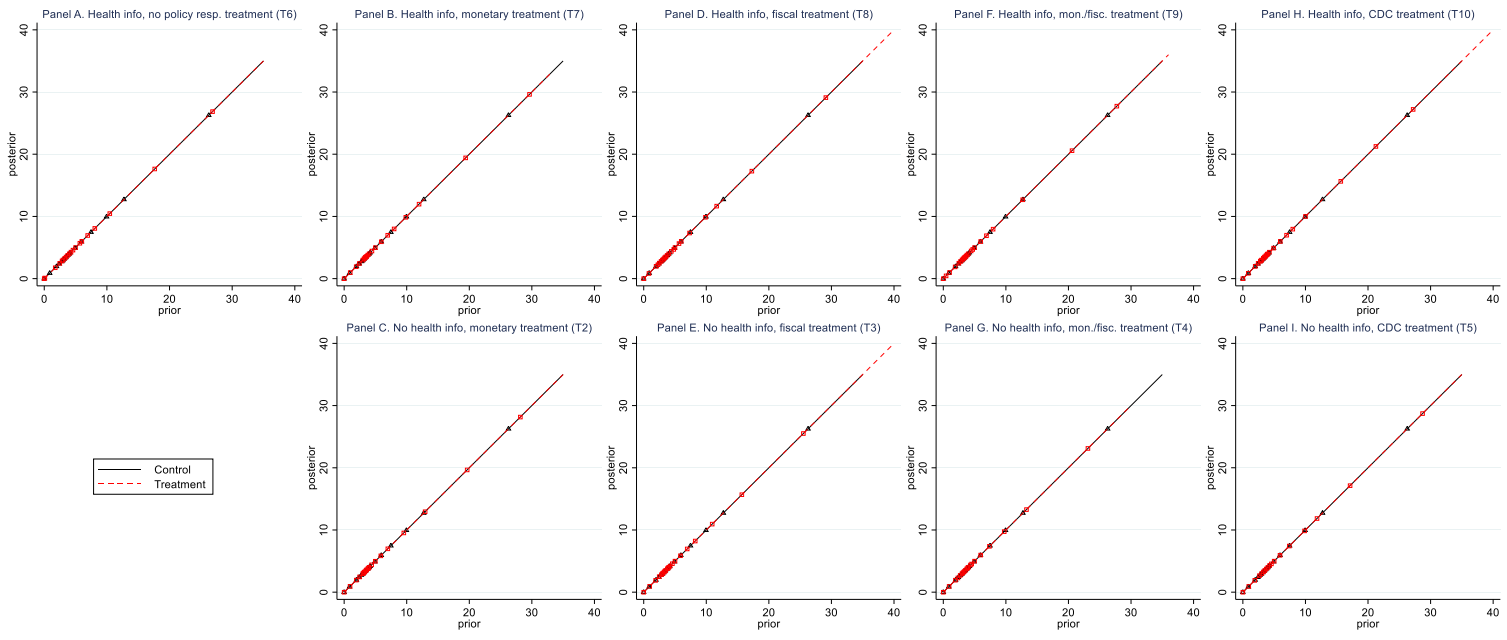


Appendix Figure 3. Treatment effect on unemployment expectations (in 3-5 years) by treatment, restrict the sample to have responses [0,40].



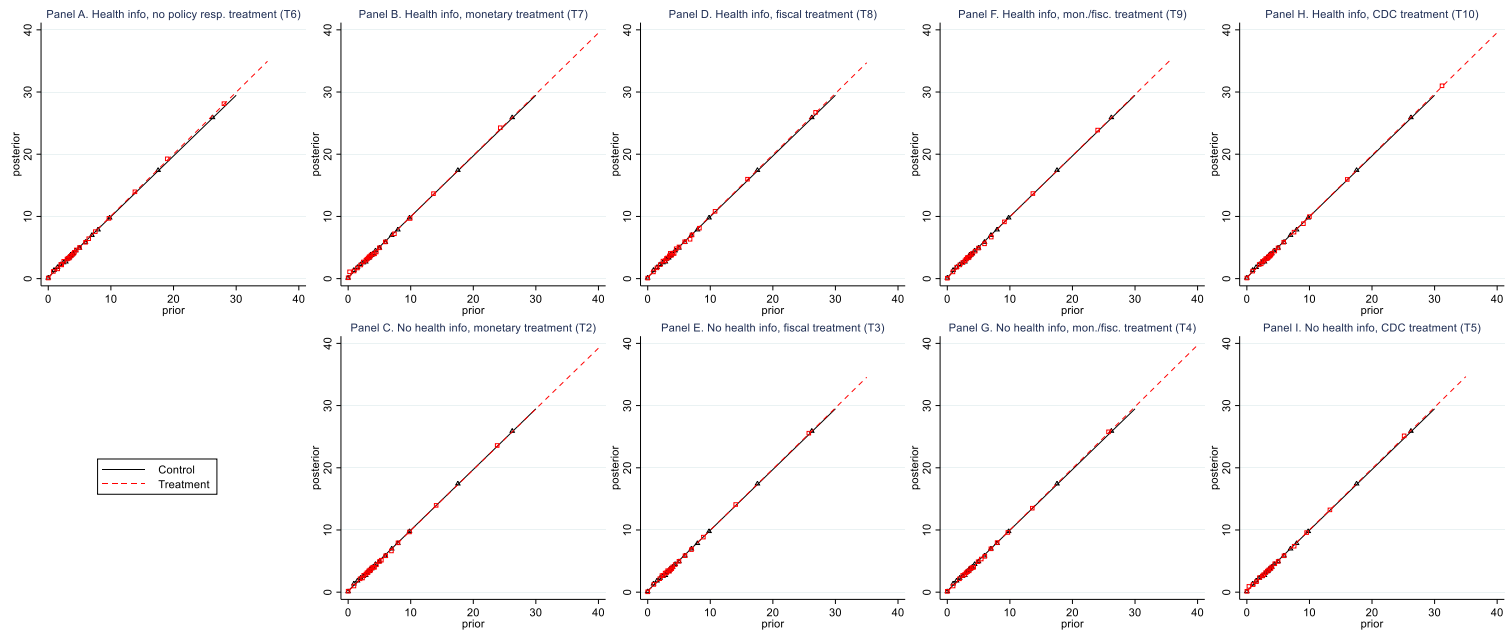
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Appendix Figure 4. Treatment effect on current mortgage rate perceptions by treatment, restrict the sample to have responses [0,40].



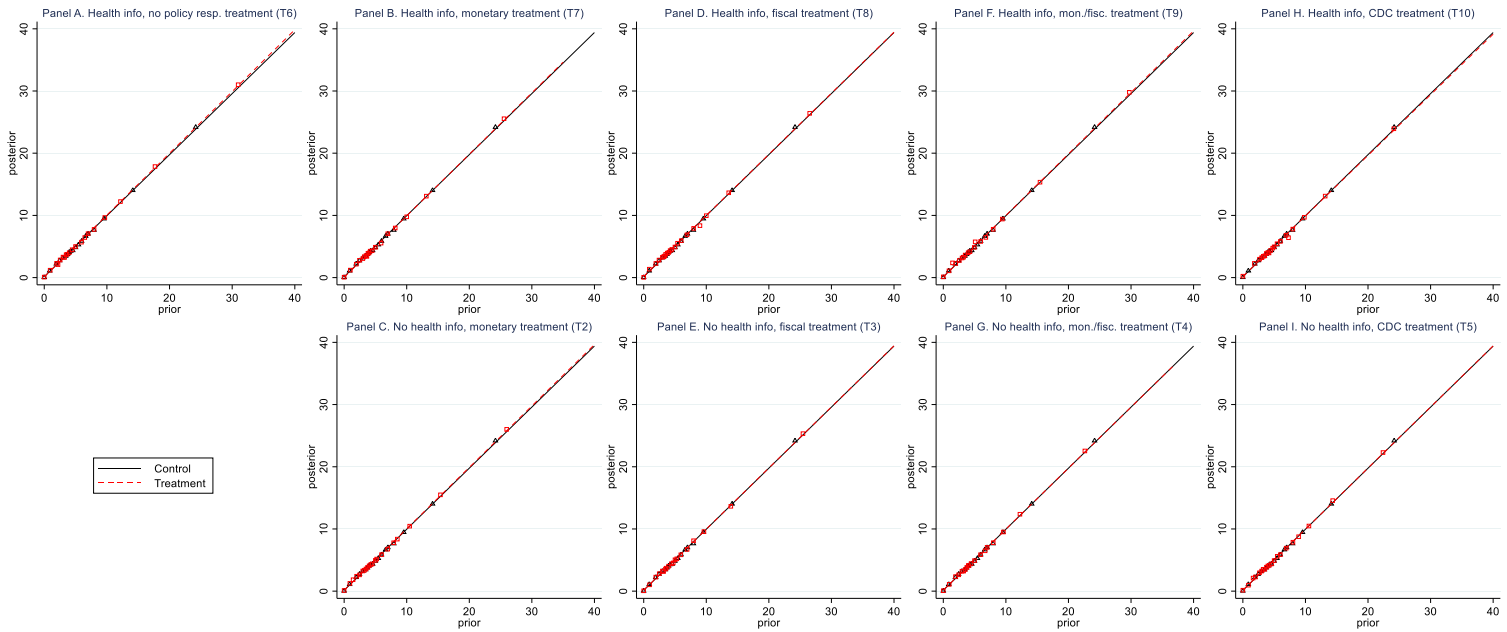
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Appendix Figure 5. Treatment effect on mortgage rate expectations (end of 2020) by treatment, restrict the sample to have responses [0,40].

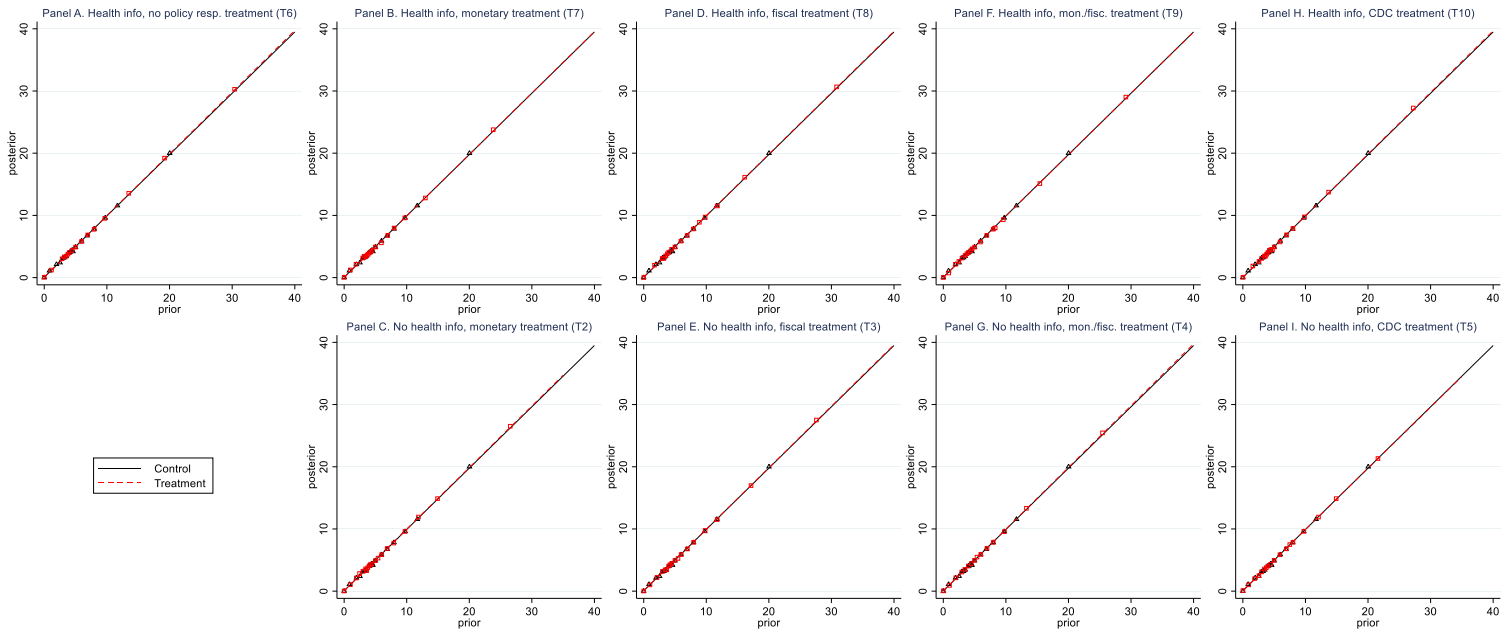


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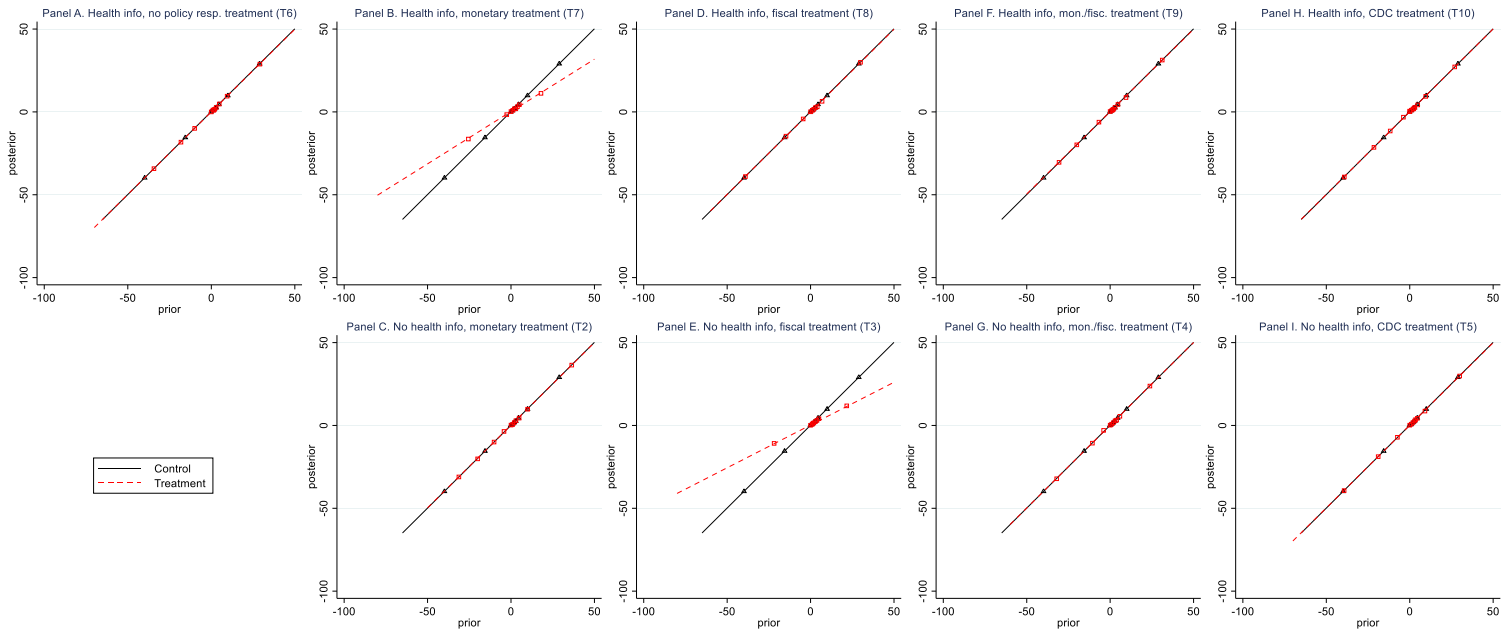
Appendix Figure 6. Treatment effect on mortgage rate expectations (end of 2021) by treatment, restrict the sample to have responses [0,40].



Appendix Figure 7. Treatment effect on mortgage rate expectations (in 5-10 years) by treatment, restrict the sample to have responses [0,40].



Appendix Figure 8. Treatment effect on expectations about household income growth (1 year ahead) by treatment.



Runs and interventions in the time of Covid-19: Evidence from money funds¹

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Liquidity restrictions on investors, like the redemption gates and liquidity fees introduced in the 2016 money market fund (MMF) reform, are meant to improve financial stability during crisis. However, we find evidence that they may have exacerbated the run on prime MMFs during the Covid-19 crisis. Severe outflows from prime MMFs amid frozen short-term funding markets led the Federal Reserve to intervene with the Money Market Mutual Fund Liquidity Facility (MMLF). By providing “liquidity of last resort,” the MMLF successfully stopped the run on prime MMFs and gradually stabilized conditions in short-term funding markets.

1 For their helpful comments, we thank Patrick McCabe and Kairong Xiao. We also thank Maher Latif and Frank Ye for excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Board of Governors or the Federal Reserve System.

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1 Introduction

In the aftermath of the 2007-09 financial crisis, financial regulators worldwide introduced a new wave of regulations aimed at promoting financial stability. Various liquidity regulations were designed to make financial institutions capable of withstanding funding stress without the need for emergency interventions. As the financial crisis revealed the fragility of money market funds (MMFs), the Securities and Exchange Commission (SEC) introduced a set of reforms to enhance the stability of the MMF industry. In particular, the 2016 MMF reform introduced new liquidity rules for prime MMFs, which can invest in relatively risky securities, such as commercial paper (CP) and negotiable certificates of deposit (CDs). The reform allows prime funds to impose redemption gates and liquidity fees on their investors when their liquidity buffer (namely weekly liquid assets (WLA), meaning assets that could be converted into cash within a week) falls below 30% of total assets.

The intention of such reforms is to endow MMFs with tools to stem investor runs on their own. Their proponents, including then-SEC Chair Mary Jo White, argued that redemption gates and liquidity fees would “mitigate [the run] risk and the potential impact for investors and markets.”¹ However, the possibility that MMFs may impose gates and fees when their liquidity buffer falls below a certain threshold could incentivize investors to run *preemptively* before such gates and fees are imposed. In a public statement released by the SEC on July 23, 2014, SEC Commissioner Kara Stein questioned whether gates and fees are the right tool to address run risk. She noted that allowing funds to impose gates and fees “could actually increase an investor’s incentive to redeem,” especially in a crisis.²

In this paper, we study the anatomy of the run on prime MMFs that occurred during the Covid-19 crisis under the new regulation that allows for the imposition of liquidity

¹For details, see <https://www.sec.gov/news/public-statement/2014-07-23-open-meeting-statement-mjw>.

²For details, see <https://www.sec.gov/news/public-statement/2014-07-23-open-meeting-statement-kms>.

restrictions. Equally importantly, we document the factors that led to the resolution of the run. We find that the possibility of imposing gates and fees may have exacerbated the run on prime MMFs (especially the less liquid ones) in March 2020. Unlike in the 2008 financial crisis and the 2011 Eurozone sovereign debt crisis, prime MMF outflows in the Covid-19 crisis were significantly related to WLAs, especially with WLAs approaching the regulatory threshold. We find that Federal Reserve emergency interventions were effective in stemming outflows from MMFs and stabilizing short-term funding markets. Our findings are consistent with the financial intermediation view of the lender of last resort (Moulton, 1918; Tucker, 2014), which holds that the lender of last resort enables financial institutions to resume the supply credit to the ultimate borrowers.

In mid-February, with increasing Covid-19 cases in the U.S. and Europe, stock prices started to plunge, accompanied by widening yield spreads on corporate bonds (panel (a) in Figure 1). By mid-March, yield spreads on various short-term funding securities, including CP and CDs, had surged to levels last seen during the 2008 financial crisis (panel (b) in Figure 1). Amid the broad risk-off sentiment, investors started to run on prime MMFs, which are major investors in the CP and CD markets. The run was concentrated among institutional investors (panel (a) in Figure 2), as they are more risk sensitive than retail investors (Gallagher et al., 2020). Within two weeks from March 9, \$96 billion (about 30% of assets under management) were withdrawn from institutional prime MMFs.

Institutional investors ran more intensely on funds with lower liquidity (Panel (b) of Figure 2). Although net flows were similar across funds with different levels of WLAs prior to mid-March, lower WLA funds experienced substantially larger outflows between mid-March and the Federal Reserve interventions. To understand whether the new rules about gates and fees have contributed to some of the outflows, we compare the run during the Covid-19 crisis to the previous two prominent MMF runs, namely the run surrounding the September 2008 Lehman bankruptcy (Duygan-Bump et al., 2013; Kacperczyk and Schnabl, 2013; Schmidt, Timmermann and Wermers, 2016) and the Eurozone sovereign

debt crisis run in the summer of 2011 (Chernenko and Sunderam, 2014; Gallagher et al., 2020). The Covid-19 and the 2008 runs are especially similar in terms of speed and intensity, with institutional prime funds losing more than 30% of assets in about 20 days (Figure 3), while the 2011 run was relatively milder and more gradual. We find that investors ran substantially more from funds with lower liquid holdings (i.e., WLA) during the 2020 crisis relative to the previous two crises. Specifically, while a 10 percentage points decrease in WLA is associated with an increase in daily outflows by merely 0.1 percentage point during the 2008 crisis, it is associated with a 1 percentage point increase in daily outflow during the Covid-19 crisis (ten times the 2008 effect). Further, funds with WLA close to the 30% regulatory threshold suffered incrementally more outflows in 2020 but not in the previous two crises. The nonlinearity of run as WLA approaches 30% during the 2020 crisis suggests an acceleration of run when investors are concerned about the potential imposition of gates and fees.³

The run on MMFs led them to hoard liquidity and refrain from investing in instruments with maturities greater than one week, putting further pressure on the already strained CP and CD markets. In response to the precarious conditions in money markets, the Federal Reserve announced in the late evening of March 18 the plan to launch the Money Market Mutual Fund Liquidity Facility (MMLF) to support MMFs and related markets. The MMLF enabled MMFs to liquidate some of their assets to meet redemptions and increased their confidence in investing in longer-tenor securities.⁴ Within one week of operations, over \$50 billion of MMF assets were sold under the MMLF.

We document a significant calming effect of the MMLF on prime MMF runs. In particular, institutional prime funds daily flows rebounded by 2.2 percentage points on average during the two weeks following the launch of MMLF. Moreover, funds with lower

³The 2016 MMF reform also required institutional prime MMFs to transact at a floating net asset value (NAV). However, we do not find evidence that lower floating NAVs drive additional outflows during the Covid-19 crisis (see Appendix Table A.2). While funds' floating NAVs saw some declines during the crisis, they were never near the "breaking the buck" threshold. In contrast, some funds' WLA fell below 30% during the crisis.

⁴Under the MMLF, banks could purchase high-quality CP and CDs from MMFs and pledge those assets at the MMLF as collateral in exchange for a cash loan for the whole life of the security. Economically, this is similar to banks selling the assets that they bought from MMFs to the Fed.

WLA experienced a stronger rebound in flows after the launch of the MMLF, suggesting that the facility is especially beneficial to funds with lower WLA.

One potential complication in evaluating the MMLF impact is that a number of liquidity and credit facilities were created by the Federal Reserve around the time of the implementation of the MMLF. Some of these facilities could potentially help stabilize prime MMF flows by improving liquidity conditions in the CP and CD markets. To address the concern that the stabilization of prime MMF flows is attributed to the improvements in CP and CD market conditions rather than the MMLF, we design two difference-in-difference tests to identify the incremental effect of the MMLF relative to other interventions. First, we exploit the presence of similar but MMLF-ineligible MMFs, namely offshore USD prime MMFs that invest in exactly the same pool of assets (including CP and CDs) and experienced similar runs (about 25% of AUMs) as institutional prime funds did prior to the launch of the MMLF. If the stabilization of institutional prime fund flows during the post-MMLF period was mainly due to improvements in the liquidity conditions in the CP and CD markets, we should observe a similar rebound in fund flows for offshore USD prime MMFs. Our results show that MMLF-eligible prime MMFs had much quicker and larger rebound in their flows following the implementation of the MMLF relative to the MMLF-ineligible offshore funds. Second, as the MMLF directly benefits MMFs with more MMLF-eligible assets prior to the launch of the MMLF, we use the security-level holdings of MMFs from their N-MFP filings at the end of February 2020 and test whether the recovery in fund flows was stronger for funds that held more MMLF-eligible assets. Our results show that this is indeed the case. In addition, we find that most of the flow-stabilizing effects of the MMLF come from MMFs' ability to pledge longer-tenor assets, namely CDs.

Liquidity conditions in the CP and CD markets also started to improve following the launch of the MMLF. As some other credit and liquidity facilities that are directly targeted at improving short-term funding market conditions were also announced/implemented around similar times, we develop various strategies to identify the MMLF impact. Specif-

ically, we exploit the differential eligibility requirements on credit ratings to evaluate the MMLF impact. Only instruments with the highest ratings are eligible under the MMLF, while other facilities accept those with lower ratings. Consistent with the MMLF impact, we find that the improvements in liquidity conditions were concentrated among top rated instruments. In addition, we show that instruments that were more heavily held by prime MMFs before the crisis experienced larger reduction in yield spreads and greater issuance volume during the post-MMLF period. Finally, given the pricing terms of the MMLF, only securities with yields greater than 125 basis points (bps) were economical for banks to pledge at the facility. We confirm in our tests that our results indeed come from securities with yields greater than 125 bps.

Our paper lies at the intersection of a few literatures. Several papers document the run on money funds in 2008, the role of sponsor support, franchise value, and informed institutional investors (McCabe, 2010; Kacperczyk and Schnabl, 2013; Schmidt, Timmermann and Wermers, 2016), as well as how money funds depleted liquidity to accommodate redemptions (Strahan and Tanyeri, 2015). The effects of the run on prime funds in 2011 are documented by Chernenko and Sunderam (2014), Ivashina, Scharfstein and Stein (2015), and Gallagher et al. (2020). Relatedly, Kacperczyk and Schnabl (2010); Covitz, Liang and Suarez (2013); Pérignon, Thesmar and Vuillemeys (2017); Gorton and Metrick (2012); Copeland, Martin and Walker (2014) document the funding freeze in asset-backed commercial paper (ABCP), CDs, and repurchase agreements in 2008. We contribute to the MMF run literature by identifying a new run pattern driven by investors' heightened sensitivity to fund liquidity, which suggests that the potential imposition of liquidity restrictions can be especially destabilizing during a crisis.

A number of papers study the effectiveness of Federal Reserve emergency lending during the 2007-09 crisis (Armantier et al., 2015; Acharya et al., 2017; Carlson and Macchiavelli, 2020). In particular, Duygan-Bump et al. (2013) study the effects of the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF) on stemming the run on money funds and normalizing ABCP yield spreads. Echoing

Duygan-Bump et al. (2013), we show the effectiveness of the MMLF in stabilizing money fund flows and bringing down CP and CD yield spreads. In addition, we show that market condition improvements are not only in lowering spreads but also in restoring issuance, and that such improvements occurred specifically for the instruments more heavily held by prime MMFs.

We also contribute to the literature on the post-2008 liquidity regulations. Macchiavelli and Pettit (2018), Roberts, Sarkar and Shachar (2018), and Xiao and Sundaresan (2020) study the impact of the liquidity coverage ratio (LCR) on maturity and liquidity transformation by broker-dealers and commercial banks. On the topic of MMF reforms, Hanson, Scharfstein and Sunderam (2015) evaluate various reform proposals and recommend to require MMFs to hold capital buffers. Notably, they also argue that redemption gates could potentially exacerbate runs on MMFs. In a theoretical framework, Cipriani et al. (2014) discuss the possibility that the introduction of redemption gates and liquidity fees may trigger preemptive runs.⁵ Baghai, Giannetti and Jäger (2018); Cipriani and La Spada (forthcoming) study the effects of the 2016 MMF reform on the premium paid by investors to maintain moneyness and on the risk-taking of the surviving prime funds. To the best of our knowledge, our paper is the first empirical study that documents the effect of the 2016 MMF reform (specifically gates and fees) on MMFs during a crisis.

Lastly, we contribute to the literature on CP and CD markets. Covitz and Downing (2007) show that both liquidity and credit risks are important determinants of CP yield spreads. Kahl, Shivdasani and Wang (2015) document that CP is an important source of short-term funding for nonfinancial firms, with the benefit of low transaction costs but carrying substantial rollover risk. Kacperczyk, Perignon and Vuillemeys (2017) study prices and issuance of CDs in Europe and find that CD issuance is sensitive to the information environment. In this paper, we show that interventions to stabilize MMFs can quickly restore the functioning of CP and CD markets.

⁵Relatedly, Ma (2015) has a structural model of repo runs and compares the implications of safe harbor and automatic stay.

2 Background

In this section we briefly describe money market funds and discuss the two MMF reforms of 2010 and 2016. We then provide some background on the MMLF and review the events in money markets surrounding the Covid-19 crisis.

2.1 Money Market Funds

Money market funds raise cash from both retail and institutional investors by issuing shares that can be redeemed on demand. Money fund managers then invest the pool of cash in a set of eligible assets. Since investors can withdraw on demand, MMFs typically hold a diversified portfolio composed of short-term high-quality debt instruments. There are three broad categories of MMFs, each facing some restrictions on the types of securities they can hold. Government funds invest in government debt (Treasury and agency debt) and repos backed by government debt. Tax-exempt funds invest in municipal and state debt. Finally, prime funds mainly invest in short-term high-quality private debt, including time deposits, CP, and CDs, as well as repos backed by government and private collateral. At the end of April 2020, the money fund industry managed around \$5 trillion in assets.

MMFs are an important source of short-term funding for governments, corporations, and banks (Hanson, Scharfstein and Sunderam, 2015) and, as part of the shadow banking system, play a notable role in the monetary policy transmission (Gorton and Metrick, 2010; Xiao, 2020). The resilience of the MMF industry has profound implications for the stability of the financial system. Against the backdrop of the 2007-09 financial crisis, which saw a prime fund “breaking the buck” due to its exposure to Lehman and a subsequent large-scale run on prime funds (McCabe, 2010; Kacperczyk and Schnabl, 2013), the SEC introduced two reforms. The first reform, implemented in 2010, required MMFs to hold a minimum amount of liquidity, limited the maturity of their portfolios, and enhanced the public disclosure of their holdings. One of the key requirements is that MMFs hold at least 30% of their assets in weekly liquid assets (WLA), namely cash,

Treasuries, certain agency notes that mature within 60 days, and assets that convert into cash (mature) within one week.⁶

The second reform, announced in 2014 and implemented in October 2016, primarily aims at making MMFs less prone to runs. It introduces two main changes. First, it requires non-government (i.e., prime and tax-exempt) funds catering to institutional investors to transact at a floating net asset value (NAV), which means that investors withdrawing their money may not receive \$1 per share, as they do under a stable NAV. Instead, they would redeem shares based on the market value of the fund portfolio. Second, the reform allows non-government funds to impose redemption gates and fees when the fund's liquidity is lower than a threshold. Specifically, if a non-government MMF's WLA falls below 30 percent of its total assets, it would be allowed to suspend redemptions for up to 10 business days in any 90-day period, and/or impose a liquidity fee of up to two percent on all redemptions.

Compared to floating NAV, gates and fees were deemed more controversial. For example, Commissioner Kara Stein noted in a public statement that “as the chance that a gate will be imposed increases, investors will have a strong incentive to rush to redeem ahead of others to avoid the uncertainty of losing access to their capital.” She further noted that “run in one fund could incite a system-wide run because investors in other funds likely will fear that they also will impose gates.” Amid such controversy, the SEC approved the 2016 reform on MMFs with a small margin, as two out of the five commissioners voted against it. In Section 4 we empirically examine whether such preemptive runs on MMFs described by Commissioner Stein occurred during the Covid-19 crisis.

⁶Prior to the 2010 MMF reform, there were no minimum liquidity requirement for money funds. The 2010 reform changed that, mandating that a minimum percentage of assets be highly liquid securities. Specifically, the SEC required that all prime MMFs must have at least 10 percent of assets in cash, U.S. Treasury securities, or securities that convert into cash within one day (the “daily liquidity” requirement), and at least 30 percent of weekly liquid assets. The reform also shortened the average maturity limits for MMFs. It restricted the maximum “weighted average life” (WAL) of a fund's portfolio from unlimited to 120 days and reduced the maximum weighted average maturity (WAM) of a fund's portfolio from 90 to 60 days.

2.2 The Money Market Mutual Fund Liquidity Facility (MMLF)

As the severity of the pandemic started to stress short-term funding markets in early March, investors began to withdraw from prime MMFs. The latter were faced with the arduous task to accommodate outflows while maintaining sizable liquidity buffers. They tried to achieve this by selling longer-term CP and CDs, but the secondary market for CP and CDs was essentially frozen. As a result, many prime funds saw their WLAs decline, some close to or even below the 30% minimum requirement. In order to preserve liquidity, prime funds stopped lending at tenors greater than one week, transmitting illiquidity to CP and CD issuers, in a downward liquidity spiral.

To restore liquidity in short-term funding markets and stabilize the MMF industry, the Federal Reserve announced the establishment of the Money Market Mutual Fund Liquidity Facility (MMLF) on March 18.⁷ The MMLF was created under the authority granted by Section 13(3) of the Federal Reserve Act, which allows the Federal Reserve to establish facilities with broad-based eligibility to lend to any market participant in case of “unusual and exigent circumstances”. Operated by the Federal Reserve Bank of Boston, the facility provided nonrecourse loans to banks for them to purchase certain high-quality assets from MMFs. The banks would then pledge the assets as collateral for the loans. Economically, pledging assets to the MMLF is similar to selling the assets to the Federal Reserve.⁸ The MMLF began operations on March 23.

Initially, MMLF-eligible assets included CP as well as government securities. The list of eligible assets was then expanded in two occasions: on March 20 to include short-term municipal debt and on March 23 to include CDs and variable-rate demand notes.⁹ The MMLF loans are priced at a fixed spread over the Primary Credit Rate (PCR, or discount

⁷For a complete timeline of the Federal Reserve interventions during the Covid-19 Crisis, see Appendix Table A.1.

⁸The principal amount of the MMLF loan is equal to the value of the collateral. The MMLF loan is made without recourse to the borrower and has the same maturity date as the collateral. In addition, on March 19, 2020, U.S. banking regulators issued a rule that effectively neutralizes the effect of asset purchases under the MMLF on banks' capital ratios.

⁹Variable-rate demand notes (VRDNs) are variable-rate notes issued by municipalities with 1-day or 7-day demand features. Tax-exempt MMFs are major investors of VRDNs.

rate), depending on the type of the collateral. For example, loans secured by CP and CDs are priced at PCR plus 100 bps.

Due to the large demand for MMLF liquidity, banks quickly set up their operation and started to purchase assets from prime MMFs as soon as the facility went into operation. The Federal Reserve's H.4.1 data shows that MMLF loans outstanding spiked to \$30.6 billion on March 25 in just two days of operations, climbed to \$52.7 billion on April 1, and reached \$53.2 billion on April 7.¹⁰

3 Data

Our dataset is compiled from multiple sources. First, we obtain share-class level MMF information from iMoneyNet. The iMoneyNet data include three files with various information reported at different frequencies. For both domestic MMFs (i.e., 2a-7 funds defined by the SEC) and offshore U.S. Dollar MMFs, we obtain assets under management (AUMs) from the daily file, and weekly liquid assets (WLA), weighted average maturity (WAM), expense ratios, investor type (institutional or retail), as well as funds' portfolio compositions from the weekly file.¹¹ Finally, additional information, such as whether a fund is affiliated with a bank, and a fund's inception time, is retrieved from the monthly file for domestic funds.

Second, the micro-level confidential CP and CD data are obtained from the Depository Trust & Clearing Corporation (DTCC). The DTCC data include both transaction level data for each trade in CP and CDs and daily total par amount outstanding for each instrument. The transaction data provide detailed information for each primary market trade, including CUSIP, transaction date, maturity date, yield, and quantity. For CP, the data also include ratings assigned by both Moody's and S&P. We rely on the DTCC

¹⁰As the runs on prime funds subsided, so did new usage at the facility. Indeed, as fewer new loans were originated while some were already maturing, MMLF loans outstanding started to decline, with \$50.7 billion outstanding on April 15 and \$48.8 billion on April 22.

¹¹In some additional analyses, we use fund floating NAVs, which were also obtained from the daily files.

data to evaluate the impact of the MMLF on the CP and the CD markets.

Finally, we complement the iMoneyNet and DTCC data with MMFs' security-level holding data from their N-MFP filings to the SEC. Each 2a-7 MMF is required to report its portfolio holdings as of every month-end in the N-MFP Form. For each security in their portfolios, MMFs report its CUSIP, asset type, amortized cost, market value, yield, and maturity among other characteristics. By merging iMoneyNet and N-MFP data based on the funds' SEC filing IDs, we are able to analyze whether funds with more MMLF-eligible assets benefited more from the MMLF. The N-MFP data also allows us to examine whether the MMLF had a larger effect on CP and CDs more heavily held by MMFs.

4 Runs on prime MMFs: what is new this time?

From late February to early March, as equity and bond markets went into a tailspin, stress in short-term funding markets also mounted and prime MMFs saw large redemptions from their institutional investors in mid-March (Figures 1 and 2).

Prime MMFs have two ways to raise cash to meet investor redemptions. The first option is to tap into their liquid assets that are readily convertible into cash, and the second option is to sell longer-term holdings, such as CP and CDs. Both options were quite limited at that time. As prime MMFs are required to hold a minimum liquidity buffer (i.e., WLA) of 30% of their assets, depleting liquidity buffers to accommodate redemptions may accelerate investors' runs from the funds, fearing an imminent imposition of redemption gates and liquidity fees. At the same time, the secondary markets for CP and CDs were essentially frozen, as CP and CD dealers, who act as intermediaries and often do not take one-sided bets, had difficulty finding third parties interested in buying those securities.¹² As the flight to liquidity emerged, the frozen short-term funding markets in turn triggered even larger redemptions from MMF investors.

¹²It is worth noting that the secondary markets for CP and CDs depend on dealer intermediation and are very illiquid even in normal times.

4.1 Empirical design and summary statistics

To gauge the magnitude of MMF runs during the Covid-19 crisis and to explore whether the 2016 MMF reform changed the nature of these runs, in this section we compare the Covid-19 run with the previous two prominent MMF runs: the financial crisis run in September 2008 and the Eurozone sovereign debt crisis run in the summer of 2011. While the exact triggers of the three runs on prime MMFs differ, they share some common features. They all start with increasing concerns about credit quality and liquidity of the assets held by prime funds and quickly spiral into widespread runs. It is worth noting that investors could run on a MMF for liquidity reasons even though the MMF has extremely low exposures to credit risk, and that illiquidity can spread quickly from one short-term funding market to another as their common lenders (MMFs) scramble for liquidity.

One crucial difference between the Covid-19 run and the 2008 and 2011 ones is that institutional investors of prime MMFs were not subject to contingent liquidity restrictions (redemption gates and liquidity fees) in either 2008 or 2011. We analyze how the liquidity restrictions introduced by the 2016 MMF reform affected investor behavior during the Covid-19 crisis. In particular, we aim to understand whether the potential imposition of gates and fees exacerbated the run on less liquid prime MMFs.

We focus on institutional prime funds for our tests.¹³ As shown in Figure 3, the 2008 and 2020 runs are remarkably similar in their outflow patterns and magnitude. They both spanned a period of about 20 days, over which they both saw outflows of more than 30% of fund AUMs. On the other hand, the 2011 run on prime funds during the Eurozone sovereign debt crisis was milder but lasted longer, resulting in a 17% decline in AUMs over a 50-day horizon. Specifically, we define “crisis” periods as: September 10–30 in 2008, June 10–August 1 in 2011 and March 6–24 in 2020. The month before the “crisis” period is defined as the “normal” period.

Table 1 presents summary statistics for the three MMF runs. During the “normal”

¹³For funds with both institutional and retail share classes, which are more common in 2008 and 2011, we strip away the retail share classes from these funds.

periods before large redemptions begin, fund size is comparable across the three events, with \$9 billion for an average institutional prime MMF, and funds on average experience little fluctuations in their AUMs. However, during the “crisis” periods, funds experience significant daily redemptions of 1.3%, 0.3%, and 2.4% of their assets in 2008, 2011, and 2020, respectively. Compared to the two previous episodes, prime funds hold substantially higher WLAs in 2020.¹⁴ In particular, only 3% of institutional prime funds have their WLAs below 35% in 2020 during the “normal” period, while 72% (44%) of such funds have WLAs lower than 35% in 2008 (2011). These findings suggest that institutional prime MMFs hold larger liquidity buffers in the post 2016-reform era.

4.2 Regression results

To assess whether the introduction of contingent liquidity restrictions changed the nature of investor runs on prime funds, we run a set of regressions that compare the flow sensitivity to WLA during the 2020 run to that during the 2008 and 2011 runs. For each run, we construct a subsample that includes both the “crisis” period and a one-month “normal” period right before the crisis. We then estimate the following regression separately for each subsample:

$$Flow_{i,t} = \beta_1 Crisis_t + \beta_2 WLA_{i,t-1} + \beta_3 Crisis_t \times WLA_{i,t-1} \\ (+\beta_4 \mathbb{1}(WLA < 35) + \beta_5 Crisis_t \times \mathbb{1}(WLA < 35)) + Controls_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $Flow_{i,t}$ is the daily percentage change in the AUM of fund i . $WLA_{i,t-1}$ (in percentage) is the share of weekly liquid assets to total assets of fund i on the previous Tuesday and $\mathbb{1}(WLA < 35)$ equals one if $WLA_{i,t-1}$ is below 35%.¹⁵ $Crisis_t$ equals one during each of the crisis periods: September 10–30 in 2008, June 10–August 1 in 2011 and March

¹⁴The definition of WLA in 2008 (i.e., before the 2010 MMF reform) is slightly different from those in 2011 and 2020, as it doesn't include Treasury securities and certain agency debt. However, prime funds' holdings of such government assets are very small.

¹⁵Flows are winsorized at the 1% and 99% levels, but alternative winsorizations or none at all yield very similar results. WLA comes from the weekly iMoneyNet data which is reported every Tuesday.

Table 1: **Summary Statistics – MMF Runs**

This table reports summary statistics of the main variables in use across the three MMF run crises. The numbers reported are averages within each of the subsamples. The 2008 Financial Crisis sample goes from Aug 4, 2008 to Sep 30, 2008, with Crisis from Sep 10 to Sep 30; the 2011 Eurozone Crisis from May 3, 2011 to Aug 1, 2011, with Crisis from Jun 10 to Aug 1; the Covid-19 Crisis from Feb 4, 2020 to Mar 24, 2020, with Crisis from Mar 6 to March 24. Normal refers to the time period before Crisis in each subsample. WLA represents weekly liquid assets as a percentage of total AUMs, and WAM is weighted average maturity. Bank Affiliated is a dummy for money funds affiliated with banks. Safe holdings include Treasury and agency debt, as shares of fund AUM. Risky holdings include unsecured CP, ABCP, and CDs.

	2008 Run		2011 Run		2020 Run	
	Normal	Crisis	Normal	Crisis	Normal	Crisis
Fund AUM (million \$)	9255.33	7467.82	9462.69	8865.48	9300.46	8038.34
Daily Flow (million \$)	11.36	-203.92	7.40	-45.38	4.18	-222.85
Daily % Flow	0.05	-1.28	0.04	-0.25	-0.04	-2.38
WLA (%)	30.87	30.72	40.01	42.72	43.14	41.69
$\mathbb{1}(WLA < 35)$	0.72	0.70	0.44	0.40	0.03	0.13
WAM(days)	43.24	42.94	40.17	37.40	30.32	34.97
Gross Yield (%)	2.65	2.73	0.26	0.23	1.82	1.58
Expense Ratio (%)	0.29	0.30	0.19	0.18	0.18	0.18
Bank Affiliated	0.48	0.49	0.55	0.46	0.46	0.46
Age (years)	11.82	12.11	14.77	14.93	18.90	18.93
Safe Holding	0.09	0.09	0.10	0.10	0.02	0.02
Risky Holding	0.59	0.59	0.53	0.52	0.54	0.54

6–24 in 2020. We control for a battery of lagged fund characteristics: $\log(\text{Fund AUM})$, weighted average maturity, abnormal gross yield (in excess of the cross-sectional mean), expense ratio, bank affiliation, fund age, safe holdings (Treasury and agency debt), and risky holdings (CP and CDs). The coefficients of interest are the ones on the interaction between $Crisis_t$ and $WLA_{i,t-1}$, which measures the additional sensitivity of flows to WLA during the crisis, as well as on the interaction between $Crisis_t$ and $\mathbb{1}(WLA < 35)$, which measures the additional daily outflows during the crisis when WLA falls below 35%. In all specifications, standard errors are two-way clustered at the fund and day levels.

Table 2 reports the results, with Columns (1)–(3), (4)–(6), and (7)–(9) displaying those for the 2008, 2011, and 2020 runs, respectively. As shown in Column (7), in the 2020 sample, although fund flows are only weakly and negatively related to WLA in normal times, their relation becomes positive and significant during the crisis. This finding suggests that funds with lower WLAs experienced stronger outflows during the Covid-19 run. A decrease by 10 percentage points in WLA is associated with an increase in daily outflows by 1 percentage point during the 2020 crisis. Considering that institutional prime MMFs experienced on average daily outflows of about 2.4% during the 2020 crisis, a one standard deviation decline in WLA (equal to 8% in 2020) explains 27% of the average daily outflow. By comparison, the relation between WLA and fund flows was ten times weaker during the 2008 run, and not even significant for the 2011 episode, as shown in Columns (1) and (4), respectively.

Table 2: MMF Liquidity and Runs: by Crisis

The three separate samples consist of institutional prime MMFs during three time periods: the Covid-19 crisis (Feb 04 to March 24); the 2011 Eurozone sovereign debt crisis (May 03 to Aug 01); and the 2008 financial crisis (Aug 04 to Sep 30). Flow is the daily percentage change in assets under management, winsorized at the 1% and 99% levels. WLA is the lagged share of weekly liquid assets to total assets and $\mathbb{1}(WLA < 35)$ equals one if WLA is below 35%. Crisis equals one from Sep 10 to Sep 30 in 2008, from Jun 10 to Aug 1 in 2011, and from Mar 6 to Mar 24 in 2020. Controls (lagged) include: log(Fund AUM), WAM, Abnormal Gross Yield (in excess of average gross yield), Expense Ratio, Bank Affiliation, Age, Safe Holding, and Risky Holding. Results are robust to not including these controls. Standard errors (in parentheses) are two-way clustered at the fund and day levels.

	Dependent Variable: Daily Percentage Flow								
	2008 Financial Crisis			2011 Eurozone Debt Crisis			2020 Covid-19 Crisis		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Crisis	-1.642*** (0.421)	-1.037*** (0.235)	-1.016** (0.492)	-0.534*** (0.155)	-0.252* (0.130)	-0.588** (0.242)	-6.833*** (2.149)	-1.963*** (0.471)	-5.862*** (1.835)
WLA	-0.010** (0.005)		-0.011 (0.008)	-0.003 (0.003)		-0.003 (0.003)	-0.050* (0.028)		-0.046 (0.030)
$\mathbb{1}(WLA < 35)$		0.124 (0.081)	-0.035 (0.227)		0.088 (0.062)	0.008 (0.071)		1.318 (1.148)	0.948 (1.147)
Crisis \times WLA	0.011* (0.006)		0.002 (0.011)	0.006 (0.003)		0.006 (0.004)	0.111** (0.042)		0.090** (0.036)
Crisis $\times \mathbb{1}(WLA < 35)$		-0.403 (0.310)	-0.484 (0.542)		-0.106 (0.126)	0.046 (0.149)		-2.404** (1.030)	-1.477* (0.855)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
obs.	5131	5248	5131	7048	7118	7048	1155	1155	1155
Adj. R ²	0.037	0.038	0.037	0.005	0.004	0.004	0.129	0.125	0.130

If the 2016 reform on contingent fees and gates led to preemptive runs on MMFs, we would expect outflows to be stronger when a fund's WLA approaches the 30% threshold. To shed light on this issue, we replace $WLA_{i,t-1}$ with $\mathbb{1}(WLA < 35)$ and re-estimate Equation 1. Consistent with the hypothesis that the fear of gates and fees accelerated outflows, funds with below-35 WLA on average suffered an additional 2.4 percentage point daily outflows during the 2020 crisis (Column (8)). Again, for both the 2008 and the 2011 runs, there is no evidence of stronger outflows when WLA falls below 35% (Columns (2) and (5)).

To further test for acceleration in runs when WLA approaches 30% during the Covid-19 crisis, we include both $WLA_{i,t-1}$ and $\mathbb{1}(WLA < 35)$ (and their interactions with the crisis dummy) when estimating Equation 1. Columns (3), (6) and (9) show that, after controlling for the linear effect of WLA, investors ran disproportionately more on funds with close-to-30 WLA only during the 2020 crisis. This finding suggests an acceleration of runs as investors become concerned about the potential imposition of fees and gates.

We also pool the three subsamples together to assess the significance of the differential flow sensitivity to WLA in the 2020 run relative to the other two episodes. Specifically, we estimate the following regression:

$$\begin{aligned} Flow_{i,t} = & \beta_1 Crisis_t + \beta_2 Crisis_t \times 2008 + \beta_3 Crisis_t \times 2011 + \beta_4 WLA_{i,t-1} \\ & + \beta_5 WLA_{i,t-1} \times 2008 + \beta_6 WLA_{i,t-1} \times 2011 + \beta_7 Crisis_t \times WLA_{i,t-1} \\ & + \beta_8 Crisis_t \times WLA_{i,t-1} \times 2008 + \beta_9 Crisis_t \times WLA_{i,t-1} \times 2011 + \mu_y + \varepsilon_{i,t}, \quad (2) \end{aligned}$$

where μ_y represents year fixed effects, 2008 and 2011 are dummy variables for the 2008 and the 2011 episodes, respectively. All other variables are defined as in Equation 1.

Results in Table 3 confirm that the sensitivity of fund flows to WLA was significantly stronger in the 2020 run than in the previous two. The coefficient of $Crisis_t \times WLA_{i,t-1}$ captures the flow sensitivity to WLA during the 2020 run and is positive and significant, indicating that lower liquidity strongly correlates with larger outflows.

On the other hand, the flow sensitivity to WLA was significantly lower in both 2008 and 2011. Indeed, the estimated coefficients of both $Crisis_t \times WLA_{i,t-1} \times 2008$ and $Crisis_t \times WLA_{i,t-1} \times 2011$ are negative and highly significant, with magnitudes similar to the coefficient of $Crisis_t \times WLA_{i,t-1}$ (Column (1)). Results change little after controlling for fund characteristics (Column (2)). We also replace $WLA_{i,t-1}$ with $1(WLA < 35)$ and re-estimate Equation 2. Column (3) shows that funds experienced stronger outflows when their WLAs fell below 35% in the 2020 run. Such reaction is significantly stronger than in either 2008 or 2011 runs. Results again remain largely unchanged after controlling for fund characteristics (Column (4)).

It is worth noting that the 2016 MMF reform not only allows institutional prime funds to impose gates and fees when their WLA falls below 30%, but it also requires them to transact at a floating NAV, meaning that buying and selling shares must take into account the market value of the fund's assets. To make sure that our results come from the possible imposition of gates and fees and not from the introduction of floating NAVs, we estimate the flow sensitivity to both WLA and floating NAV. As shown in Appendix Table A.2, we do not find evidence that lower NAVs significantly drive outflows during the Covid-19 crisis. One possible reason behind this finding is that MMFs' floating NAVs actually stayed far above the threshold for "breaking the buck" (i.e., falling below 0.995) during the Covid-19 crisis, while WLAs for some funds have fallen close to or even below 30%. Indeed, among all institutional prime MMFs, the lowest NAV that a fund ever reached during the 2020 crisis was 0.998, while the lowest WLA during the same crisis period was 27%.

5 The effect of the MMLF on prime MMFs

The severe run on prime MMFs during the Covid-19 crisis led the Fed to intervene by introducing the MMLF, which greatly alleviated MMFs' liquidity pressures and helped thaw the frozen CP and CD markets. The usage of the MMLF was massive. Within

Table 3: MMF Liquidity and Runs

The sample consists of domestic institutional prime funds during three time periods: the Covid-19 crisis (Feb 04 to Mar 24); the 2011 Eurozone debt crisis (May 03 to Aug 01); and the 2008 financial crisis (Aug 04 to Sep 30). Flow is the daily percentage change in AUM. WLA is the lagged share of weekly liquid assets to total assets and $\mathbb{1}(WLA < 35)$ equals one if WLA is below 35%. Crisis equals one from Sep 10 to Sep 30 in 2008, from Jun 10 to Aug 1 in 2011, and from Mar 6 to Mar 24 in 2020. Controls (lagged) include: log(Fund AUM), WAM, Abnormal Gross Yield (in excess of mean), Expense Ratio, Bank Affiliation, Age, Safe Holding, and Risky Holding. Standard errors (in parentheses) are two-way clustered at the fund and day levels.

	Dependent Variable: Daily Percentage Flow			
	(1)	(2)	(3)	(4)
Crisis \times WLA	0.110*** (0.042)	0.112*** (0.042)		
Crisis \times WLA \times 2008	-0.097** (0.043)	-0.100** (0.043)		
Crisis \times WLA \times 2011	-0.105** (0.042)	-0.106** (0.042)		
Crisis \times $\mathbb{1}(WLA < 35)$			-2.552** (1.093)	-2.489** (1.053)
Crisis \times $\mathbb{1}(WLA < 35) \times$ 2008			2.082* (1.145)	2.068* (1.106)
Crisis \times $\mathbb{1}(WLA < 35) \times$ 2011			2.466** (1.101)	2.404** (1.062)
Crisis	-6.947*** (2.121)	-7.008*** (2.126)	-2.119*** (0.486)	-2.114*** (0.486)
Crisis \times 2008	5.224** (2.171)	5.360** (2.170)	1.117** (0.536)	1.094** (0.540)
Crisis \times 2011	6.435*** (2.132)	6.492*** (2.139)	1.873*** (0.496)	1.858*** (0.496)
WLA	-0.013 (0.014)	-0.023 (0.016)		
WLA \times 2008	0.009 (0.015)	0.015 (0.017)		
WLA \times 2011	0.011 (0.015)	0.017 (0.016)		
$\mathbb{1}(WLA < 35)$			1.131 (0.961)	1.123 (0.969)
$\mathbb{1}(WLA < 35) \times$ 2008			-1.096 (0.971)	-1.013 (0.958)
$\mathbb{1}(WLA < 35) \times$ 2011			-1.021 (0.954)	-1.010 (0.949)
Obs.	13535	13334	13727	13521
Adj. R ²	0.038	0.040	0.038	0.040
Controls		✓		✓
Year FE	✓	✓	✓	✓

the first seven business days of its operations, MMFs in total were able to sell about \$53 billion assets to the facility, which were about 8% of all prime fund assets, or 24% of all institutional prime fund assets as of March 25.¹⁶

In this section, we empirically evaluate the effect of the MMLF in abating large-scale outflows from prime MMFs, especially for the less liquid funds. We then design two sets of difference-in-difference tests to show that the effects we document can be largely attributed to the MMLF rather than other contemporary interventions. The first set of tests differentiates between MMFs that are eligible to the MMLF and those that are not, and the second set of tests exploits the variations in the amount of pledgable assets among the MMFs eligible to the MMLF.

5.1 Prime MMF flows around the launch of the MMLF

We define the two weeks before the implementation of the MMLF as the pre-MMLF period (i.e., March 9 to March 20, business days only) and the two weeks immediately following implementation as the MMLF period (i.e., March 23 to April 3, business days only). We choose to use the implementation date, rather than the announcement date of the MMLF to evaluate the MMLF impact because the main challenges facing MMFs were in liquidating longer tenor assets, especially CDs. However, CDs were not considered as eligible assets for the MMLF until the day of its implementation. Partially reflecting this challenge, institutional prime MMFs lost 11% of total assets to redemptions between March 18 and March 23.

Using a sample that covers both retail and institutional prime funds and spans both the pre- and post-MMLF periods (i.e., from March 9 to April 3), we start with estimating

¹⁶The Federal Reserve's H.4.1 data shows that MMLF loans outstanding spiked to \$30.6 billion on March 25 in just two days of operations, and climbed to \$52.7 billion on April 1 (i.e., seventh business day after the operation began). Public MMF data from ICI shows that as of March 25, 2020, prime funds in total manage \$659 billion of assets, and institutional prime MMFs have \$223 billion of assets.

the following panel regression:

$$Flow_{i,t} = \beta_1 MMLF_t + Controls_{i,t-1} + \varepsilon_{i,t}, \quad (3)$$

where $MMLF_t$ is a dummy that takes the value of one during the MMLF period. $Controls_{i,t-1}$ includes fund characteristics as defined in Equation 1.

Results in Table 4 show that, after controlling for fund characteristics, prime funds' daily flows on average rebounded by 1 percentage point in the MMLF period (Column (1)). We show that the rebound in fund flows was mainly concentrated among institutional funds. Specifically, we create a dummy, *Institutional* that takes the value of one for prime institutional funds, and re-estimate Equation 3 by including both *Institutional* and its interaction with $MMLF_t$ as explanatory variables. Column (2) shows that relative to retail funds, institutional funds saw their daily flows rebound by 2.3 percentage points after the launch of the MMLF, significant at the 1% level. Using the subsample that only covers institutional funds for the same time period, we re-estimate Equation 3 and confirm that this is indeed the case (Column (3)). The MMLF effect on institutional fund flows is twice as strong as for the full sample.

Earlier we found that institutional funds with lower WLAs, especially those closer to the 30% threshold, experienced larger outflows during the days leading up to the launch of MMLF. Of particular interest is the situation of these less liquid funds after the introduction of the MMLF. For that purpose, we continue to focus on the subsample for institutional funds and estimate the following regression:

$$Flow_{i,t} = \beta_1 MMLF_t + \beta_2 WLA_{i,t-1} + \beta_3 MMLF_t \times WLA_{i,t-1} + \varepsilon_{i,t}. \quad (4)$$

Consistent with our previous findings that investors ran on funds with lower WLA in the crisis, the coefficient of $WLA_{i,t-1}$ is negative and highly significant. Interestingly, this flow sensitivity to WLA largely dissipated after the introduction of the MMLF. The coefficient of the interaction between $WLA_{i,t-1}$ and $MMLF_t$ is negative and highly significant. It is

Table 4: **Effects of the MMLF on Prime MMFs**

The daily sample goes from March 9, 2020 to April 3, 2020 and contains both retail and institutional prime funds. Columns (1) and (2) include both retail and institutional funds while Columns (3) to (5) only institutional. Flow is the daily percentage change in assets under management. Institutional equals one for institutional prime funds. MMLF equals one from March 23 (when the MMLF becomes operational) onwards. Controls (lagged) include: log(Fund AUM), WAM, Abnormal Gross Yield (in excess of mean), Expense Ratio, Bank Affiliation, Age, Safe Holding, and Risky Holding. Standard errors (in parentheses) are two-way clustered at the fund and day levels.

	Dependent Variable: Daily Percentage Flow				
	Retail & Institutional		Institutional		
	(1)	(2)	(3)	(4)	(5)
MMLF	1.063** (0.441)	-0.143 (0.226)	2.123*** (0.733)	6.704** (2.706)	6.621** (2.526)
Institutional		-1.834*** (0.556)			
MMLF \times Institutional		2.298*** (0.731)			
WLA				0.146*** (0.049)	0.146*** (0.041)
MMLF \times WLA				-0.110** (0.052)	-0.109** (0.047)
Controls	✓	✓	✓		✓
Obs.	1340	1340	700	700	700
Adj. R ²	0.020	0.081	0.057	0.077	0.094

also similar in magnitude to the coefficient of $WLA_{i,t-1}$, suggesting that investors mostly stopped reacting to fund liquidity levels after the introduction of the MMLF. Our results remain unchanged after we control for fund characteristics (Column (5)). In sum, these findings suggest that the MMLF significantly attenuated the sensitivity of flows to the liquidity of the fund (WLA), which characterized the crisis dynamics. Indeed, the ability of a fund to access the MMLF made its current liquidity less of a concern given the availability of plentiful “liquidity of last resort” at the MMLF.

5.2 Identifying the MMLF effect on prime MMFs

One potential concern about our findings is that they might be driven by policy actions other than the introduction of the MMLF. Indeed, around the same time that the MMLF was announced, a number of liquidity and credit facilities were created by the Federal Reserve and the stance of monetary policy significantly eased (see Appendix Table A.1). One could argue that the stabilization of prime fund flows that started on March 23 may be attributed to the improvements in CP and CD market conditions brought by the announcement of the Commercial Paper Funding Facility (CPFF) on March 17 and the launch of the Primary Dealer Credit Facility (PDCF) on March 20.¹⁷ One could also argue that the rebound in prime fund flows might simply reflect a boost in risk sentiment brought by other policy actions, such as the resumption of open-market asset purchases.

To address these concerns, we design a number of tests to identify an MMLF-specific effect. If the stabilization of institutional prime fund flows during the post-MMLF period was mainly due to improvements in the liquidity conditions of the CP and CD markets, we should observe a similar rebound in fund flows for offshore USD prime MMFs, who invest in essentially the same pool of assets, including CP and CDs, and experienced similar runs prior to the launch of the MMLF as institutional prime funds did.¹⁸ Our

¹⁷CPFF allows top rated CP issuers to obtain CP funding directly from the Federal Reserve, and PDCF allows the primary dealers to obtain repo funding from the Federal Reserve against the pledge of eligible collaterals, including CP and CDs.

¹⁸Offshore USD funds share many similar features with prime institutional funds. In addition to holding similar types of assets, they are subject to similar regulations. In fact, the majority of offshore

identification comes from the fact that offshore funds are not eligible to participate in the MMLF due to their foreign investor base. Therefore, the offshore USD funds serve as ideal control group to test whether the broad-based improvement in short-term funding market conditions, rather than the MMLF, led to the stabilization of domestic prime fund flows.

Specifically, we use a sample that includes both domestic institutional prime funds and offshore USD prime funds and that covers the period from two weeks before to two weeks after the launch of the MMLF. We then estimate the following regression:

$$Flow_{i,t} = \beta_1 Domestic_i + \beta_2 MMLF_t + \beta_3 Domestic_i \times MMLF_t + Controls_{i,t-1} + FE_i + \varepsilon_{i,t}, \quad (5)$$

where $Domestic_i$ is a dummy that equals one for domestic institutional prime funds, and zero otherwise. All other variables are defined as in Equation 3. We control for time-varying fund characteristics and fund fixed effects. Standard errors are two-way clustered at the fund and day levels.

Results in the first two columns of Table 5 dispute the argument that broad-based improvements in short-term funding market conditions drove the rebound in prime fund flows. During the two weeks following the MMLF, fund flows increased significantly more for domestic funds relative to their offshore counterparts. Although USD prime funds also experienced a rebound in flows, the magnitude is much smaller and not statistically significant (Column (1)). Our results are qualitatively the same when we control for date fixed effects (Column (2)).

We also explore potential differences in the speed of recovery between the two types of funds after the launch of the MMLF. We divide the MMLF period into the first week of operations (*WeekOne*) and the second week (*WeekTwo*). We then estimate the following

prime funds are also subject to redemption gates and liquidity fees. Furthermore, it is common for some large fund families to have both U.S. prime funds and offshore USD prime funds under their management. During the crisis period, assets in offshore USD prime funds also dropped by about 25%.

regression:

$$\begin{aligned} Flow_{i,t} = & \beta_1 Domestic_t + \beta_2 WeekOne_t + \beta_3 WeekTwo_t + \beta_4 WeekOne_t \times Domestic_i \\ & + \beta_5 WeekTwo_t \times Domestic_i + Controls_{i,t-1} + FE_i + \varepsilon_{i,t}. \end{aligned} \quad (6)$$

Column (3) of Table 5 shows that offshore funds actually suffered weak outflows (although not statistically significant) during the first week after the launch of the MMLF, while those of the domestic funds recovered by 1.6 percentage points. Only during the second week of the MMLF period did offshore funds experience a significant rebound in flows similar to domestic funds, as shown by the positive and highly significant coefficient of *WeekTwo_t* and the insignificant coefficient of its interaction with *Domestic_i*. Our results remain robust when we further control for date fixed effects. In sum, the differences in both magnitude and speed of recovery between domestic and offshore funds are consistent with a significant effect of the MMLF on domestic prime MMFs.

To further test whether the stabilization of prime fund flows was due to the launch of the MMLF, we study whether the recovery in fund flows was stronger for funds that held more MMLF-eligible assets. Ideally, one would obtain the security-level holdings of each fund right before the launch of the MMLF and examine whether those holding more MMLF-eligible assets experienced a greater recovery in flows. However, such information is not available. The best alternative that we rely on is the security-level holdings of each fund at the end of February 2020, obtained from their N-MFP filings. We believe the end-of-February holdings of MMFs provide a rather accurate picture for MMFs' pre-MMLF holdings of MMLF-eligible assets, which are longer-term CP and CDs. Between early March and the operations of the MMLF, trading in these assets was likely to be very limited given that the secondary markets for CP and CDs were mostly frozen, while MMFs were reluctant to purchase new CP and CDs with maturities longer than one week. To ensure that we capture the share of a fund's assets that can be actually pledged when the MMLF is launched, we classify securities held at the end of February as eligible if

Table 5: Institutional Prime Funds vs. Offshore USD Prime Funds

The daily sample goes from March 9, 2020 to April 3, 2020 and contains domestic institutional prime funds and offshore USD prime funds. Flow is the daily percentage change in assets under management. Domestic equals one for domestic institutional prime funds. MMLF equals one from March 23 (when the MMLF becomes operational) onwards. MMLF_W1 equals one during the first week of the post-MMLF period and MMLF_W2 during the second week. Controls include WLA, Abnormal Gross Yield (in excess of mean), Risky Holding, and Safe Holding, as of the past Tuesday for domestic funds and past Friday for offshore funds. Standard errors (in parentheses) are two-way clustered at the fund and day levels.

	(1)	(2)	(3)	(4)
			Flow	
MMLF	0.640 (0.791)			
MMLF × Domestic	1.390* (0.688)	1.592* (0.765)		
MMLF_W1			-0.284 (1.046)	
MMLF_W1 × Domestic			1.914** (0.808)	2.079** (0.852)
MMLF_W2			1.699*** (0.523)	
MMLF_W2 × Domestic			0.999 (0.687)	1.111 (0.769)
Obs.	1113	1113	1113	1113
Adj. R ²	0.061	0.140	0.069	0.141
Controls	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓
Date FE		✓		✓

they can be pledged at the MMLF (ABCP, unsecured CP, and CDs with A1/P1 rating or higher) and if they mature at least one week after the MMLF starts operations, namely on April 1 or later.¹⁹ Given the extremely strained liquidity conditions in the CP and CD secondary markets, these eligible CP and CDs held by prime funds at February month-end are very likely to be still held on March 23 when the MMLF starts operations. We find that the average (median) share of a fund's assets that are MMLF-eligible is 26% (36%) for institutional prime MMFs in our sample.

Using the sample that includes only institutional prime funds for the time window that includes both the pre- and MMLF periods, we estimate the following regression:

$$Flow_{i,t} = \beta_1 MMLF_t + \beta_2 \%Eligible_i + \beta_3 MMLF_t \times \%Eligible_i + \varepsilon_{i,t}, \quad (7)$$

where $\%Eligible_i$ is the share of MMLF-eligible assets relative to the AUM of fund i , as of February 28. All other variables are defined as in Equation 3. Standard errors are two-way clustered at the fund and day levels.

Results in Table 6 support the view that the MMLF helped to stabilize prime fund flows. Column (1) shows that the interaction between $\%Eligible_i$ and $MMLF_t$ has a positive and significant effect on flows, indicating that prime funds with more MMLF-eligible holdings experienced a larger rebound in flows after the MMLF was launched. Compared to CDs, most CP has shorter time to maturity. To test whether prime funds benefited more from pledging longer-tenor assets, we therefore break down MMLF-eligible assets into eligible CP and eligible CDs, and define $\%EligibleCP_i$ and $\%EligibleCD_i$ accordingly. We then replace $\%Eligible_i$ with either $\%EligibleCP_i$ or $\%EligibleCD_i$ and re-estimate Equation 7. Results in columns (2), (3), (5), and (6) indicate that most of the stability-enhancing effects of the MMLF come from the ability to pledge longer-tenor assets, namely CDs. Indeed, after controlling for fund characteristics, the coefficient

¹⁹Treasuries and agency debt are also MMLF-eligible but are excluded from this measure, as prime MMFs on average only hold about 2% of these government securities, which are also considered as their liquid assets. Anecdotal evidence suggests that Treasuries and agency debt were almost never pledged as collateral under the MMLF.

of the interaction between $MMLF_t$ and $\%EligibleCP_i$ declines in magnitude and is no longer statistically significant. However, that of $\%EligibleCD_i$ remains positive and highly significant. Overall, our difference-in-difference analyses lend strong support to the view that the MMLF significantly calmed prime fund investors and stopped outflows.

Table 6: MMLF-Eligible Assets and Fund Flows

The daily sample goes from March 9, 2020 to April 3, 2020 and contains institutional prime funds. Flow is the daily percentage change in assets under management. MMLF equals one from March 23 (when the MMLF becomes operational) onwards. % Eligible is the percentage of AUM invested A1/P1/F1-rated CP and CDs that mature at least one week after the operations of the MMLF began on March 23. % Eligible is based on security holdings as of the end of February. % Eligible (CP, CD) is the percentage of AUM invested in eligible CP (including ABCP) or CD, respectively. Controls (lagged) include: WLA, log(Fund AUM), WAM, Abnormal Gross Yield (in excess of mean), Expense Ratio, Bank Affiliation, Age, Safe Holding, and Risky Holding, as of the past Tuesday. Standard errors (in parentheses) are two-way clustered at the fund and day levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Flow					
MMLF	1.153 (0.670)	1.310* (0.701)	1.125* (0.639)	0.955 (0.602)	1.125* (0.641)	0.917 (0.568)
% Eligible	-0.028 (0.020)		-0.002 (0.016)			
MMLF × % Eligible	0.034* (0.017)		0.031* (0.017)			
% Eligible CP	-0.036 (0.035)				0.009 (0.028)	
MMLF × % Eligible CP	0.051* (0.029)				0.045 (0.030)	
% Eligible CD			-0.070 (0.042)		-0.022 (0.034)	
MMLF × % Eligible CD			0.077** (0.034)		0.073** (0.034)	
Controls				✓	✓	✓
Obs.	540	540	540	540	540	540
Adj. R ²	0.064	0.058	0.071	0.102	0.102	0.102

6 The effect of the MMLF on CP and CD markets

As the MMLF stabilized their flows and liquidity conditions, prime funds were once again able to purchase CP and CDs at tenors greater than one week. In this section, we evaluate the impact of the MMLF on CP and CD markets by focusing on the set of instruments that are more likely to benefit from the MMLF. In particular, given that money funds tend to lend to firms with which they have pre-existing relationships (Chernenko and Sunderam, 2014; Li, 2017), we expect the MMLF effect to be stronger for firms that rely more heavily on money funds for funding. In addition, since only top rated CP is MMLF-eligible and only CP issued at a rate higher than the MMLF borrowing rate is economically meaningful to pledge, we would expect stronger MMLF effects for those instruments.

We start by using DTCC's transaction level data for trades in all U.S. commercial paper. These data contain information regarding each CP issuance, such as yield, amount issued, and the rating received from Moody's and S&P. As CP can be rated differently by these two rating agencies, we follow the principle used by the MMLF in determining the CP's credit quality and assign a composite rating to each CP on each day. The composite rating is used to control for rating fixed effects. Specifically, we give a numeric value to each notch of S&P/Moodys short term rating, with 1, 2, and 3 denoting A-1(including A-1+)/P-1, A-2/P-2, A-3/P3 respectively. For ratings below these three categories, we assign a value of 4. If an instrument is rated by only one of the two rating agencies, the rating it receives is set to be its composite rating. For a CP rated by both agencies, we take the lower of the two ratings as its composite rating. CP with ratings belonging to the top two notches together account for 91% of the data, with those in the top notch alone accounting for 62%. Based on the number of days to maturity, we also assign each CP to one of the following ten term buckets: overnight, 1 and 2 weeks, 1, 2, 3, 4, 5, 6 and 9 months.²⁰ For each CP issuance, its spread to OIS is calculated by subtracting from

²⁰Trades in these 10 term buckets together account for over 99% of the data. CP with time to maturity longer than 9 months are excluded from our study due to very limited issuance at those terms.

its yield the OIS rate for the same term bucket. To construct our sample, we calculate the volume weighted average spread across instruments issued by the same CP issuer j , on the same day t , and within the same term bucket m ($Spread_{j,t,m}$). Our final dataset consists of all the issuer-day-term level observations for the period that spans two weeks before and two weeks after the launch of the MMLF, namely from March 9, 2020 to April 3, 2020.

Our first identification strategy focuses on testing the differential effect of the MMLF across CP with different credit quality. To be considered MMLF-eligible, CP must belong to the top rating category. If the MMLF stabilized the CP market following its launch on March 23, we should expect such effect to be stronger among MMLF-eligible CP, namely with top rating. To test this hypothesis, we create the dummy $TopRating_{j,t}$ that takes the value one if CP issuer j 's composite rating is equal to 1 on day t , and estimate the following panel regression:

$$Spread_{j,t,m} = \beta MMLF_t \times TopRating_{j,t} + \mu_j + \mu_t + \mu_m + \mu_r + \varepsilon_{j,t,m} \quad (8)$$

where $MMLF_t$ is a dummy for the two weeks following the launch of MMLF, and μ_j , μ_t , μ_m , μ_r represent issuer, day, maturity, and rating fixed effects, respectively. Standard errors are two-way clustered at the issuer and day levels. Consistent with the MMLF design, Table 7 (column (1)) shows that spreads in top rated CP declined by more following the launch of the facility. The coefficient of the interaction of $MMLF_t$ and $TopRating_{j,t}$ is negative and highly significant. The magnitude is also economically meaningful. A1/P1-rated CP experienced an additional 45 bps decline in spreads compared to other lower-rated CP during the two weeks post MMLF.

Our second test identifies the MMLF effect by building on our earlier analysis on the impact of the MMLF on money fund flows. Since financial and non-financial borrowers rely on MMFs for funding to different degrees, we test whether borrowers that depend more on MMFs saw a greater benefit from the MMLF than borrowers less dependent on

MMFs. For that purpose, we use data on security level holdings by MMFs from their monthly N-MFP filings to the SEC. For each CP issuer, we aggregate the total amount of its CP held by money funds at the end of February 2020. We then normalize the number by the average daily CP outstanding amount during February 2020 for each issuer (data obtained from DTCC) and name it $ShareMMF_{j,t}$. We hypothesize that if the MMLF has stabilized the CP market by stemming money fund outflows, its impact on spreads would be stronger for CP more heavily held by money funds prior to its implementation.

To test this hypothesis, we replace $TopRating_{j,t}$ with $ShareMMF_{j,t}$ and re-estimate Equation 8. Consistent with the MMLF lowering CP spreads through its impact on money fund flows, the coefficient of the interaction between $MMLF_t$ and $ShareMMF_{j,t}$ is negative and highly significant (Table 7, column (2)), suggesting that spreads declined more for CP more heavily held by money funds. As prime funds are unlikely to sell CP with short maturity to the MMLF since they would turn into cash quickly anyway, we re-estimate Equation 8 by excluding overnight paper and get somewhat stronger results (Table 7, column (3)).

It is worth noting that right before the launch of the MMLF, the Fed created the Primary Dealer Credit Facility (PDCF) to aid primary dealers in supporting smooth market functioning (see Appendix Table A.1). As the credit extended to primary dealers under the PDCF improved dealers funding conditions, one might argue that it could have also contributed to the improvement in CP spreads during the post MMLF period. While we are not able to exclude the possibility that PDCF has also caused CP spreads to narrow, we also note that the MMLF effect we identified earlier is likely to be above and beyond the PDCF effect. Unlike the MMLF, the PDCF accepts both A1/P1 and A2/P2 CP as eligible collateral. Therefore, focusing on the additional decline in spreads for A1/P1 CP likely captures the additional effect that the MMLF had on CP spreads. Moreover, dealers can pledge at the PDCF commercial paper that they bought from all sorts of market participants, not just money funds. Therefore, finding a stronger effect in issuers whose CP is more heavily held by prime funds suggests that the MMLF had

Table 7: MMLF effects on CP spreads

The daily sample goes from March 9, 2020 to April 3, 2020 and contains CP data at the issuer-day-term level. Columns (1) and (2) include all observations while column (3) only issuance of term (excluding overnight) CP. Spread is the difference in percentage points between the CP rate and the OIS rate at equivalent maturity (fed fund rate if overnight). TopRating equals one for the A1/P1 rated CP (the highest rating). MMLF equals one after the MMLF implementation date of March 23, 2020. ShareMMF is the share of an issuer’s CP held by MMFs by the end of February 2020. Standard errors (in parentheses) are two-way clustered at the issuer and day levels.

	(1)	(2)	(3)
	Spread		
TopRating × MMLF	-0.446**		
	(0.167)		
ShareMMF × MMLF		-1.050***	-1.178***
		(0.318)	(0.270)
Sample	Full	Full	Term
Obs.	7,820	7,820	4,911
Adj. R ²	0.825	0.821	0.829
Term FE	✓	✓	✓
Rating FE	✓	✓	✓
Issuer FE	✓	✓	✓
Day FE	✓	✓	✓

a significant effect over and above the PDCF. This finding also alleviates the concern that the CP spread improvements post MMLF were driven by the announcement of the Commercial Paper Funding Facility (CPFF) on March 17, as its CP purchases are broad-based and independent from how much is usually held by MMFs. In addition, the fact that we also find a similar effect on the CD market, as discussed later in this section, further supports an MMLF, rather than a CPFF, effect.

In addition to cheaper credit, the MMLF was also believed to have contributed to more robust CP issuance across tenors. In the several days prior to the creation of the MMLF, new CP issuance dropped precipitously and many market participants viewed the CP market as being essentially frozen. Once the run on prime MMFs abated due to the liquidity of last resort provided by the MMLF, MMFs were once again willing to buy CP, knowing that they could pledge it back to the MMLF to monetize it in case of future runs.

To understand the MMLF effect on CP issuance, we use the same CP sample and estimate the following panel regression:

$$\text{Log}(\text{Issuance})_{j,t,m} = \beta \text{MMLF}_t \times \text{TopRating}_{j,t} + \mu_j + \mu_t + \mu_m + \mu_r + \varepsilon_{j,t,m} \quad (9)$$

where $\text{Log}(\text{Issuance})_{j,t,m}$ is the log of one plus the amount issued by borrower j on day t with time to maturity within maturity bucket m . Since not issuing debt is valuable information, we consider issuer-day-term observations with no issuance as zero issuance, leading to $\text{Log}(\text{Issuance})_{j,t,m}$ being equal to zero in those cases.

Results in Table 8 support the view that the MMLF improved the CP market by restarting new issuance. Top rated CP issuers experienced larger increase in issuance volume in the post MMLF period (column (1)). In addition, borrowers that rely more heavily on MMFs to obtain funding were able to borrow more after the introduction of the MMLF. When we replace $\text{TopRating}_{j,t}$ with $\text{ShareMMF}_{j,t}$ and re-estimate Equation 9, the coefficient of the interaction of MMLF_t and ShareMMF_t is indeed positive and

highly significant (column (2)). The MMLF effects are evident when we focus only on term CP (column (3)).

One salient feature of the MMLF is its pricing schedule. Banks can pledge CP and CDs and obtain funding by paying a rate of 125 bps (100 bps above the discount window's primary credit rate). Because of the MMLF pricing, CP issued at 125 bps or higher would be quite attractive for MMFs to buy because they could be liquidated to the MMLF without either the MMF or the bank incurring a loss. Therefore, the MMLF effect should be stronger for CP issued at 125 bps or higher.

Using this pricing feature, we develop our third test to identify the MMLF effect on the CP market. Specifically, we re-estimate Equation 9 separately for CP issued at rates above and below 125 bps. We find evidence consistent with the hypothesis that CP which is economical to pledge (with rate above 125 bps) benefited particularly from the MMLF. Indeed, columns (4) and (5) of Table 8 show that issuance restarted significantly more for CP issuers with more reliance on MMFs only when the CP rate is above 125 bps. The coefficient of the interaction between *MMLF* and *ShareMMF* is positive and highly significant for CP with rates above 125 bps, but negative and not significant for rates below. Excluding overnight issuance yields similar findings (columns (6) and (7)). The limited effects of the MMLF on issuance of cheaper CP (with rate below 125 bps) suggests that MMFs were not particularly interested in purchasing these instruments since they may not have been able to liquidate them at the MMLF in case of need.

Similar MMLF effects are also evident in the CD market. Using the DTCC data for CDs, we estimate both spread to OIS and issuance volume at the issuer-term-day level and study the additional impact of *ShareMMF* after the launch of the MMLF. Results in Table 9 are again consistent with the stabilization effects that the MMLF had on short-term funding markets. Borrowers more reliant on funding from MMFs experienced significantly larger declines in borrowing costs and a greater increase in issuance volume after the introduction of the MMLF (columns (1) and (2)). In addition, the issuance effect is concentrated among CD instruments offering more than 125 bps, similarly to

Table 8: MMLF effects on CP issuance

The daily sample goes from March 9, 2020 to April 3, 2020 and contains CP data at the issuer-day-term level. Log(Issuance) is the log of one plus the amount issued by a certain firm in a given day. TopRating equals one for the A1/P1 rated CP (the highest rating). MMLF equals one after the MMLF implementation date of March 23, 2020. ShareMMF is the share of an issuer's CP held by MMFs by the end of February 2020. Standard errors (in parentheses) are two-way clustered at the issuer and day levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(Issuance)			Log(Issuance)			
Primary Mkt Rate:	All	All	All	$\geq 125bps$	$< 125bps$	$\geq 125bps$	$< 125bps$
TopRating \times MMLF	3.012***						
	(0.733)						
ShareMMF \times MMLF		3.894**	3.897**	4.228**	-1.073	4.208**	-1.055
		(1.541)	(1.542)	(1.682)	(0.933)	(1.675)	(0.930)
Sample	Full	Full	Term	Full	Full	Term	Term
Obs.	99,000	99,000	89,100	99,000	99,000	89,100	89,100
Adj. R ²	0.521	0.517	0.516	0.393	0.564	0.393	0.565
Rating FE	✓	✓	✓	✓	✓	✓	✓
Issuer FE	✓	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓	✓
Term FE	✓	✓	✓	✓	✓	✓	✓

what we found for CP instruments (columns (3) and (4)).²¹

Table 9: MMLF effects on CD spreads and issuance

The daily sample goes from March 9, 2020 to April 3, 2020 and contains CD data at the issuer-day-term level. The sample includes CDs with maturities between 1 week and 1 year. Spread is the difference in percentage points between the CD yield and the OIS rate at equivalent maturity. Log(Issuance) is the log of one plus the amount issued by a certain firm in a given day. MMLF equals one after the MMLF implementation date of March 23, 2020. ShareMMF is the share of an issuer’s CD held by MMFs by the end of February 2020. Standard errors (in parentheses) are two-way clustered at the issuer and day levels.

	(1)	(2)	(3)	(4)
	Spread	Log(Issuance)	Log(Issuance)	
Original Rate:			$\geq 125bps$	$< 125bps$
ShareMMF \times MMLF	-0.532**	0.946*	0.680**	0.275
	(0.249)	(0.462)	(0.263)	(0.298)
Sample	Full	Full	Full	Full
Obs.	389	10,880	10,880	10,880
Adj. R ²	0.679	0.060	0.041	0.034
Issuer FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Term FE	✓	✓	✓	✓

Once again, the fact that the spread reduction and increased issuance effects are concentrated among instruments that are economically viable to pledge at the MMLF and those more heavily purchased by MMLF-eligible participants, namely money funds, suggests that the MMLF provided stability benefits in addition to any effect coming from the PDCF.

²¹The sample size for CD is smaller than that for CP due to the fact that CDs have significantly longer maturities and therefore they do not need to be rolled over as frequently as it is the case for CP. Also, there are more CP issuers, both financial and non-financial, than CD issuers, which are mostly foreign banks raising dollar funding.

7 Conclusion

Liquidity restrictions on investors, like the redemption gates and liquidity fees introduced in the 2016 MMF reform, are meant to reduce the incentives to run on MMFs during crisis. In this paper we compare three runs on prime MMFs, two of which happened prior to the introduction of contingent liquidity restrictions on investors and one that occurred after these rules were put in place. We find evidence consistent with the notion that the introduction of redemption gates and liquidity fees, which was meant to curb runs, may have exacerbated the run on prime MMFs during the Covid-19 crisis, especially on the less liquid funds.

We show that the launch of the MMLF was effective on stemming prime fund outflows and normalizing short-term funding market conditions. Using a battery of identification strategies and several micro-level data sets on the MMFs, CP and CDs, we show that the stabilization of prime fund flows and recovery in the CP and CD market conditions can indeed be attributed to the launch of the MMLF.

Our findings raise the question on whether the fragility in the MMF industry and more generally in the short-term funding markets could be addressed by current MMF regulations. While the Federal Reserve's intervention with the MMLF provided "liquidity of last resort" to MMFs during the Covid-19 crisis, more research and collaborative regulatory efforts are warranted in the future to enhance the stability of the MMF industry.

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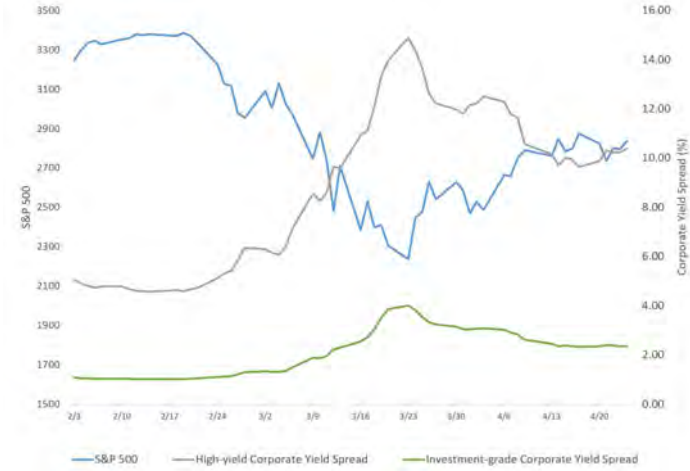
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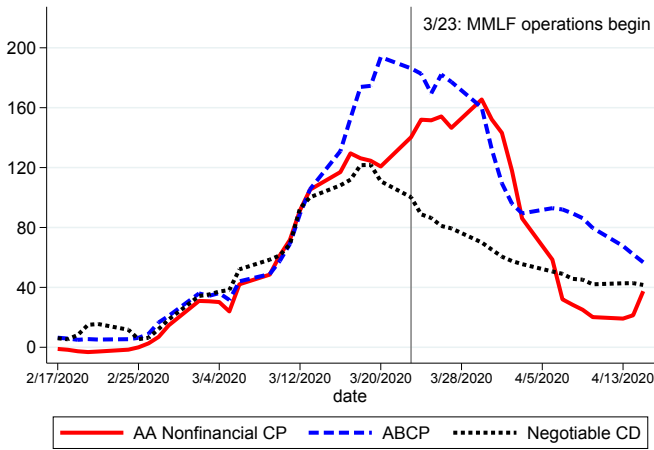
Figure 1: Distress in Funding Markets during the Covid-19 Crisis

Panel (a) shows the evolution of the S&P 500 index and the yield spreads of investment-grade and high-yield corporate bonds during the Covid-19 crisis. Panel (b) plots the evolution of the yield spreads to OIS of a few representative short-term securities: 1-month AA nonfinancial commercial paper (CP), ABCP, and negotiable CDs.

(a) Equity Prices and Bond Yield Spreads



(b) Yield Spreads on 1-month CP & CD (in basis points)

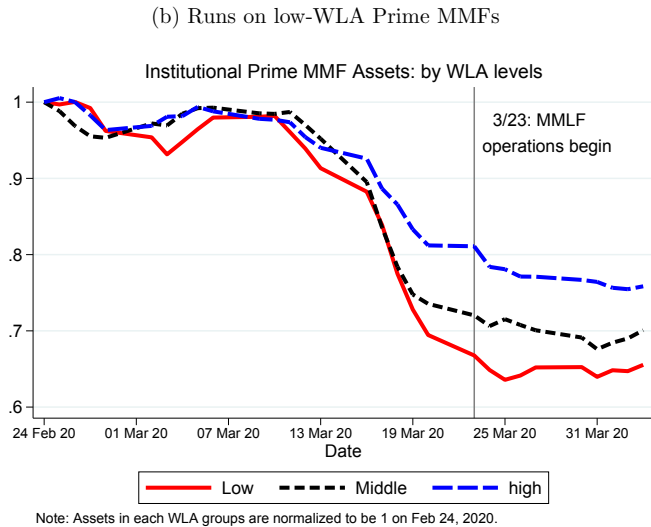
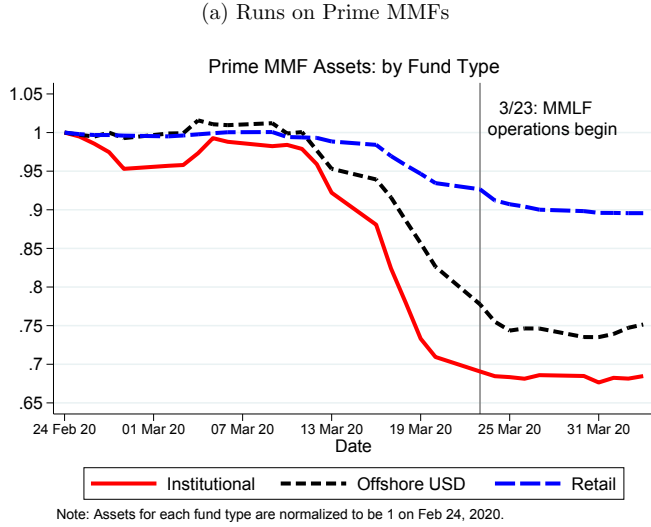


Note: Yield spreads are calculated as three-day moving averages.

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Figure 2: **Runs on MMFs during the Covid-19 Crisis**

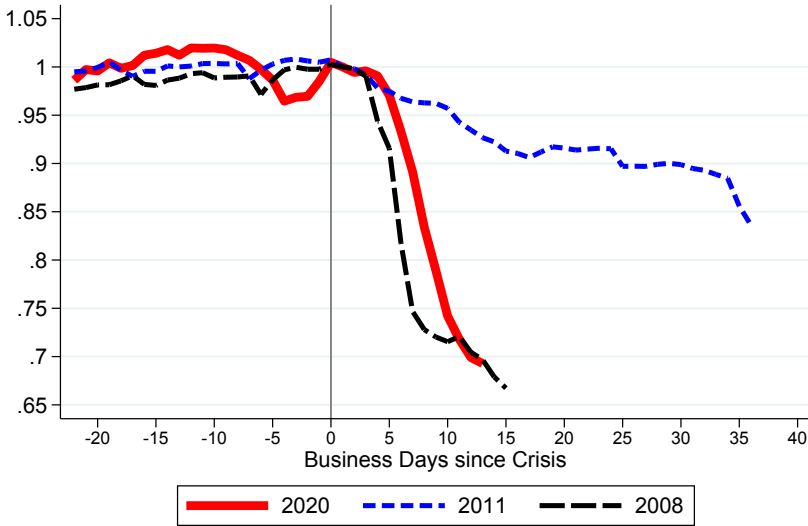
Panel (a) plots the AUMs of institutional and retail prime MMFs, as well as offshore prime funds during the Covid-19 crisis, all normalized to one on February 24, 2020. Panel (b) plots the AUMs of institutional prime MMFs in the top, middle, and bottom terciles based on their weekly liquidity asset (WLA) holdings, rebalanced every Wednesday, and assets in each WLA group are normalized to one on February 24, 2020.



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Figure 3: Comparison of Three MMF Runs

The chart shows runs on institutional prime MMFs during the 2008 financial crisis (September 10–30, 2008), 2011 Eurozone sovereign debt crisis (June 10–August 1, 2011), and the 2020 Covid-19 crisis (March 6–24, 2020), with AUMs for each crisis normalized to one on date zero of the crisis.



Note: AUMs for each crisis are normalized to be 1 on date 0 of the crisis.

Appendix: MMLF and other emergency facilities

There are a couple of other Federal Reserve facilities that were announced around the time of the MMLF announcement and might also have some impact on the CP and CD markets. The Commercial Paper Funding Facility (CPFF) was announced on March 17. CPFF supports liquidity in the CP market by purchasing paper directly from issuers and by giving investors confidence that issuers will be able to roll maturing CP. However, the CPFF was not operational until April 14, where the market conditions had improved substantially since MMLF operations began on March 23.

There are several important differences between CPFF and MMLF. First, while CPFF buys newly issued CP, MMLF loans are secured by assets that are purchased by banks from MMFs existing holdings. Second, collaterals under MMLF can have maturity ranging from overnight to 12 months, while CPFF only buys 3-month CP. Lastly, the pricing of CP under MMLF and CPFF are quite different. To access the CPFF, issuers must pay an upfront facility fee equal to 10 basis points of the maximum amount of its commercial paper that CPFF may own. Under CPFF, for A1/P1 rated commercial paper, pricing will be based on the then-current 3-month overnight index swap (OIS) rate plus 110 basis points and for commercial paper rated A2/P2/F2, then-current 3-month OIS rate plus 200 basis points. On the other hand, MMLF has no facility fees. MMLF loans secured by CP are priced at PCR plus 100 bps.

The Primary Dealer Credit Facility (PDCF) was also announced on March 17. PDCF provides credit to primary dealers of the New York Fed against a broad range of collateral, including CP and CD. The maximum maturity of PDCF loans is 90 days and PDCF loans are priced at PCR regardless of loan maturity or collateral.

There are several important differences between PDCF and MMLF. First, PDCF is open only to the 24 primary dealers, while MMLF is accessible by all US banks, affiliates of US bank holding companies, and US branches of foreign banks. Second, PDCF loans have maturity up to 90 days, while MMLF loans have maturity up to 12 months. Third,

under PDCF, primary dealers cannot pledge securities issued by themselves as collateral for loans. There is no such limitation on MMLF collateral. Fourth, PDCF loans do not have preferential treatment with respect to regulatory capital ratios, and are made with recourse beyond the pledged collateral to the primary dealers. MMLF loans do not affect banks capital ratios and have no recourse. Fifth, A2/P2-rates CP and CDs are eligible collateral for PDCF loans, while MMLF loans only accept A1/P1-rates CP and CDs as collateral. Last, the PDCF loans are priced at a fixed rate equal to the PCR, regardless of collateral type or loan maturity and loan amount is limited to the amount of margin-adjusted eligible collateral. MMLF loans have no margin-adjustments and are priced at a fixed spread over PCR, depending on the type of the collateral.

Table A.1: **Timeline of Main Federal Reserve Interventions**

This table summarizes the timeline of major interventions by the Federal Reserve during the Covid-19 crisis. CPFF refers to the Commercial Paper Funding Facility; PDCF to Primary Dealer Credit Facility; MMLF to Money Market Mutual Fund Liquidity Facility; PMCCF to Primary Market Corporate Credit Facility; SMCCF to Secondary Market Corporate Credit Facility; TALF to Term Asset-Backed Securities Loan Facility; PPPLF to Paycheck Protection Program Lending Facility; MLF to Municipal Liquidity Facility; MSLP to Main Street Lending Program. Finally, VRDNs stands for variable rate discount notes and CDs for certificates of deposit.

Date	Federal Reserve Actions & Announcement
March 3, 2020	Cut interest rate by 50 bps
March 15, 2020	Cut interest rates by another 100 bps to [0, 25] bps
March 15, 2020	Asset purchases resumed (\$500 bln Treasuries; \$200 bln agency MBS)
March 15, 2020	Primary credit rate (discount window) lowered to 25 bps
March 15, 2020	US dollar liquidity swap lines with major foreign central banks
March 17, 2020	Announcement of CPFF (to be operational on April 14)
March 17, 2020	Announcement of PDCF (to be operational on March 20)
March 18, 2020	Announcement of MMLF (to be operational on March 23)
March 20, 2020	MMLF expanded to accept short-term municipal debt
March 23, 2020	FOMC removes upper limit on asset purchases
March 23, 2020	MMLF became operational
March 23, 2020	MMLF expanded to accept VRDNs and CDs
March 23, 2020	Announcement of PMCCF & SMCCF & TALF
April 9, 2020	Announcement of PPPLF & MLF & MSLP

Table A.2: Effect of floating NAV on flows

The daily sample goes from February 4 to March 24, 2020 and contains institutional prime funds. Flow is the daily percentage change in assets under management. Crisis equals one from March 6 to March 24. NAV_to_1 equals $(1 - \text{lagged NAV})$ times 100 and $\mathbb{1}(NAV < 1)$ equals one if lagged NAV is below 1. WLA is the lagged share of weekly liquid assets to total assets. Controls (lagged) include: $\log(\text{Fund AUM})$, WAM, Abnormal Gross Yield (in excess of mean), Expense Ratio, Bank Affiliation, Age, Safe Holding, and Risky Holding, as of the previous Tuesday. Standard errors (in parentheses) are two-way clustered at the fund and day level.

	(1)	(2)	(3)	(4)
	Flow			
Crisis	-2.435*** (0.501)	-2.133*** (0.664)	-4.746*** (1.713)	-5.019** (2.222)
NAV_to_1	-1.964 (5.551)		-6.924 (7.047)	
Crisis \times NAV_to_1	-7.481 (7.864)		-1.794 (8.525)	
$\mathbb{1}(NAV < 1)$		-0.164 (0.210)		-0.046 (0.413)
Crisis \times $\mathbb{1}(NAV < 1)$		-0.753 (0.757)		-0.696 (0.916)
WLA			-0.033 (0.032)	-0.035 (0.034)
Crisis \times WLA			0.066* (0.035)	0.073* (0.041)
Obs.	1,089	1,089	1,089	1,089
Adj. R ²	0.122	0.115	0.140	0.134
Controls			✓	✓

Bringing back the jobs lost to Covid-19: The role of fiscal policy

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Covid-19 induced job losses occurred predominantly in industries with intensive worker-client interaction as well as in pink-collar and blue-collar occupations. We study the ability of fiscal policy to stabilize employment by occupation and industry during the Covid-19 crisis. We use a multi-sector, multi-occupation macroeconomic model and investigate different fiscal policy instruments that help the economy recover faster. We show that fiscal stimuli foster job growth for hard-hit pink-collar workers, whereas stimulating blue-collar job creation is more challenging. A cut in labor taxes performs best in stabilizing total employment and the employment composition.

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1 Introduction

Job losses in the Covid-19 recession stand out in comparison to those in other recessions in two ways. First, the Covid-19 downturn is enormous and is unfolding at unprecedented speed. From February to April 2020, the monthly average of total private employment fell by more than 20 million jobs, and the unemployment rate skyrocketed from 3.5% to 14.7%.¹ Second, it is an unusual mix of workers who are struck by job losses. In a typical recession, job losses are concentrated in construction and manufacturing industries and in blue-collar occupations (Hoynes, Miller, and Schaller 2012). This time, job losses have occurred to a great extent in sectors with a high intensity of worker-client interaction. Between February and April 2020, over 10 million jobs have been lost in “retail trade” and “leisure and hospitality” industries alone. The most affected major occupation group is service occupations with an employment drop of one third from February to April 2020. In general, so-called pink-collar workers (workers in sales and service occupations) have suffered most, followed by blue-collar workers.² The latter suffered from heavy job losses, too, as in any downturn. In contrast, white-collar workers were affected relatively mildly.³

While there is no role for aggregate demand management as long as public-health measures bring down the economy’s potential output, aggregate demand management is relevant when restrictions are relaxed such that potential output can return toward its pre-crisis level. Then, a fiscal stimulus can be a tool to accelerate the recovery of actual output and employment. When this time has come, economic policy should not only concentrate on pushing up the total number of jobs but should also be concerned with the industry mix and –in particular– the occupation mix of employment to avoid excessive losses of industry-specific and occupation-specific human capital. Kambourov and Manovskii (2009) show that displaced workers’ future earnings losses are three times larger when they are unable to find a job in their initial occupation. The costs of switching occupations are estimated to be as high as several annual earnings for switches between major

¹Due to pandemic-related classification problems in the CPS, the released BLS employment statistics are likely even to understate the severity of the downturn, and the April unemployment rate could be closer to 20%, see https://www.bls.gov/news.release/archives/empst_05082020.htm. Preliminary data for May 2020 show first indications of a beginning rebound on the labor market.

²Some commentators referred to the Covid-19 recession as a “pink-collar recession” (Celina Ribeiro in *The Guardian*, May 23, 2020; Nancy Wang on *Forbes*, May 24, 2020). Due to the high share of women in pink-collar occupations and sectors with a high intensity of worker-client interaction, Covid-induced job losses for women have been much higher than during typical recessions (Alon, Doepke, Olmstead-Rumsey, and Tertilt 2020).

³See Adams-Prassl, Boneva, Golin, and Rauh (2020) for real-time data on Covid-19 related job losses by worker characteristics including industry and occupation.

occupation groups (see Artuç and McLaren, 2015, and Cortes and Gallipoli, 2018). Moreover, the returns to occupational tenure are found to be almost as large as the total returns to labor-market experience and to exceed the returns to firm or industry tenure, see, e.g., Shaw (1984), Kambourov and Manovskii (2009), and Sullivan (2010). This evidence suggests that stabilization policy can reduce the economic costs of the Covid-19 pandemic if, during the recovery, fiscal policy promotes job creation in the occupation groups hit hardest by the crisis. In this paper, we conduct a model-based analysis of the effectiveness of different fiscal-policy measures in pursuing this goal.

To clarify the scope of our analysis, it is helpful to apply Olivier Blanchard's taxonomy of the roles of fiscal policy in the Covid-19 crisis.⁴ According to Blanchard, the first role of fiscal policy is infection-fighting, i.e., to spend much on testing and create incentives for firms to produce necessary medical equipment. The second role is disaster relief, i.e., to provide transfers and loans to liquidity-constrained households and firms in order to avoid excessive hardship and bankruptcies. The third role is aggregate demand management when infections are under control, and restrictions can be relaxed. We focus on the third role (aggregate demand management) and, to isolate this role, we assume that policy is or has been successful in the first two roles. Our model has no interaction between infections and economic activity (i.e., infections are under control in the model) and abstracts from consumption heterogeneity or bankruptcies (i.e., disaster relief is successful in the model).⁵

To study the effects of fiscal-policy stimulus in the Covid-19 recovery, we use a multi-sector, multi-occupation New Keynesian business-cycle model. We distinguish between two large sectors of the economy and three broad occupation groups. Following Kaplan, Moll, and Violante (2020), we differentiate between a "social" sector that comprises industries with high physical proximity between clients and workers, such as retail trade and hospitality, and a "distant" sector where less face-to-face contact is required. Our broad occupation groups are, first, white-collar occupations such as management, professional, and office occupations, second, blue-collar occupations such as production or construction occupations, and, third, service and sales ("pink-collar") occupations.

⁴See, for example, Olivier Blanchard: Designing the fiscal response to the Covid-19 pandemic. <https://www.piie.com/blogs/realtime-economic-issues-watch/designing-fiscal-response-covid-19-pandemic>

⁵For model-based analyses of the interaction between infections and economic activity, see, for example, Acemoglu, Chernozhukov, Werning, and Whinston (2020), Eichenbaum, Rebelo, and Trabandt (2020), and Krueger, Uhlig, and Xie (2020).

Our model generates heterogeneity in occupational employment dynamics as a consequence of i) a composition effect due to heterogeneous employment changes across sectors with different average occupation mixes and ii) changes in the occupation mix within sectors due to differences in the substitutability with capital services across occupations (similar to Autor and Dorn 2013 and Bredemeier, Juessen, and Winkler 2020). In particular, labor provided by blue-collar occupations is, on average, more easily substitutable with capital than labor provided by white-collar and pink-collar occupations.

We calibrate the model to the U.S. economy and expose it to a “Covid-19 shock” that generates employment losses by industry and occupation, as seen in spring 2020. Hence, employment falls particularly sharply in the social sector as well as in blue-collar and pink-collar occupations. We then perform the following policy experiments: Nine months after the Covid-19 shock hits the economy, expansionary fiscal policy supports its recovery. We consider a variety of fiscal stimuli, both spending-based and tax-based. We further differentiate between spending packages that differ in how strongly they are directed toward a specific sector as well as between capital and labor income tax cuts.

Our results show that, in general, expansionary fiscal-policy measures promote employment growth disproportionately in the social sector and in pink-collar occupations, which counteracts the substantial losses these groups experience due to the Covid-19 crisis. By contrast, most fiscal stimulus measures exert only a low push on blue-collar employment and are hence ineffective in promoting the recovery for this group of workers. Comparing the different fiscal stimulus measures, our results show that directing spending strongly toward one of the sectors does not impact too strongly on the composition of the created jobs due to counteracting changes in the sectoral composition of private demand and the occupation mix within sectors. Even a spending expansion directed strongly toward the distant sector fosters blue-collar employment the least. The measure that quickens the recovery in blue-collar work most strongly and, in general, achieves the most significant stabilization of the occupation composition after the imminent Covid-19 crisis is a cut in tax rates on labor income.

Our paper contributes to the literature on fiscal policy during the Covid-19 crisis. Bayer, Born, Luetticke, and Müller (2020) quantify the effectiveness of disaster relief in limiting the economic

fallout from the Covid-19 pandemic by computing multipliers for the transfer component of the CARES Act in an estimated heterogenous-agents New Keynesian model. Likewise, Faria-e-Castro (2020) uses a two-agent New Keynesian model to compute the effectiveness of different types of fiscal policy instruments in cushioning the immediate effects of the Covid-19 shock, including a quantification of the impact of the CARES Act. Our paper complements these works in that it analyzes the impact of different fiscal instruments that support aggregate demand once potential output returns toward its pre-crisis level. Moreover, our focus is on how fiscal policy affects employment possibilities of workers, which are, in no small degree, determined by the labor-market situation in the worker's industry and occupation. Bredemeier, Juessen, and Winkler (2020) provide evidence of differences in the impact of government spending shocks on pink-collar relative to blue-collar employment and develop a business-cycle model that can explain these heterogeneous occupational employment dynamics. This paper extends our previous work in two important dimensions. First, we investigate the effects of a variety of fiscal policy instruments – different spending-based programs as well as cuts in labor and capital taxes. Second, we conduct a model-based analysis of potential fiscal policy measures in the recovery after a Covid-19 shock, which we calibrate to mimic the labor market during the Covid-19 crisis.⁶

The remainder of this paper is organized as follows. In Section 2, we present the model, its calibration, and how we model the Covid-19 crisis. In Section 3, we present results on the impacts of a variety of fiscal stimulus measures, which are aimed at helping the economy recover, on employment by occupation and sector. Section 4 concludes.

2 Model

We consider a two-sector economy consisting of firms, households, and the government. We will calibrate the model such that there is a “social” sector and a “distant” sector, following the classification by Kaplan, Moll, and Violante (2020). Firms in each sector produce differentiated goods under monopolistic competition and face costs of price adjustment. Production inputs are capital services and three types of occupational labor – pink-collar, blue-collar, and white-collar

⁶In general, our paper is related to the literature on the distributional consequences of fiscal policy, see, amongst others, Anderson, Inoue, and Rossi (2016), Giavazzi and McMahon (2012), Johnson, Parker, and Souleles (2006), Misra and Surico (2014), Brinca, Holter, Krusell, and Malafry (2016), Kaplan and Violante (2014), and McKay and Reis (2016).

labor. The output of each sector is used for investment, consumption, and government spending. Households are families whose members differ by occupation and can work in either sector. The government consists of a monetary and a fiscal authority. The monetary authority sets the short-term nominal interest rate. The fiscal authority collects income taxes, issues short-term government bonds, pays transfers, and purchases goods from both sectors for government consumption.

Before we describe the model in detail, we highlight the decisive factors through which the model can generate heterogeneity in the responses of employment to economic shocks. First, sectors can be affected differently by economic shocks leading to different employment responses across sectors. This leads to heterogeneity in the responses of occupational employment through a *composition effect* as long as the occupation mix of employment differs across sectors. Consider, for example, a demand shock that boosts economic activity mainly in the social sector, which employs a disproportionate share of pink-collar workers (think about a fiscal stimulus targeted directly toward the social sector). For a given occupation mix within sectors, the associated employment boom brings about predominantly pink-collar jobs since pink-collar jobs are concentrated in the social sector. Of course, the strength of this channel depends on how differently sectoral employment responds to the shock. If, in our example, changes in private demand weaken the demand stimulus targeted toward the social sector considerably, employment in the social sector may not increase significantly more strongly than in other sectors.

A second channel that can generate heterogeneity in the employment responses to economic shocks relates to *capital-labor substitution*. In our model, there is a change in the occupation mix of employment within sectors when we allow for differences across occupations in the short-run substitutability between labor and capital services, that is, the stock of physical capital times the intensity with which it is used. In particular, we build on the notion that labor provided by blue-collar occupations is, on average, more easily substitutable with capital services than labor provided by pink-collar and white-collar occupations (similar to Autor and Dorn 2013). To understand how this can lead to changes in the occupation mix of employment, consider a positive shock to aggregate demand again, now affecting both sectors equally. In response to the shock, firms in both sectors demand more factor inputs to meet increased product demand, which puts upward pressure on factor costs. Given the fact that the short-run supply of capital services is

relatively more elastic compared to the supply of labor, factor costs change in favor of capital use compared to labor. Therefore, firms raise their demand for capital services more than their demand for labor. The disproportionate surge in capital usage lowers the marginal productivity of its closer substitute, blue-collar employment, relative to pink-collar or white-collar employment. Thus, firms change their occupation mix in favor of pink-collar and white-collar work, employing now a higher share of pink-collar workers than before (see Bredemeier, Juessen, and Winkler 2020). Of course, a shock that directly affects the relative costs of labor in a way such that labor becomes cheaper relative to capital (for example, a cut in labor income taxes), will lead to the opposite result. In this case, blue-collar workers will benefit disproportionately as firms substitute away from capital services toward labor.

The occupation mix within a sector has implications for the overall employment effects of fiscal policy within a sector. The less easily labor can be substituted by capital within an industry, the higher will be the job multiplier in the industry. This is the case in the social sector, which employs a disproportionate share of pink-collar workers. By contrast, in industries that employ relatively many blue-collar workers, additional government purchases lead to comparatively moderate employment boosts as firms in such sectors meet the increased demand by raising their use of capital services predominantly.

We expose our model economy to a Covid-19 shock. Following Eichenbaum, Rebelo, and Trabandt (2020), we use stochastic wedges to construct a Covid-19 scenario that matches empirical job losses by sector and occupation group in spring 2020. The wedges combine aspects of both supply and demand disturbances, in line with the evidence by Brinca, Duarte, and Faria-e-Castro (2020). In particular, we incorporate stochastic wedges between producer prices and the total consumer cost of a good as well as between firms' labor costs and workers' effective net labor income. The price wedge in the social sector can be interpreted as the additional cost associated with trading this sector's output in times of social distancing. The labor market wedges can be interpreted as the extra cost required to provide labor services during the pandemic. These costs are plausibly heterogeneous across occupations since occupations differ considerably in terms of work-from-home possibilities (see, e.g., Dingel and Neiman 2020).

2.1 Model description

Households. There is a continuum of infinitely-lived households, with mass normalized to one. Each household supplies pink-collar, blue-collar, and white-collar labor to both sectors. Household members are not allowed to switch their occupation, in line with empirical evidence that occupation switches are associated with substantial costs (see, e.g., Kambourov and Manovskii, 2009, Artuç and McLaren, 2015, Cortes and Gallipoli, 2018) and occur rarely (see, e.g., Moscarini and Thomsson, 2007, Fujita and Moscarini, 2013, Foote and Ryan, 2014). We assume a unitary household that cares about its total consumption level of a composite good (consisting of goods of both sectors) and receives disutility from all types of labor – pink-collar labor, n_t^p , blue-collar labor, n_t^b , and white-collar labor, n_t^w . With this modeling assumption, our analysis should be understood as a positive analysis. At the same time, our model is not supposed to allow a normative analysis of the distributional effects of stabilization policy.

Each household maximizes lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, n_t^p, n_t^b, n_t^w), \tag{1}$$

where $\beta \in (0, 1)$ is the households' discount factor and c_t is consumption of a composite good, defined as an aggregate of consumption of the sector-1 good, $c_{1,t}$, and consumption of the sector-2 good, $c_{2,t}$, with substitution elasticity $\mu > 0$,

$$c_t = \left(\zeta^{\frac{1}{\mu}} \cdot (c_{1,t})^{\frac{\mu-1}{\mu}} + (1 - \zeta)^{\frac{1}{\mu}} \cdot (c_{2,t})^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}. \tag{2}$$

Given a decision on the composite consumption good c_t , the household allocates optimally the expenditure on consumption of good 1 and good 2 by minimizing total expenditures $(1 + \wedge_{1,t})p_{1,t}c_{1,t} + (1 + \wedge_{2,t})p_{2,t}c_{2,t}$, subject to (2), where $p_{1,t}$ and $p_{2,t}$ are the prices of the sectoral goods and $\wedge_{1,t}$ and $\wedge_{2,t}$ are good-specific wedges that follow exogenous stochastic processes with mean zero. These wedges, among other wedges discussed below, allow us to capture the Covid-19 downturn in our model. In particular, the Covid-induced sector-specific collapses in demand will be triggered by sector-specific increases in the price wedges.

Following Horvath (2000), we assume that members of each household supply labor to firms in

both sectors according to

$$n_t^o = \left((\aleph^o)^{-\frac{1}{\omega}} \cdot (n_{1,t}^o)^{\frac{1+\omega}{\omega}} + (1 - \aleph^o)^{-\frac{1}{\omega}} \cdot (n_{2,t}^o)^{\frac{1+\omega}{\omega}} \right)^{\frac{\omega}{1+\omega}}, \quad \text{for } o = p, b, w. \quad (3)$$

The parameter $\omega > 0$ controls the degree of labor mobility across sectors. For $\omega \rightarrow \infty$, labor can be freely reallocated and all sectors pay the same hourly wage at the margin. For $\omega < \infty$ there is a limited degree of sectoral labor mobility and sectoral wages are not equalized. Given a decision on n_t^p , n_t^b , and n_t^w the household allocates optimally the supply of labor to sectors 1 and 2 by maximizing, for $o = p, b, w$, real wage income $(1 - \wedge_t^o) (w_{1,t}^o n_{1,t}^o + w_{2,t}^o n_{2,t}^o)$, subject to (3), where $w_{1,t}^o$ and $w_{2,t}^o$ are sector-specific real wages for white-collar, blue-collar, and pink-collar labor. The term \wedge_t^o is an occupation-specific wedge that follows an exogenous stochastic process with mean zero. In our model, the Covid-induced occupation-specific employment losses will be matched by changes in occupation-specific labor wedges.

Following Jaimovich and Rebelo (2009), the period utility function $u(c_t, n_t^p, n_t^b, n_t^w)$ takes a form that allows to parameterize the wealth effect on labor supply:

$$\frac{\left(c_t - \left(\frac{\Omega^p}{1+1/\eta} (n_t^p)^{1+1/\eta} + \frac{\Omega^b}{1+1/\eta} (n_t^b)^{1+1/\eta} + \frac{\Omega^w}{1+1/\eta} (n_t^w)^{1+1/\eta} \right) x_t \right)^{1-1/\sigma} - 1}{1 - 1/\sigma}, \quad (4)$$

where $\sigma > 0$ is the intertemporal elasticity of substitution in consumption, $\Omega^p > 0$, $\Omega^b > 0$, and $\Omega^w > 0$ are scale parameters, x_t is a weighted average of current and past consumption evolving over time according to

$$x_t = c_t^\chi x_{t-1}^{1-\chi}, \quad (5)$$

$\chi \in (0, 1]$ governs the wealth elasticity of labor supply, and $\eta > 0$ is the Frisch elasticity of labor supply in the limiting case $\chi \rightarrow 0$. In this case, there is no wealth effect on labor supply and preferences are of the type considered by Greenwood, Hercowitz, and Huffman (1988).

The household's period-by-period budget constraint (in real terms) is given by

$$\begin{aligned}
 c_t + \frac{(1 + \wedge_{1,t})p_{1,t}}{p_t}i_{1,t} + \frac{(1 + \wedge_{2,t})p_{2,t}}{p_t}i_{2,t} + b_t = & \\
 (1 + r_{t-1})\frac{b_{t-1}}{\pi_t} + (1 - \tau_t^k) \left(r_{1,t}^k \tilde{k}_{1,t} + r_{2,t}^k \tilde{k}_{2,t} \right) + T_t + d_t & \\
 + (1 - \tau_t^n) \left[w_t^p n_t^p + w_t^b n_t^b + w_t^w n_t^w \right] & \\
 - \frac{(1 + \wedge_{1,t})p_{1,t}}{p_t}e(u_{1,t})k_{1,t-1} - \frac{(1 + \wedge_{2,t})p_{2,t}}{p_t}e(u_{2,t})k_{2,t-1}, & \quad (6)
 \end{aligned}$$

where $p_t = (\zeta \cdot [(1 + \wedge_{1,t})p_{1,t}]^{1-\mu} + (1 - \zeta) \cdot [(1 + \wedge_{2,t})p_{2,t}]^{1-\mu})^{1/(1-\mu)}$ is the price of the composite good c_t , $i_{s,t}$ is investment into physical capital in sector s (where $s = 1, 2$), b_{t-1} is the beginning-of-period stock of real government bonds, τ_t^n is the labor tax rate, τ_t^k is the capital tax rate, $\tilde{k}_{s,t}$ are capital services in sector s , $r_{s,t}^k$ is the sector-specific rental rate of capital services, $k_{s,t-1}$ denotes the beginning-of-period capital stock in sector s , $u_{s,t}$ is capital utilization in sector s , $e(u_{s,t})$ are the costs of capital utilization in sector s , T_t are government transfers, $d_t = d_{1,t} + d_{2,t}$ are dividends from the ownership of firms in both sectors, r_t is the nominal interest rate, $\pi_t = p_t/p_{t-1}$ is consumer price inflation, and $w_t^o = (\aleph^o \cdot ((1 - \wedge_t^o)w_{1,t}^o)^{1+\omega} + (1 - \aleph^o) \cdot ((1 - \wedge_t^o)w_{2,t}^o)^{1+\omega})^{1/(1+\omega)}$ is the aggregate real wage for occupation $o = p, b, w$.

Following Ramey and Shapiro (1998), we assume that capital goods for a particular sector must be produced within that sector. Thus, the capital stock in each sector evolves according to

$$k_{s,t} = (1 - \delta)k_{s,t-1} + \left(1 - \frac{\kappa_i}{2} \left(\frac{i_{s,t}}{i_{s,t-1}} - 1 \right)^2 \right) i_{s,t}, \quad s = 1, 2, \quad (7)$$

where $\delta \in (0, 1)$ is the capital depreciation rate and $\frac{\kappa_i}{2} (i_{s,t}/i_{s,t-1} - 1)^2$ represents investment adjustment costs with $\kappa_i \geq 0$.

Households choose capital utilization rates $u_{s,t}$, which transform physical capital in sector s into capital services $\tilde{k}_{s,t}$ according to $\tilde{k}_{s,t} = u_{s,t}k_{s,t-1}$. Costs of capital utilization are given by

$$e(u_{s,t}) = \delta_1(u_{s,t} - 1) + \frac{\delta_2}{2}(u_{s,t} - 1)^2, \quad s = 1, 2,$$

which implies the absence of capital utilization costs at the deterministic steady state in which capital utilization is normalized to $u_s = 1$. The elasticity of capital utilization with respect to the rental rate of capital, evaluated at the steady state, is given by $\Delta = \delta_1/\delta_2 > 0$. As capital is

predetermined, Δ corresponds to the short-run elasticity of the supply of capital services.

Households choose quantities $(c_t, x_t, b_t, k_{s,t}, i_{s,t}, u_{s,t}, n_t^b, n_t^p, \text{ and } n_t^w)$, taking as given the set of prices $(w_t^p, w_t^b, w_t^w, p_t, p_{s,t}, r_{s,t}^k, \text{ and } r_t)$, dividends (d_t) , transfers (I_t) , taxes (τ_t^n, τ_t^k) , and wedges $(\Lambda_{s,t}, \Lambda_t^b, \Lambda_t^p, \Lambda_t^w)$ to maximize (1) subject to (5), (6) and (7). First-order conditions can be found in the Appendix.

Firms. Each sector $s = 1, 2$ produces a final good and a continuum of intermediate goods indexed by j , where j is distributed over the unit interval. Each intermediate good is produced by a single firm. There is monopolistic competition in the markets for intermediate goods. Final goods firms in each sector use intermediate goods $y_{j,s,t}$, taking as given their price $p_{j,s,t}$, and sell the output $y_{s,t}$, at the competitive price $p_{s,t}$. The production function of the sector- s final good is $y_{s,t} = \left(\int_0^1 y_{j,s,t}^{(\epsilon-1)/\epsilon} di \right)^{\epsilon/(\epsilon-1)}$, where $\epsilon > 1$ is the elasticity of substitution between different varieties.

Firm j in sector s produces its output $y_{j,s,t}$ using capital services $\tilde{k}_{j,s,t}$, three types of labor, blue-collar labor $n_{j,s,t}^b$, pink-collar labor $n_{j,s,t}^p$, and white-collar labor $n_{j,s,t}^w$, and the following nested CES production technology:

$$y_{j,s,t} = y_{j,s} \cdot \left(v_s \cdot \left(\frac{v_{j,s,t}^p}{v_{j,s}^p} \right)^{\frac{\iota-1}{\iota}} + (1 - v_s) \cdot \left(\frac{n_{j,s,t}^w}{n_{j,s}^w} \right)^{\frac{\iota-1}{\iota}} \right)^{\frac{\iota}{\iota-1}}, \tag{8}$$

where $v_{j,s,t}^p$ is a normalized CES bundle of $v_{j,s,t}^b$ and pink-collar labor, given by

$$v_{j,s,t}^p = v_{j,s}^p \cdot \left(\alpha_s \cdot \left(\frac{v_{j,s,t}^b}{v_{j,s}^b} \right)^{\frac{\theta-1}{\theta}} + (1 - \alpha_s) \cdot \left(\frac{n_{j,s,t}^p}{n_{j,s}^p} \right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}},$$

where $v_{j,s,t}^b$ is, in turn, a normalized CES bundle of capital services and blue-collar labor:

$$v_{j,s,t}^b = v_{j,s}^b \cdot \left(\gamma_s \cdot \left(\frac{\tilde{k}_{j,s,t}}{\tilde{k}_{j,s}} \right)^{\frac{\phi-1}{\phi}} + (1 - \gamma_s) \cdot \left(\frac{n_{j,s,t}^b}{n_{j,s}^b} \right)^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}}.$$

The parameter $\phi > 0$ captures the elasticity of substitution between capital services and labor in the representative blue-collar occupation, the parameter $\theta > 0$ captures the elasticity of substitution between capital services and labor in the representative pink-collar occupation, and the parameter ι captures the elasticity of substitution between capital services and labor in the representative white-collar occupation. The parameters $v_s \in (0, 1)$, $\alpha_s \in (0, 1)$, and $\gamma_s \in (0, 1)$ reflect factor intensities in

production. The normalization of the CES production technology allows to disentangle the factor intensities v_s , α_s , and γ_s from the elasticities of substitution ι , ϕ , and θ (see, e.g., León-Ledesma, McAdam, and Willman 2010).

The firm chooses $\tilde{k}_{j,s,t}$, $n_{j,s,t}^w$, $n_{j,s,t}^b$, and $n_{j,s,t}^p$ to minimize its costs (deflated by the consumer price index p_t)

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left\{ w_{s,t}^b n_{j,s,t}^b + w_{s,t}^p n_{j,s,t}^p + w_{s,t}^w n_{j,s,t}^w + r_{s,t}^k \tilde{k}_{j,s,t} + \frac{\kappa_{n,s}}{2} \left[\left(\frac{n_{j,s,t}^w}{n_{j,s,t-1}^w} - 1 \right)^2 + \left(\frac{n_{j,s,t}^b}{n_{j,s,t-1}^b} - 1 \right)^2 + \left(\frac{n_{j,s,t}^p}{n_{j,s,t-1}^p} - 1 \right)^2 \right] \frac{(1 + \wedge_{s,t}) p_{s,t}}{p_t} y_{s,t} \right\}, \quad (9)$$

subject to (8), where $\frac{\kappa_{n,s}}{2} \left(n_{j,s,t}^o / n_{j,s,t-1}^o - 1 \right)^2$ are quadratic labor adjustment costs for occupation $o = w, p, b$, expressed in units of the final consumption good, where the sector-specific parameter $\kappa_{n,s} \geq 0$ measures the extent of labor adjustment costs in the respective sector. The firm takes factor prices as given. The term $\beta^t \lambda_t / \lambda_0$ denotes the stochastic discount factor for real payoffs, where λ_t is the marginal utility of real income of the representative household that owns the firm.

The firm faces a quadratic cost of price adjustment. It chooses its price $p_{j,s,t}$ to maximize the discounted stream of profits, expressed in units of the final consumption good,

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left(\frac{p_{j,s,t}}{p_t} \cdot y_{j,s,t} - mc_{j,s,t} \cdot y_{j,s,t} - \frac{\psi}{2} \left(\frac{p_{j,s,t}}{p_{j,s,t-1}} - 1 \right)^2 \frac{(1 + \wedge_{s,t}) p_{s,t}}{p_t} y_{s,t} \right), \quad (10)$$

subject to the demand function for variety j , $y_{j,s,t} = (p_{j,s,t} / p_{s,t})^{-\epsilon} y_{s,t}$, where $y_{s,t}$ is aggregate demand for the good of sector s , $p_{j,s,t} / p_{s,t}$ is the relative price of variety j within the sector, and $p_{s,t} = \left(\int_0^1 p_{j,s,t}^{1-\epsilon} di \right)^{1/(1-\epsilon)}$ is the price index of sector s . $mc_{j,s,t}$ denotes real marginal costs. The final term in (10) represents the costs of price adjustment, where $\psi \geq 0$ measures the degree of nominal price rigidity. Firms' first-order conditions can be found in the Appendix.

Market clearing, monetary and fiscal policy. The fiscal authority finances transfers and an exogenous stream of government spending g_t by labor and capital taxes. The government consumption bundle comprises goods 1 and 2 in a similar way than that of households,

$$g_t = \left(\zeta_g^{\frac{1}{\mu}} \cdot (g_{1,t})^{\frac{\mu-1}{\mu}} + (1 - \zeta_g)^{\frac{1}{\mu}} \cdot (g_{2,t})^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}, \quad (11)$$

where ζ_g determines the steady-state share of good 1 in total government spending while, for simplicity, the elasticity of substitution between the two goods, μ is the same as for households. The government budget constraint (in real terms) reads

$$\frac{p_{g,t}}{p_t} g_t + T_t + (1 + r_{t-1}) \frac{b_{t-1}}{\pi_t} = b_t + \tau_t^n \left(w_t^b n_t^b + w_t^p n_t^p + w_t^w n_t^w \right) + \tau_t^k \left(r_{1,t}^k \tilde{k}_{1,t} + r_{2,t}^k \tilde{k}_{2,t} \right), \tag{12}$$

where $p_{g,t} = \left(\zeta_g \cdot [(1 + \wedge_{1,t}) p_{1,t}]^{1-\mu} + (1 - \zeta_g) \cdot [(1 + \wedge_{2,t}) p_{2,t}]^{1-\mu} \right)^{1/(1-\mu)}$ is the price index of government spending and g_t follows an exogenous stochastic process with mean g . For a given g_t , the government determines its purchases of goods 1 and 2 such as to minimize purchasing costs. Tax rates, τ_t^k and τ_t^n , follow exogenous stochastic processes with means τ^k and τ^n . Government spending and tax shocks are contemporaneously financed by adjustments in government debt. In order to guarantee the stability of government debt, transfers follow the rule $\log(T_t) = (1 - \rho_T) \log(T) + \rho_T \log(T_{t-1}) - \gamma_b \cdot (b_{t-1} - b)/y$, where the parameter γ_b is positive and sufficiently large.

Monetary policy is described by the augmented Taylor rule

$$\log((1 + r_t)/(1 + r)) = \delta_\pi \log(\pi_t/\pi) + \delta_y \log(y_t/y) + \delta_g \log(g_t/g), \tag{13}$$

where the parameters $\delta_\pi > 1$ and $\delta_y \geq 0$ measure the responsiveness of the nominal interest rate to consumer price inflation and aggregate output, respectively, where aggregate output, y_t , is defined as $y_t = (p_{1,t}/p_t) y_{1,t} + (p_{2,t}/p_t) y_{2,t}$. Following Nakamura and Steinsson (2014), the nominal interest rate may also directly respond to government spending, with responsiveness measured by δ_g .

Goods market clearing requires aggregate production in sector s , $y_{s,t}$, to be equal to aggregate demand for the sector- s good which includes sector-specific resources needed for capital utilization, price adjustment, labor adjustment, and product and labor wedges:

$$y_{s,t} = (1 + \wedge_{s,t}) \left(c_{s,t} + i_{s,t} + g_{s,t} + e(u_{s,t}) k_{s,t-1} + \frac{\psi}{2} (\pi_{s,t} - 1)^2 y_{s,t} + \frac{\kappa_{n,s}}{2} \left[\left(\frac{n_{s,t}^b}{n_{s,t-1}^b} - 1 \right)^2 + \left(\frac{n_{s,t}^p}{n_{s,t-1}^p} - 1 \right)^2 + \left(\frac{n_{s,t}^w}{n_{s,t-1}^w} - 1 \right)^2 \right] y_{s,t} + \frac{p_t}{p_{s,t}} \left(\wedge_t^p w_{s,t}^p n_{s,t}^p + \wedge_t^b w_{s,t}^b n_{s,t}^b + \wedge_t^w w_{s,t}^w n_{s,t}^w \right) \right), \quad s = 1, 2. \tag{14}$$

Data-consistent employment. As the goods-market clearing conditions (14) show, the model economy produces some goods which are then wasted due to the wedges on goods and labor markets ($\wedge_{s,t}$ for $s = 1, 2$ and \wedge_t^o for $o = p, b, w$). We define data-consistent employment measures which corrects for the production of goods used to “pay” for the inefficiencies modeled by the wedges. Specifically, data-consistent employment by sector, $l_{s,t}$ ($s = 1, 2$), by occupation, l_t^o ($o = p, b, w$), as well as data-consistent aggregate employment, l_t , are given by

$$l_{s,t} = \frac{1}{1 + \wedge_{s,t}} \left(n_{s,t}^p (1 - \wedge_t^p) + n_{s,t}^b (1 - \wedge_t^b) + n_{s,t}^w (1 - \wedge_t^w) \right), \quad (15)$$

$$l_t^o = (1 - \wedge_t^o) \left(\frac{n_{1,t}^o}{1 + \wedge_{1,t}} + \frac{n_{2,t}^o}{1 + \wedge_{2,t}} \right), \quad (16)$$

and

$$l_t = l_t^w + l_t^b + l_t^p = l_{1,t} + l_{2,t}. \quad (17)$$

2.2 Data, calibration, and the Covid-19 shock

The parametrization is a combination of using empirical estimates for the U.S. from the literature for some parameters and calibrating others. Before we describe the calibration in detail, we first describe the data on industry and occupation used to calibrate the model.

We use Kaplan, Moll, and Violante (2020)’s classification of NAICS industries as either part of the social sector or the distant sector. Table A.1 in the Appendix shows this sectoral classification. The 23 major occupations groups from the 2018 Standard Occupational Classification System are aggregated into the white-collar, blue-collar, and pink-collar occupation groups as shown in Table A.2 in the Appendix.

We use the 2018 BLS industry-occupation matrix to determine the size of our three-occupation groups as well as their distribution over our two sectors. As can be seen in Table 1, the social sector uses pink-collar labor relatively intensively, whereas the distant sector is blue-collar intensive. White-collar employment, by contrast, is almost equally distributed across the two industry groups. We calculate average wages by occupation using the May 2018 National Occupational Employment and Wage Estimates from the Occupational Employment Statistics. Workers in white-collar occupations earn the highest hourly wage rates (approximately \$33), followed by blue-collar workers with an average hourly wage rate of roughly \$23. Workers in pink-collar occupations earn the

Table 1: Share of aggregate employment in sector-occupation group cells.

	social sector	distant sector	Σ
white-collar occupations	23.4%	21.4%	44.7%
blue-collar occupations	6.0%	17.8%	23.8%
pink-collar occupations	26.3%	5.1%	31.4%
Σ	55.7%	44.3%	100%

Notes: Results aggregated from the 2018 BLS industry-occupation matrix.

least, having an average wage rate of about \$16 per hour.

We calibrate the model such that sector 1 is the social sector, and sector 2 is the distant sector. One period is one quarter. The intertemporal elasticity of substitution in consumption, σ , is set to 1. We use the estimates in Schmitt-Grohé and Uribe (2012) to quantify the wealth elasticity $\chi = 0.0001$, the elasticity of capital utilization $\Delta = \delta_1/\delta_2 = 3$, and the investment adjustment costs $\kappa_i = 9$. We set the Frisch elasticity of labor supply, which equals the parameter η when χ is close to zero, to 0.72, taken from Bredemeier, Gravert, and Juessen (2019).

We use the U.S. estimate for the degree of labor mobility across sectors by Horvath (2000) and set $\omega = 1$. We set the elasticity of substitution between goods within a sector to $\epsilon = 6$ implying a steady-state markup of prices over marginal costs equal to 20%. The elasticity of substitution in consumption between the goods of both sectors is set to $\mu = 1$. For some goods, this value tends to overestimate the substitutability between social-sector products and the average distant-sector good. For example, it is difficult to think about consumers substituting health services for the typical distant-sector good. However, there are arguably also goods for which the degree of substitutability is far higher. For example, consumers can easily switch from buying products at bricks and mortar retailers (social sector) to online shopping (distant sector). We, therefore, choose the standard Cobb-Douglas case of $\mu = 1$ as our baseline value.

The quarterly capital depreciation rate, δ , and the discount factor, β , are set to $\delta = 0.022$ and $\beta = 0.9927$. These values imply an aggregate capital to output ratio of 3.6 and an annualized real interest rate of around 3 percent. We parameterize the cost of price adjustment, ψ , to generate a slope of the Phillips curve consistent with a probability of adjusting prices in the Calvo model equal to 1/3, as estimated by Smets and Wouters (2007). This delivers $\psi \approx 30$. The steady-state

tax rates and the annualized steady-state debt to GDP ratio are set to $\tau^n = 0.28$, $\tau^k = 0.36$, and $b/(4y) = 0.63$, as calculated by Trabandt and Uhlig (2011). The responsiveness of government transfers to changes in government debt is set to $\gamma_{sb} = 0.1$ to ensure debt sustainability. The coefficients of the Taylor rule measuring the responsiveness of the interest rate to inflation and output are set to $\delta_\pi = 1.5$ and $\delta_y = 0.5/4$, as proposed by Taylor (1993). We impose a zero net inflation steady state ($\pi = 1$).

The steady-state share of government spending in total output is set to the standard value of 0.2. We set the autocorrelation of government spending to $\rho_g = 0.9$. To calibrate the parameter ζ_g , which determines the distribution of government spending across sectors, we use the information on government spending for education and health services, the major components of public spending in the social sector. According to data from the World Bank Database and Congressional Budget Office, expenditures of federal, state, and local governments amount to 5% of GDP for education and 6% of GDP for health services, net of tax preferences. Hence, we consider government expenditure in the social sector to be 11% of GDP. With a total share of government spending in GDP of 20%, this gives a share of social-sector government expenditures in total government expenditures of $\zeta_g = 0.55$.

The weights on labor in the utility function, Ω^p , Ω^b , and Ω^w , are chosen to generate a steady-state occupation mix of employment consistent with the empirical counterpart displayed in Table 1. We set the share parameters \aleph^p , \aleph^b , \aleph^w , v_1 , v_2 , α_1 , α_2 , γ_1 , γ_2 , and ζ to match the composition of occupations across industries displayed in Table 1 as well as the relative occupational wages rates along with a labor income share of 67%. We achieve these calibration targets by setting $\zeta = 0.5$, $\aleph^p = 0.84$, $\aleph^b = 0.25$, $\aleph^w = 0.52$, $\alpha_1 = 0.45$, $\alpha_2 = 0.9$, $\gamma_1 = 0.64$, $\gamma_2 = 0.51$, $v_1 = 0.5$, and $v_2 = 0.54$.

The following parameters are taken from Bredemeier, Juessen, and Winkler (2020), where we parameterize a multi-sector, multi-occupation New Keynesian business cycle model to match the estimated effects of U.S. government spending shocks. The parameter δ_g , which captures the responsiveness of the nominal interest rate to government spending, is $\delta_g = -0.364$. In Bredemeier, Juessen, and Winkler (2020), we use this value to match the estimated government spending multiplier. Furthermore, we believe that monetary accommodation describes monetary policy

during and in the aftermath of the Covid-19 crisis rather well.⁷ The parameters governing the size of labor adjustment costs in both sectors are $\kappa_{n,1} = 1.03$ and $\kappa_{n,2} = 3.33$. These values match the empirical evidence on the response of relative sectoral employment to government spending shocks, together with a weighted average of labor adjustment costs of 1.85, as estimated by Dib (2003). The elasticities of substitution with capital services are $\phi = 2.7$ for blue-collar work, $\theta = 0.07$ for pink-collar work, and $\iota = 1$ for white-collar work, respectively. In Bredemeier, Juessen, and Winkler (2020), we show that these values rationalize the relative occupational employment dynamics in response to U.S. government spending shocks. At the same time, they imply an average elasticity of substitution between capital services and labor of one, as in the canonical Cobb-Douglas case.

Covid-19 shock. We expose the model economy to a “Covid-19” shock, which we calibrate to match the spring-2020 job losses and their distribution over sectors and occupation groups. The Covid-19 scenario we consider is not meant to explain the labor market outcomes in the Covid-19 crisis as we mostly use exogenous wedges to match empirical observations. The scope of our Covid-19 scenario is to set the scene for the policy analyses described in the next section, which we want to conduct in an environment mimicking the labor-market situation during the Covid-19 crisis as closely as possible. In particular, we want to analyze the ability of fiscal policy to create jobs where they were lost. While, in a model like ours, the isolated effects of a shock, e.g., a fiscal policy innovation, are barely affected by the state of the economy when the shock hits, it is worth mentioning that these isolated effects are not our primary focus. Instead, our aim is to study how well the distribution of jobs created by different fiscal policy impulses fits the needs in the Covid crisis, i.e., the distribution of job losses due the Covid shock.

For the aggregate employment drop and its expected future development, we use the May 2020 Interim Economic Projections by the Congressional Budget Office (CBO), <https://www.cbo.gov/publication/56368>. The CBO expects employment in the second quarter of 2020 to be 25.6 million lower than in the last quarter of 2019, which corresponds to a drop by about 17% relative to 2019 employment levels. While acknowledging the severe uncertainty about how the crisis continues to unfold, the CBO forecasts a gradual return starting immediately after the initial bust in spring 2020, and that job losses will have halved by the second quarter of 2021. These

⁷It does not appear reasonable to assume that, in the near term, monetary policy will lean against a fiscal expansion that aims to help the economy recover faster.

Table 2: Shares of 2018 employment and Covid-related employment losses by worker group.

Worker group	Share of 2018 employment	Share of Covid-19 job losses
<i>Sectors</i>		
distant	44.3%	29.1%
social	55.7%	70.9%
<i>Occupation groups</i>		
white-collar	44.7%	33%
blue-collar	22.9%	27%
pink-collar	31.4%	39%

Notes: Own calculations based on Adams et al. (2020) and BLS industry-occupation matrix.

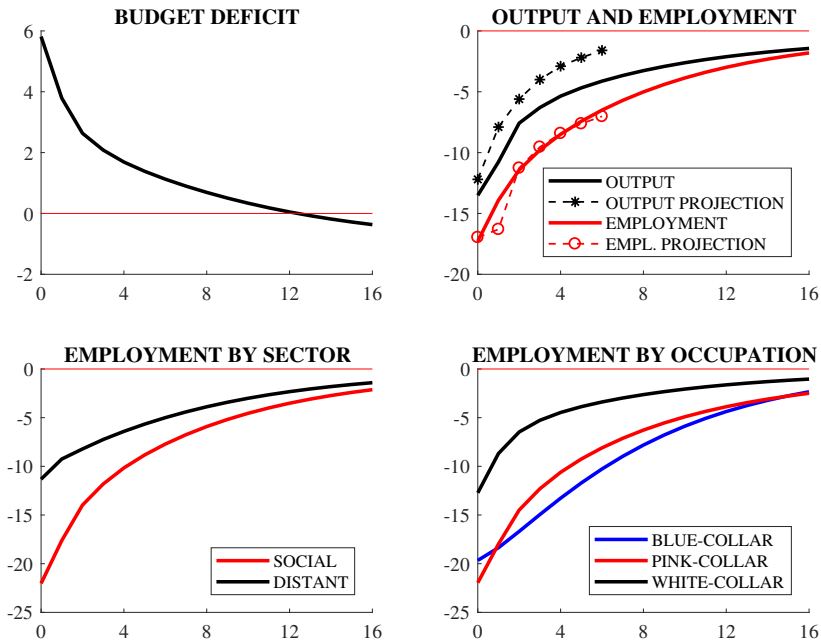
projections are in line with the preliminary BLS employment statistics for May which showed first signs of a beginning rebound. It is worth mentioning that the CBO projections incorporate the assumption that current laws generally remain unchanged and that no significant additional emergency funding is provided. The CBO projections thus constitute a useful baseline scenario against which we can analyze the effects of different fiscal policy measures in the crisis.

Regarding the distribution of job losses over sectors and occupations, we use the numbers reported by Adams-Prassl, Boneva, Golin, and Rauh (2020). They performed a real-time survey on Covid-19 related job losses and report percentage employment losses by occupation and industry. We multiply these numbers with the 2018 employment level to obtain absolute numbers, which we then add by sectors and occupation groups. We then calculate the distribution of total job losses over sectors and occupation groups.⁸ Results are shown in Table 2. More than 7 out of 10 Covid-related job losses occurred in the social sector, and about 4 in 10 occurred in pink-collar occupations. The overall employment loss reported by Adams-Prassl, Boneva, Golin, and Rauh (2020) is 18% and hence similar to the number implied by the CBO projections.

Our analysis does not seek to explain these developments, which likely have to do with opportunities to work from home (relatively pronounced for white-collar occupations) and the sectoral

⁸Adams-Prassl, Boneva, Golin, and Rauh (2020) do not differentiate between retail and wholesale trade and do not report job losses for subcategories of transportation and warehousing industries. We use CES employment data for March to distribute the job losses reported by Adams-Prassl, Boneva, Golin, and Rauh (2020) for wholesale and retail trade as well as for transportation and warehousing to their respective subcategories. The CES numbers for March show that employment in wholesale trade increased from February. To remain conservative, we attribute all job losses reported by Adams-Prassl, Boneva, Golin, and Rauh (2020) for wholesale and retail trade to retail trade. Similarly, the CES numbers for March do not indicate employment losses in the truck, pipeline, and storage industries. Accordingly, we attribute all job losses reported by Adams-Prassl, Boneva, Golin, and Rauh (2020) for transportation and storage to the social sector.

Figure 1: Baseline Covid-19 scenario



Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. All other variables in percent of their own steady-state values.

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composition of employment by occupation (pink-collar occupations make up a major share of employment in the social sector). These phenomena are outside the model, and we use the “wedges” to generate the observed phenomena. In particular, we calibrate the innovations to the wedges to generate a 17% drop in aggregate employment on impact (in quarter zero), which is distributed over the different sectors and occupations, as summarized in Table 2. Moreover, we model the stochastic wedge processes as an autoregressive process of order one and set the autocorrelation to 0.86 to match as closely as possible the employment path projected by the CBO.

Subject to these shocks, the model produces profiles for the main variables depicted in Figure 1. We assume that the economy was at its steady state before the crisis. All variables are expressed in percentage deviations from their pre-crisis (steady-state) levels, except for the budget deficit, which we measure in percent of steady-state GDP. The vertical axis displays quarters after the shock. We consider quarter “0” as the second quarter of 2020.

The model predicts the budget deficit to rise by 5.8% percent of steady-state GDP in response to the crisis. In our model, this is a consequence of the collapse in tax revenues only as we do not

model the budgetary costs of infection-fighting and disaster relief. Therefore, the actual budgetary costs of the Covid-19 crisis are likely higher. In April 2020, the CBO projected the deficit for the year 2020 to increase by 7.7 percent of 2019 GDP.⁹

The upper-right panel of Figure 1 shows the path of output and employment in our scenario. As targeted, aggregate employment (solid red line) falls by 17% on impact and then recovers gradually. Over the course of two years, the employment recovery fits the CBO projections (dashed red lines with circles) rather well such that the AR(1) assumption for the wedges seems adequate. Also the response of output, which is non-targeted in our scenario, is relatively similar to the CBO projections. Our model predicts that output (solid black line) plummets by 13% in the second quarter of 2020, which is only slightly larger than in the CBO projection (dashed black line with asterisks). Output in the model recovers somewhat more slowly than projected by the CBO, but the overall shape is similar.

The lower panels of the figure show the responses of employment by occupation and sector. While the initial job losses by sector and occupation are targeted in our calibration of the Covid-19 shock, we do not target a sector-specific or occupation-specific speed of recovery. The model predicts blue-collar employment to recover more slowly than pink-collar employment, making it the occupation group with the most significant employment loss relative to pre-Covid levels from fall 2020 onward.

3 Policy scenarios

In this section, we study the effects of aggregate demand management in the Covid-19 recovery as projected by our model. We consider three different, discretionary, government spending expansions that differ by the distribution of purchases across sectors and three tax cut scenarios that differ by the treatment of capital and labor income. As discussed in the introduction, we focus on aggregate demand management when the infection rate is under control and most restrictions on economic activity are relaxed. While it remains uncertain when these conditions will be met, we choose the first quarter of 2021 as the starting point of aggregate demand management. We quantify the size of the expansionary impulse to achieve a full recovery of aggregate employment

⁹We calculate this number as the projected increase in the deficit-to-GDP ratio minus the projected percentage decline in GDP. The May outlook does not include a deficit forecast.

by the third quarter of 2021. While this constitutes an ambitious goal, we want to compare policy measures that have the same effect on total employment, which allows us to concentrate on their differential effects on the employment composition.

3.1 Spending expansions

We first consider expansions in government spending. Our focus is on the disaggregated employment developments during the recovery. As discussed in Section 2, disaggregated employment dynamics in our model are driven by two channels, one that relates to differences in economic activity across sectors and their resulting composition effects and one that relates to capital-labor substitution within industries. In the recovery supported by spending expansions, these two channels work as follows.

The spending stimulus boosts aggregate demand, which leads to increased factor demand and, hence, tends to promote the recovery of employment. Mechanically, the more additional government purchases accrue in any given sector, the more strongly the recovery in this sector tends to be accelerated. Via *composition effects*, this can also help stimulate the employment recovery for those occupation groups strongly represented in this sector.

The increase in factor demand also promotes the recovery in factor prices. This is more pronounced for labor, which is in less elastic supply than capital services. Therefore, firms return production toward normal levels by predominantly raising their use of capital services, which remain cheap. The more intensive use of capital lowers the marginal productivity of its close substitute, blue-collar labor, weakening the recovery of blue-collar work. On the contrary, the more intensive use of capital raises the marginal productivity of its close complement, pink-collar labor, reinforcing the recovery of pink-collar employment. The increase in white-collar employment, for which the elasticity of substitution with capital services is equal to unity, lies in between the increase of pink-collar and blue-collar labor employment. At the sectoral level, the *capital-labor substitution* channel, in isolation, implies that a spending expansion tends to promote the employment recovery relatively strongly in sectors that employ many pink-collar workers and more weakly in industries employing relatively many blue-collar workers. Put differently, the job multiplier is higher in pink-collar intensive sectors.

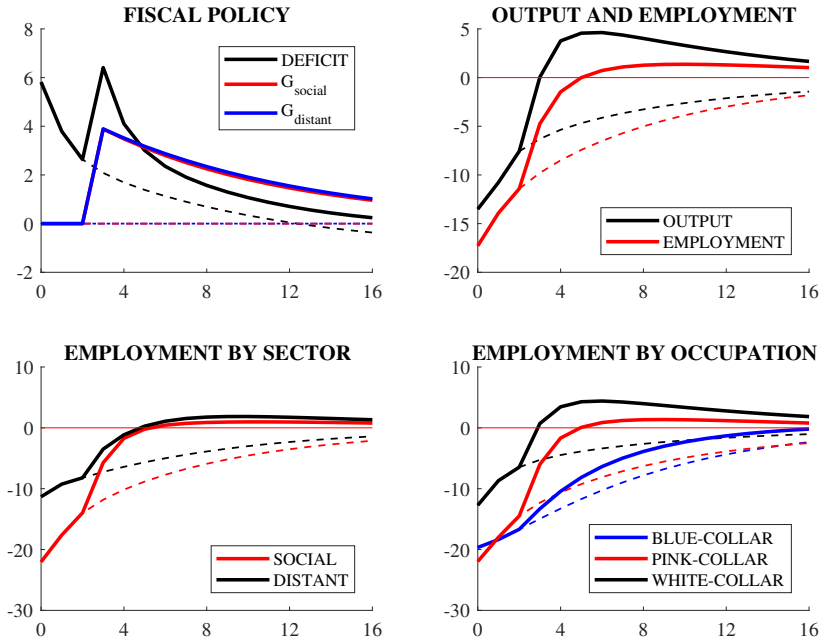
As we will discuss in detail below, the distribution of government spending across sectors shapes the recovery of employment by sector, but it does not affect considerably the strength and speed of the employment recovery by occupation. This indicates that composition effects due to sectors having a different occupation mix play only a limited role and that the capital-labor substitution channel is most important for the occupational employment effects of spending expansions.

Distributing additional purchases evenly across sectors. We start with a fiscal stimulus where the government increases its purchases in both sectors by the same amount. The upper-left panel of Figure 2 shows spending in both sectors as well as the primary fiscal deficit in percent of steady-state GDP. In this scenario, additional government purchases amount to 7.8% of quarterly steady-state GDP (corresponding to about \$1.7 trillion using 2019 GDP numbers) in the first quarter of 2021 (quarter 3 of our analysis). The stimulus is then slowly phased out with autocorrelation of 0.9. Over a four-year horizon, additional government spending amounts to 60% of quarterly steady-state GDP or about \$13 trillion. The government attributes half of the spending boost to each of the two sectors, so 3.9% of a quarterly GDP initially or about 30% of a quarterly GDP (about \$6.5 trillion) over four years. Recall that the size of the impulse is chosen to bring aggregate employment (displayed in the upper-right panel of Figure 2) back to its steady state by the third quarter of 2021 (quarter 5). For the time thereafter, the model predicts a moderate boom in aggregate employment. The boost to aggregate demand accelerates the recovery of output strongly. Output returns to its pre-crisis level relatively quickly, overshoots, and gradually returns to the steady state thereafter.

The lower-left panel of Figure 2 shows that the employment composition by sector is stabilized successfully by the spending boost. From early 2021 (quarter 4) on, the lines in the figures are close together, indicating that employment losses relative to steady state in both sectors are proportional to steady-state sector size. This appears surprising at first, given the substantial Covid-19 job losses in the social sector and the symmetry of the fiscal package. The reason is that the job multiplier in the social sector, which employs relatively many pink-collar workers, is larger than in the distant sector, which employs relatively many blue-collar workers.

Although the sectoral composition of employment is back to normal rather quickly in this scenario, its occupational composition is destabilized for over four years, see the lower-right panel

Figure 2: Covid-19 recovery with an equal spending expansion across sectors

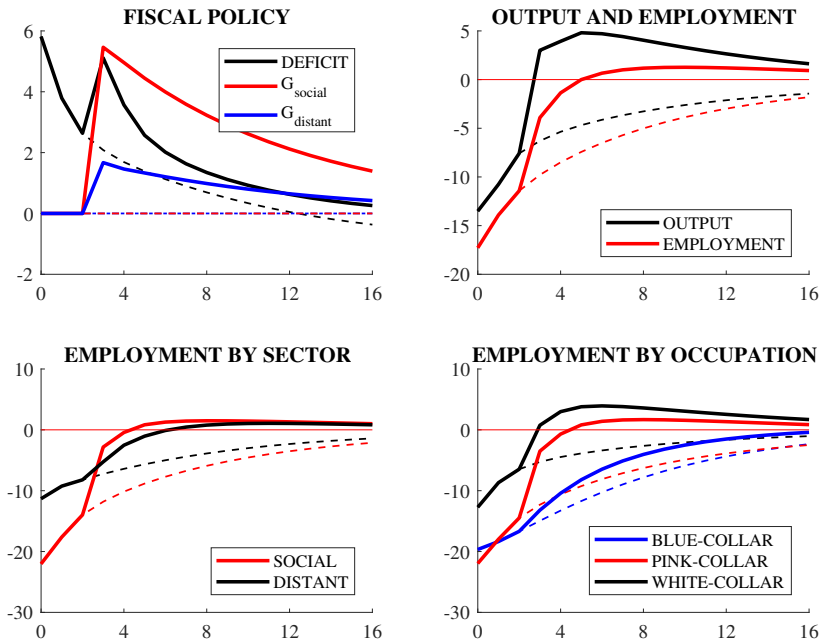


Notes: Deviations from steady state. Budget deficit and government spending by sector in percent of steady-state GDP. All other variables in percent of their own steady-state values. Dashed lines show Covid-19 scenario without fiscal policy intervention.

of Figure 2. Until 2024, employment is biased toward white-collar occupations and away from blue-collar occupations. White-collar employment is back to steady state already in the quarter of the fiscal stimulus and above steady state for the three consecutive years. By contrast, it takes almost four years for blue-collar employment to recover to its pre-Covid level. Pink-collar employment lies in between, with a return to steady state by fall 2021 (quarter 5) and a post-Covid boom that is less pronounced but of similar duration as the one for white-collar employment. As explained before, the reason why blue-collar employment benefits the least from the demand stimulus lies in its relatively high degree of substitutability with capital services, weakening its recovery relative to other occupation groups.

Spending expansion biased toward social sector. We now investigate a scenario where three-quarters of the government’s additional expenditures accrue in the social sector. Such a stimulus package can be thought of as primarily expanding public education or health expenditures. The total stimulus now amounts to roughly 7.1% of steady-state GDP or \$1.5 trillion of which about \$1.15 trillion is spent in the social sector, see the upper-left panel of Figure 3. The responses of

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Figure 3: Covid-19 recovery with a spending expansion strongly directed into the social sector

Notes: Deviations from steady state. Budget deficit and government spending by sector in percent of steady-state GDP. All other variables in percent of their own steady-state values. Dashed lines show Covid-19 scenario without fiscal policy intervention.

aggregate employment and output, shown in the upper-right panel of Figure 3, are similar to the scenario with an equal spending expansion across sectors as the sizes of the stimulus packages are chosen to achieve a full recovery of aggregate employment in quarter 5.

The lower-left panel shows the sector-specific employment recoveries. Not surprisingly, directing more spending toward the social sector induces this sector to recover more quickly. Social-sector employment, though hit harder by the Covid-19 shock, reaches its pre-crisis level in quarter 5 (roughly by summer 2021). By contrast, distant-sector employment takes until quarter 7 to recover completely. Given that the symmetric spending expansion stabilizes the economy's sectoral composition rather successfully (see Figure 2), it is not surprising that a package directed disproportionately into the social sector overshoots in this respect, destabilizing the sector mix toward the social sector.

The quantitative effect on sector-specific employment is relatively small compared to the strong directing of government spending toward the social sector. It is dampened by reactions of private demand, which shifts toward the distant sector as goods and services produced in the social sector

become relatively more expensive due to the surge in the government's demand for them.

As can be seen in the lower-right panel, the fiscal stimulus package directed mostly into the social sector accelerates the recovery of pink-collar employment in particular since pink-collar employment is represented disproportionately in the social sector. However, this composition effect is relatively moderate. In quarter 3 (when the fiscal stimulus comes into force), the spending expansion boosts the recovery of pink-collar work by only about 2.5 percentage points more relative to the unbiased spending expansion (see Figure 2).

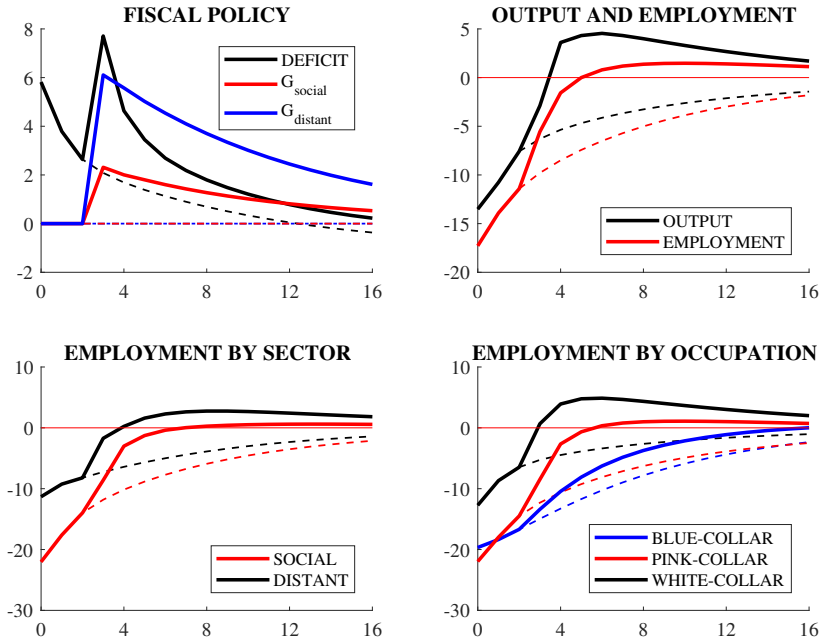
Blue-collar employment recovers somewhat more slowly in this scenario compared to the symmetric spending boost as it makes up only a small part of the workforce in the social sector where much of the direct effects of the stimulus takes effect. For this reason, directing government expenditures disproportionately into the social sector does not help to stabilize the economy's occupation mix. However, differences between the two scenarios with respect to the response of blue-collar employment are quantitatively negligible and amount to only about 0.1 percentage points around the end of 2021.

Overall, differences in occupation-specific employment dynamics to the unbiased spending expansion are small. There are two reasons for this result. First, employment by sector does not respond strongly to directing the stimulus to the hardest-hit sector since endogenous counteracting responses of private spending are strong. Second, within-sector effects, driven by differences in capital-labor substitutability across occupations, are powerful and dominating the impact on employment by occupation.

Spending expansion biased toward distant sector. In this scenario, we analyze how far a spending expansion directed toward the distant sector can foster job creation for blue-collar workers. In particular, we consider a fiscal stimulus package in which around three-quarters of the additional purchases accrue in the distant sector. Here, the total hike in government expenditures amounts to 8.4% of steady-state GDP (or about \$1.8 trillion) in quarter 3. Of these expenditures, the government channels \$1.35 trillion into the distant sector, see the upper-left panel of Figure 4. Again, the model-predicted acceleration of the recovery from the Covid-19 shock does not differ substantially from the other scenarios, see the upper-right panel of Figure 4.

As can be seen in the lower-left panel, employment in the distant sector recovers substantially

Figure 4: Covid-19 recovery with a spending expansion strongly directed into the distant sector



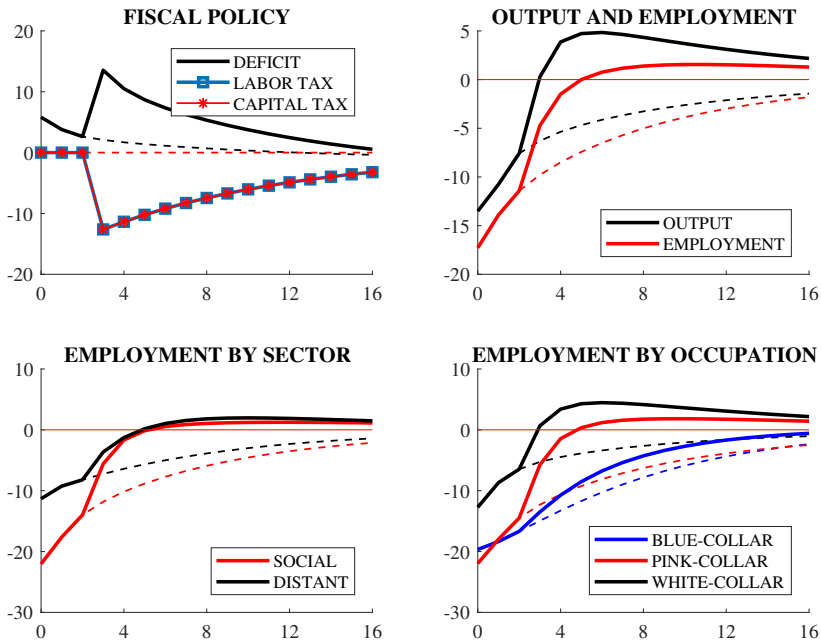
Notes: Deviations from steady state. Budget deficit and government spending by sector in percent of steady-state GDP. All other variables in percent of their own steady-state values. Dashed lines show Covid-19 scenario without fiscal policy intervention.

more quickly than employment in the social sector. This is due to the distant sector not being hit as hard by the Covid-19 shock and boosted disproportionately by fiscal stimulus. As a consequence of these two effects, the spending package directed mostly into the distant sector induces a destabilization of the economy’s sectoral mix over the entire four years shown in the figure.

The sectoral destabilization may come at the benefit of a more substantial occupational stabilization, in particular an additional boost to the recovery of blue-collar employment. However, the lower-right panel of Figure 4 shows that the employment effects, by occupation, of directing the spending stimulus into the distant sector are small. Blue-collar employment recovers only slightly more strongly compared to the other packages. The responses of blue-collar employment differ barely across scenarios, amounting to only about 0.2 percentage points. Again, this can be explained by two countervailing influences. First, the biased spending expansion leads to an increase in the relative price of distant-sector goods, which induces households and firms to switch part of their expenditure to the social sector. Second, there are substantial changes in the occupation-mix within sectors favoring pink-collar and white-collar employment.

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Figure 5: Covid-19 recovery with a symmetric reduction in capital and labor income tax rates



Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. Tax rates in percentage points. All other variables in percent of their own steady-state values. Dashed lines show Covid-19 scenario without fiscal policy intervention.

3.2 Tax cuts

We now turn to tax cuts as an alternative to expanding government purchases. First, we consider a scenario where the government cuts tax rates on both capital and labor income by the same absolute amount. We then turn to a scenario where only taxes on labor income are reduced and, finally, consider a cut only in taxes on capital income.

Cut in taxes on labor income and capital income. To start with, we consider a reduction in tax rates on both labor income and capital income by 13 percentage points in quarter 3 of our analysis, which achieves the target of a completed recovery of aggregate employment by quarter 5. When it takes effect, the tax cut leads to a surge in the primary fiscal deficit of about ten percent of steady-state GDP, or about \$2.15 trillion, see the upper-left panel of Figure 5.

The tax cut makes the use of production factors cheaper for firms, which hence return production toward pre-crisis levels. The upper-right panel of Figure 5 shows that this takes place relatively quickly, and that output has fully recovered shortly after the tax stimulus. This and

the subsequent post-Covid boom are similar to the spending expansions considered before. The duration of the employment recovery is, by construction, precisely the same across scenarios and reflects the target of a full aggregate employment recovery half a year after the stimulus. The relation between output and employment is not affected substantially by whether the fiscal stimulus is executed via a spending expansion or a symmetric tax cut.

Turning to the disaggregated effects of the stimulus, the mechanisms are similar to those at play in response to the spending expansions. As firms are incentivized to take back some of the reduction of factor demand, the recovery of factor prices is accelerated. As in the spending scenarios, this effect is more pronounced for labor, which is less elastically supplied than are capital services. As a consequence, firms act more quickly in bringing back their use of capital services toward pre-crisis levels while they are more reluctant toward calling back workers. This substitution toward capital services slows down most strongly the recovery of employment in blue-collar occupations where capital-labor substitution is easiest. Again, this also impacts on sectoral employment as relatively little jobs are created by the stimulus in industries with many blue-collar workers and hence a high average degree of capital-labor substitutability.

Hence, the employment effects of the tax stimulus are more substantial in the social sector, and the tax cuts predominantly help this sector accelerate its recovery. The lower-left panel of Figure 5 shows that the social sector catches up to the distant sector around summer 2021, and both sectors experience somewhat parallel smooth upturns afterward. These developments are similar to those in the unbiased spending scenario considered in Figure 2.

The occupational employment dynamics displayed in the lower-right panel of Figure 5 also resemble those from the spending expansions. The tax stimulus accelerates the pink-collar recovery but pink-collar employment remains persistently below white-collar employment in terms of deviation from steady state. Blue-collar employment reaches its pre-crisis level as late as four years after the Covid-19 shock and workers in these occupations do not enjoy a post-Covid boom.

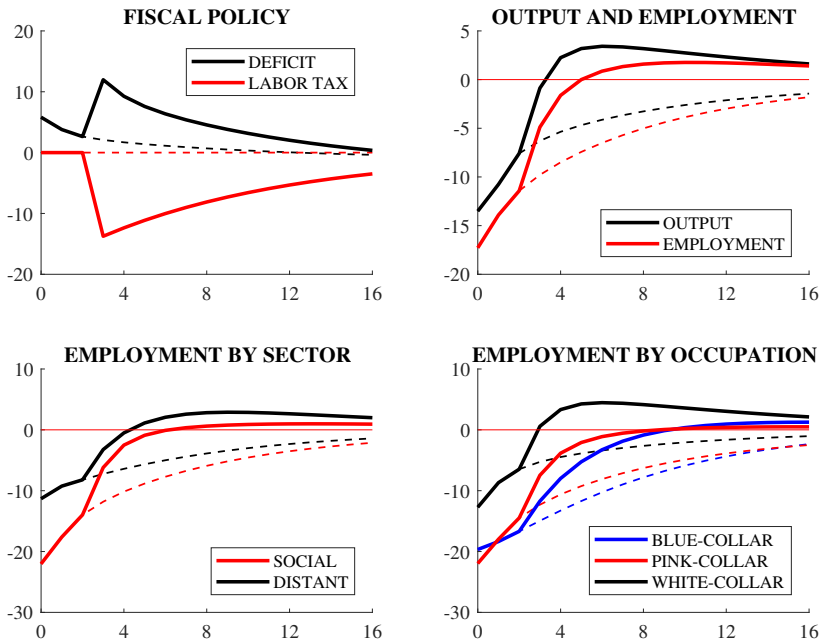
Labor income tax cut. Here, we consider a scenario where tax rates on labor income are cut but not those on capital income. This is an interesting scenario because the policy stimulus directly affects relative factor prices, which play an essential role in the transmission from fiscal policy to disaggregated employment dynamics. The tax rate on labor income has to be cut by about 13

percentage points to achieve the stabilization of aggregate employment. This tax cut would let the deficit surge by approximately 10% of a quarterly steady-state GDP, about \$2.2 trillion, see the upper-left panel of Figure 6. The aggregate employment effects are again similar to the ones in the other scenarios, which is a consequence of targeting the speed of the employment recovery. As the upper-right panel of Figure 6 shows, the recovery of output is less strongly accelerated than in the other scenarios as the stimulus only makes labor but not capital services less expensive for firms.

The disaggregated effects of the labor income tax cut differ from those of the stimulus measures in the previous scenarios. Cutting taxes on labor but not on capital alters the relative price of the two factors directly. With labor becoming relatively cheaper, firms return production to normal levels mostly by hiring more workers, whereas the use of capital services is raised only modestly. This shift in the composition of factors away from capital services and toward labor tends to increase the marginal product of blue-collar work, which is a close substitute for capital services. In contrast, it tends to decrease the marginal product of pink-collar work, which is a complement to capital services. This counteracts the tendency for strong employment effects in pink-collar occupations and in industries that employ many pink-collar workers. By contrast, firms' demand for blue-collar labor recovers more strongly than under the other stimulus programs. Through composition effects, this also leads to an accelerated recovery in the distant sector where relatively many blue-collar workers are employed. At the same time, it slows down the recovery in the social sector, compared to the stimulus measures discussed before. As a consequence, the sectoral composition of the economy is not as strongly stabilized as it is by the symmetric tax cut or the unbiased spending boost. The lower-left panel of Figure 6 shows that the social sector lags behind the distant sector in terms of employment for the entire four years we consider.

As seen in the lower-right panel of Figure 6, the labor income tax cut achieves a substantially more pronounced stabilization of employment by occupation than the other stimulus measures. As the labor income tax stimulus promotes job growth in blue-collar occupations considerably, blue-collar workers are not left behind during the recovery under this policy scenario. Blue-collar employment recovers far more quickly than in any other scenario, achieving a full recovery to pre-crisis levels by mid-2022.

Figure 6: Covid-19 recovery with a reduction in the labor income tax rate

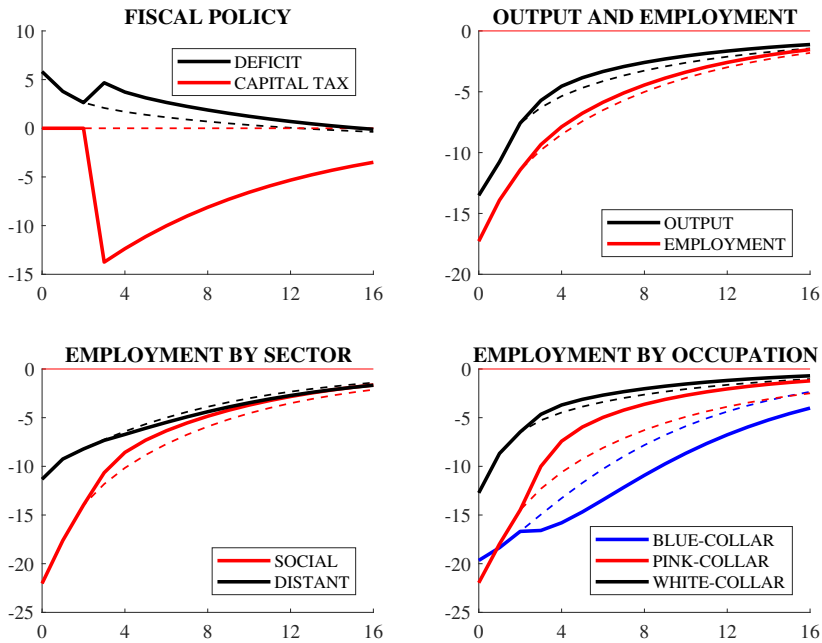


Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. Tax rates in percentage points. All other variables in percent of their own steady-state values. Dashed lines show Covid-19 scenario without fiscal policy intervention.

Capital income tax cut. Finally, we consider a scenario where only tax rates on capital income are cut but not those on labor income. This policy change only affects a small part of aggregate income and, hence, any given absolute change in the capital tax rate affects economic activity less strongly than the same change in, e.g., the labor income tax. In particular, the effects on employment are small since employment is affected only indirectly. For this reason, we refrain from the stabilization target for aggregate employment as an immense cut of capital income tax rates would be needed to achieve it. Instead, we consider a reduction in tax rates on capital income by the same amount as tax rates on labor income are reduced in the previous scenario. In particular, tax rates on capital are reduced by 13 percentage points which leads to a deficit surge of about 2.5% of pre-crisis GDP (or about \$500 billion), see upper-left panel of Figure 7.

This stimulus accelerates the aggregate recovery only slightly, see the upper-right panel of Figure 7. Given the relatively small stimulus considered in this scenario, this is not surprising. As a consequence of the change in relative factor prices, the capital-tax stimulus fosters the output recovery more strongly than the employment recovery.

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Figure 7: Covid-19 recovery with a reduction in the capital income tax rate

Notes: Deviations from steady state. Budget deficit in percent of steady-state GDP. Tax rates in percentage points. All other variables in percent of their own steady-state values. Dashed lines show Covid-19 scenario without fiscal policy intervention.

At the disaggregated level, effects are the opposite of those of the labor-tax stimulus considered before. When the government directly reduces the costs of using capital services, the tendency of stimulus measures to promote job growth for pink-collar workers and leave out blue-collar workers are reinforced. Regarding sectors, this translates into a strong bias of the created jobs toward the social sector. Quantitatively, our results show that the recoveries of employment in the distant sector (lower-left panel of Figure 7) and blue-collar occupations (lower-right panel of Figure 7) are even slowed down by the stimulus. The latter is especially remarkable due to blue-collar workers' substantial exposure to crisis-related job losses.

4 Conclusion

The massive job losses in the Covid-19 crisis were disproportionately borne by workers in retail trade, hospitality, and other contact-intensive industries as well as by workers in blue-collar, sales, and service occupations. Given the high costs of switching industry or occupation, the total economic cost of the Covid-19 crisis can be reduced if policy achieves stabilization not only of

aggregate employment but also of the composition of employment, i.e., manages to foster rapid job growth in particular in those industries and occupations that were hit hardest by the crisis.

In this paper, we analyze the ability of different fiscal stimulus measures to achieve this goal. To do so, we use a multi-sector, multi-occupation dynamic stochastic general equilibrium model to study the effects of different types of fiscal policy instruments on employment by occupation and industry. In the model, heterogeneity in employment responses to a fiscal stimulus results from two channels. First, government spending can be distributed unevenly across sectors leading to disproportionate job growth in industries where purchases are increased considerably and affecting occupational employment through composition effects. Second, differences in the substitutability with capital services across occupations induce fiscal policy to create job growth predominantly in those occupations where labor is a complement to capital services.

Our model predicts that the two groups of occupations hit hard by the Covid-19 recession, pink-collar and blue-collar workers, profit differentially from a fiscal stimulus. All types of fiscal stimulus promote job growth in pink-collar occupations considerably. In this sense, fiscal policy is successful in helping create jobs where they were lost during the Covid-19 crisis – labeled as a “pink-collar recession” by some commentators. But this recession has, as previous ones, also struck blue-collar workers hard. To create jobs for this group of workers, a fiscal stimulus has to be designed in specific ways to circumvent or at least weaken the mechanisms that dampen the employment gains for blue-collar workers. The fiscal-policy measure best suited to stabilize the economy’s occupation composition after the imminent Covid-19 crisis is a cut in labor income taxes.

The white-collar occupation group, which is relatively mildly affected by the Covid-19 crisis, enjoys some employment growth in all stimulus scenarios. Independent of how the fiscal stimulus is set up in detail, the recovery of white-collar employment is accelerated considerably. This implies that fiscal policy during the Covid-19 recovery also helps create jobs where not so many were lost in the first place.

Regarding sectoral employment, the weak capital-labor substitutability in the social sector, i.e., in industries with intensive face-to-face contacts between workers and customers, brings about pronounced job growth induced by fiscal stimulus measures in this sector. In our model analysis,

this mechanism leads to a relatively quick stabilization of the economy's industry mix even when a fiscal policy does not target the social sector explicitly.

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Appendix

Equilibrium conditions

This appendix collects the equilibrium conditions of our model. In a symmetric equilibrium, $y_{s,t} = y_{j,s,t}$, $\tilde{k}_{j,s,t} = \tilde{k}_{s,t}$, $n_{j,s,t}^p = n_{s,t}^p$, $n_{j,s,t}^b = n_{s,t}^b$, $n_{j,s,t}^w = n_{s,t}^w$, $mc_{j,s,t} = mc_{s,t}$, and $p_{j,s,t} = p_{s,t}$. Let $\pi_{s,t} = p_{s,t}/p_{s,t-1}$ denote gross price growth in sector s . The first-order conditions of firms in sector $s = 1, 2$ are then given by

$$y_{s,t} = y_{j,s} \cdot \left(v_s \cdot \left(\frac{v_{j,s,t}^p}{v_{j,s}^p} \right)^{\frac{\iota-1}{\iota}} + (1 - v_s) \cdot \left(\frac{n_{j,s,t}^w}{n_{j,s}^w} \right)^{\frac{\iota-1}{\iota}} \right) \tag{A.1}$$

$$v_{j,s,t}^p = v_{j,s}^p \cdot \left(\alpha_s \cdot \left(\frac{v_{j,s,t}^b}{v_{j,s}^b} \right)^{\frac{\theta-1}{\theta}} + (1 - \alpha_s) \cdot \left(\frac{n_{j,s,t}^p}{n_{j,s}^p} \right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} \tag{A.2}$$

$$v_{j,s,t}^b = v_{j,s}^b \cdot \left(\gamma_s \cdot \left(\frac{\tilde{k}_{j,s,t}}{\tilde{k}_{j,s}} \right)^{\frac{\phi-1}{\phi}} + (1 - \gamma_s) \cdot \left(\frac{n_{j,s,t}^b}{n_{j,s}^b} \right)^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}} \tag{A.3}$$

$$mc_{s,t} \cdot mpk_{s,t} = r_{s,t}^k \tag{A.4}$$

$$mc_{s,t} \cdot mpl_{s,t}^b = w_{s,t}^b + \kappa_{n,s} \left(\frac{n_{s,t}^b}{n_{s,t-1}^b} - 1 \right) \frac{(1 + \wedge_{s,t})p_{s,t}}{p_t} \frac{y_{s,t}}{n_{s,t-1}^b} - \kappa_{n,s} \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{n_{s,t+1}^b}{n_{s,t}^b} - 1 \right) \frac{(1 + \wedge_{s,t+1})p_{s,t+1}}{p_{t+1}} y_{s,t+1} \left(\frac{n_{s,t+1}^b}{(n_{s,t}^b)^2} \right) \right\} \tag{A.5}$$

$$mc_{s,t} \cdot mpl_{s,t}^p = w_t^p + \kappa_{n,s} \left(\frac{n_{s,t}^p}{n_{s,t-1}^p} - 1 \right) \frac{(1 + \wedge_{s,t})p_{s,t}}{p_t} \frac{y_{s,t}}{n_{s,t-1}^p} - \kappa_{n,s} \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{n_{s,t+1}^p}{n_{s,t}^p} - 1 \right) \frac{(1 + \wedge_{s,t+1})p_{s,t+1}}{p_{t+1}} y_{s,t+1} \left(\frac{n_{s,t+1}^p}{(n_{s,t}^p)^2} \right) \right\} \tag{A.6}$$

$$mc_{s,t} \cdot mpl_{s,t}^w = w_t^w + \kappa_{n,s} \left(\frac{n_{s,t}^w}{n_{s,t-1}^w} - 1 \right) \frac{(1 + \wedge_{s,t})p_{s,t}}{p_t} \frac{y_{s,t}}{n_{s,t-1}^w} - \kappa_{n,s} \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{n_{s,t+1}^w}{n_{s,t}^w} - 1 \right) \frac{(1 + \wedge_{s,t+1})p_{s,t+1}}{p_{t+1}} y_{s,t+1} \left(\frac{n_{s,t+1}^w}{(n_{s,t}^w)^2} \right) \right\} \tag{A.7}$$

$$mpk_{s,t} = v_s \cdot \alpha_s \cdot \gamma_s \cdot \left(\frac{y_s}{\tilde{k}_s} \right) \left(\frac{y_{s,t}/y_s}{v_{s,t}^p/v_s^p} \right)^{1/\iota} \left(\frac{v_{s,t}^p/v_s^p}{v_{s,t}^b/v_s^b} \right)^{1/\theta} \left(\frac{v_{s,t}^b/v_s^b}{\tilde{k}_{s,t}/\tilde{k}_s} \right)^{1/\phi} \tag{A.8}$$

$$mpl_{s,t}^b = v_s \cdot \alpha_s \cdot (1 - \gamma_s) \cdot \left(\frac{y_s}{n_s^b} \right) \left(\frac{y_{s,t}/y_s}{v_{s,t}^p/v_s^p} \right)^{1/\iota} \left(\frac{v_{s,t}^p/v_s^p}{v_{s,t}^b/v_s^b} \right)^{1/\theta} \left(\frac{v_{s,t}^b/v_s^b}{n_{s,t}^b/n_s^b} \right)^{1/\phi} \tag{A.9}$$

$$mpl_{s,t}^p = v_s \cdot (1 - \alpha_s) \left(\frac{y_s}{n_s^p} \right) \left(\frac{y_{s,t}/y_s}{v_{s,t}^p/v_s^p} \right)^{1/\iota} \left(\frac{v_{s,t}^p/v_s^p}{n_{s,t}^p/n_s^p} \right)^{1/\theta} \tag{A.10}$$

$$mpl_{s,t}^w = (1 - v_s) \cdot \left(\frac{y_s}{n_s^w} \right) \cdot \left(\frac{y_{s,t}/y_s}{n_{s,t}^w/n_s^w} \right)^{1/\iota} \tag{A.11}$$

$$\begin{aligned} \psi(\pi_{s,t} - 1)\pi_{s,t} &= \psi\beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \frac{y_{s,t+1}}{y_{s,t}} \frac{\wedge_{s,t+1}}{\wedge_{s,t}} \frac{\pi_{s,t+1}}{\pi_{t+1}} (\pi_{s,t+1} - 1)\pi_{s,t+1} \right\} \\ &+ \epsilon \left(mc_{s,t} - \frac{p_{s,t}(\epsilon - 1)}{p_t \epsilon} \right) \end{aligned} \tag{A.12}$$

The first-order conditions of the household problem are given by

$$c_{1,t} = \zeta \left(\frac{(1 + \wedge_{1,t})p_{1,t}}{p_t} \right)^{-\mu} c_t \tag{A.13}$$

$$c_{2,t} = (1 - \zeta) \left(\frac{(1 + \wedge_{2,t})p_{2,t}}{p_t} \right)^{-\mu} c_t \tag{A.14}$$

$$1 = \left(\zeta \cdot \left(\frac{(1 + \wedge_{1,t})p_{1,t}}{p_t} \right)^{1-\mu} + (1 - \zeta) \cdot \left(\frac{(1 + \wedge_{2,t})p_{2,t}}{p_t} \right)^{1-\mu} \right)^{1/(1-\mu)} \tag{A.15}$$

$$n_{1,t}^p = \aleph^p \left(\frac{(1 - \wedge_t^p)w_{1,t}^p}{w_t^p} \right)^\omega n_t^p \tag{A.16}$$

$$n_{2,t}^p = (1 - \aleph^p) \left(\frac{(1 - \wedge_t^p)w_{2,t}^p}{w_t^p} \right)^\omega n_t^p \tag{A.17}$$

$$n_{1,t}^b = \aleph^b \left(\frac{(1 - \wedge_t^b)w_{1,t}^b}{w_t^b} \right)^\omega n_t^b \tag{A.18}$$

$$n_{2,t}^b = (1 - \aleph^b) \left(\frac{(1 - \wedge_t^b)w_{2,t}^b}{w_t^b} \right)^\omega n_t^b \tag{A.19}$$

$$n_{1,t}^w = \aleph^w \left(\frac{(1 - \wedge_t^w)w_{1,t}^w}{w_t^w} \right)^\omega n_t^w \tag{A.20}$$

$$n_{2,t}^w = (1 - \aleph^w) \left(\frac{(1 - \wedge_t^w)w_{2,t}^w}{w_t^w} \right)^\omega n_t^w \tag{A.21}$$

$$w_t^p = \left(\aleph^p \cdot ((1 - \wedge_t^p)w_{1,t}^p)^{1+\omega} + (1 - \aleph^p) \cdot ((1 - \wedge_t^p)w_{2,t}^p)^{1+\omega} \right)^{1/(1+\omega)} \tag{A.22}$$

$$w_t^b = \left(\aleph^b \cdot ((1 - \wedge_t^b)w_{1,t}^b)^{1+\omega} + (1 - \aleph^b) \cdot ((1 - \wedge_t^b)w_{2,t}^b)^{1+\omega} \right)^{1/(1+\omega)} \tag{A.23}$$

$$w_t^w = \left(\aleph^w \cdot ((1 - \wedge_t^w)w_{1,t}^w)^{1+\omega} + (1 - \aleph^w) \cdot ((1 - \wedge_t^w)w_{2,t}^w)^{1+\omega} \right)^{1/(1+\omega)} \tag{A.24}$$

$$\lambda_t = \xi_t + \chi \tilde{\lambda}_t \frac{x_t}{c_t} \tag{A.25}$$

$$x_t = c_t^\chi x_{t-1}^{1-\chi} \tag{A.26}$$

$$\tilde{\lambda}_t = -\xi_t \Omega_t + \beta(1 - \chi) E_t \left\{ \tilde{\lambda}_{t+1} \frac{x_{t+1}}{x_t} \right\} \tag{A.27}$$

$$\Omega_t = \frac{\Omega^p}{1 + 1/\eta} (n_t^p)^{1+1/\eta} + \frac{\Omega^b}{1 + 1/\eta} (n_t^b)^{1+1/\eta} + \frac{\Omega^w}{1 + 1/\eta} (n_t^w)^{1+1/\eta} \tag{A.28}$$

$$\lambda_t = \beta E_t \left\{ \lambda_{t+1} \frac{(1 + r_t)}{\pi_{t+1}} \right\} \tag{A.29}$$

$$\begin{aligned} \lambda_t q_{s,t} &= \beta E_t \left\{ \lambda_{t+1} \left((1 - \tau_{t+1}^k) r_{s,t+1}^k u_{s,t+1} \right. \right. \\ &\quad \left. \left. - \frac{(1 + \wedge_{s,t+1})p_{s,t+1}}{p_{t+1}} e(u_{s,t+1}) + q_{s,t+1}(1 - \delta) \right) \right\} \end{aligned} \tag{A.30}$$

$$\frac{(1 + \wedge_{s,t})p_{s,t}}{p_t} = q_{s,t} \left(1 - \frac{\kappa_i}{2} \left(\frac{i_{s,t}}{i_{s,t-1}} - 1 \right)^2 - \kappa_i \left(\frac{i_{s,t}}{i_{s,t-1}} - 1 \right) \frac{i_{s,t}}{i_{s,t-1}} \right) + \beta \text{E}_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} q_{s,t+1} \kappa_i \left(\frac{i_{s,t+1}}{i_{s,t}} - 1 \right) \left(\frac{i_{s,t+1}}{i_{s,t}} \right)^2 \right\} \tag{A.31}$$

$$(1 - \tau_t^k) r_{s,t}^k = \frac{(1 + \wedge_{s,t})p_{s,t}}{p_t} (\delta_1 + \delta_2(u_{s,t} - 1)) \tag{A.32}$$

$$w_t^b (1 - \tau_t^n) \lambda_t = \Omega^b (n_t^b)^{1/\eta} x_t \xi_t \tag{A.33}$$

$$w_t^p (1 - \tau_t^n) \lambda_t = \Omega^p (n_t^p)^{1/\eta} x_t \xi_t \tag{A.34}$$

$$w_t^w (1 - \tau_t^n) \lambda_t = \Omega^w (n_t^w)^{1/\eta} x_t \xi_t \tag{A.35}$$

$$\xi_t = (c_t - \Omega_t x_t)^{-\frac{1}{\sigma}} \tag{A.36}$$

$$k_{s,t} = (1 - \delta) k_{s,t-1} + \left(1 - \frac{\kappa_i}{2} \left(\frac{i_{s,t}}{i_{s,t-1}} - 1 \right)^2 \right) i_{s,t} \tag{A.37}$$

$$e(u_{s,t}) = \delta_1 (u_{s,t} - 1) + \frac{\delta_2}{2} (u_{s,t} - 1)^2 \tag{A.38}$$

where $s = 1, 2$, and λ_t , $q_{s,t} \lambda_t$, and \tilde{t}_t denote Lagrange multipliers on the household's budget constraint, the capital accumulation equations, and the definition of x_t , respectively, where $q_{s,t}$ is the shadow value of installed capital in sector s .

Fiscal and monetary policy are described by

$$\frac{p_{g,t}}{p_t} g_t + T_t + (1 + r_{t-1}) \frac{b_{t-1}}{\pi_t} = b_t + \tau_t^n (w_t^b n_t^b + w_t^p n_t^p + w_t^w n_t^w) + \tau_t^k (r_{1,t}^k \tilde{k}_{1,t} + r_{2,t}^k \tilde{k}_{2,t}) \tag{A.39}$$

$$g_{1,t} = \zeta_g \left(\frac{(1 + \wedge_{1,t}) p_{1,t}}{p_{g,t}} \right)^{-\mu} g_t \tag{A.40}$$

$$g_{2,t} = (1 - \zeta_g) \left(\frac{(1 + \wedge_{2,t}) p_{2,t}}{p_{g,t}} \right)^{-\mu} g_t \tag{A.41}$$

$$\frac{p_{g,t}}{p_t} = \left(\zeta_g \cdot \left(\frac{(1 + \wedge_{1,t}) p_{1,t}}{p_t} \right)^{1-\mu} + (1 - \zeta_g) \cdot \left(\frac{(1 + \wedge_{2,t}) p_{2,t}}{p_t} \right)^{1-\mu} \right)^{1/(1-\mu)} \tag{A.42}$$

$$\log g_t = (1 - \rho_g) \log g + \rho_g \log g_{t-1} + \varepsilon_t^g \tag{A.43}$$

$$\log (T_t) = (1 - \rho_T) \log (T) + \rho_T \log (T_{t-1}) - \gamma_b \cdot (b_{t-1} - b) / y \tag{A.44}$$

$$\tau_t^n - \tau^n = \rho_\tau (\tau_{t-1}^n - \tau^n) + \varepsilon_t^{\tau^n} \tag{A.45}$$

$$\tau_t^k - \tau^k = \rho_\tau (\tau_{t-1}^k - \tau^k) + \varepsilon_t^{\tau^k} \tag{A.46}$$

$$\log ((1 + r_t)/(1 + r)) = \delta_\pi \log (\pi_t/\pi) + \delta_y \log (y_t/y) + \delta_g \log (g_t/g) \tag{A.47}$$

The following conditions describe goods market clearing for good $s = 1, 2$, inflation in sector s , and aggregate output y_t :

$$y_{s,t} = (1 + \wedge_{s,t}) \left(c_{s,t} + i_{s,t} + g_{s,t} + e(u_{s,t})k_{s,t-1} + \frac{\psi}{2} (\pi_{s,t} - 1)^2 y_{s,t} + \frac{\kappa_{n,s}}{2} \left[\left(\frac{n_{s,t}^b}{n_{s,t-1}^b} - 1 \right)^2 + \left(\frac{n_{s,t}^p}{n_{s,t-1}^p} - 1 \right)^2 + \left(\frac{n_{s,t}^w}{n_{s,t-1}^w} - 1 \right)^2 \right] y_{s,t} + \frac{p_t}{p_{s,t}} \left(\wedge_t^p w_{s,t}^p n_{s,t}^p + \wedge_t^b w_{s,t}^b n_{s,t}^b + \wedge_t^w w_{s,t}^w n_{s,t}^w \right) \right) \quad (\text{A.48})$$

$$\pi_{s,t} = \frac{p_{s,t}/p_t}{p_{s,t-1}/p_{t-1}} \pi_t, \quad s = 1, 2 \quad (\text{A.49})$$

$$y_t = (p_{1,t}/p_t)y_{1,t} + (p_{2,t}/p_t)y_{2,t} \quad (\text{A.50})$$

We define data-consistent employment by sector $s = 1, 2$, occupation $o = p, b, w$, as well as aggregate employment as follows:

$$l_{s,t} = \frac{1}{1 + \wedge_{s,t}} \left(n_{s,t}^p (1 - \wedge_t^p) + n_{s,t}^b (1 - \wedge_t^b) + n_{s,t}^w (1 - \wedge_t^w) \right), \quad (\text{A.51})$$

$$l_t^o = (1 - \wedge_t^o) \left(\frac{n_{1,t}^o}{1 + \wedge_{1,t}} + \frac{n_{2,t}^o}{1 + \wedge_{2,t}} \right), \quad (\text{A.52})$$

and

$$l_t = l_t^w + l_t^b + l_t^p = l_{1,t} + l_{2,t}. \quad (\text{A.53})$$

Classifications of industries and occupations

Table A.1: Assignment of NAICS industries to social and distant sector.

Industry	Sector
Agriculture, forestry, fishing and hunting	distant
Mining, quarrying, and oil and gas extraction	distant
Utilities	distant
Construction	distant
Manufacturing	distant
Wholesale trade	distant
Retail trade	social
Transportation and warehousing	
Warehousing and storage	distant
Truck transportation	distant
Pipeline transportation	distant
All other	social
Information	distant
Finance and insurance	distant
Real estate and rental and leasing	social
Professional, scientific, and technical services	distant
Management of companies and enterprises	distant
Administrative and support and waste management and remediation services	distant
Educational services; state, local, and private	social
Healthcare and social assistance	social
Arts, entertainment, and recreation	social
Accommodation and food services	social
Other services (except public administration)	social
Government	n.a.

Source: Kaplan, Moll, and Violante (2020).

Table A.2: Assignment of SOC occupations to white-collar, blue-collar, and pink-collar occupation groups

Occupation	Group
Management occupations	white-collar
Business and financial operations occupations	white-collar
Computer and mathematical occupations	white-collar
Architecture and engineering occupations	white-collar
Life, physical, and social science occupations	white-collar
Community and social service occupations	pink-collar
Legal occupations	white-collar
Education, training, and library occupations	white-collar
Arts, design, entertainment, sports, and media occupations	white-collar
Healthcare practitioners and technical occupations	white-collar
Healthcare support occupations	pink-collar
Protective service occupations	blue-collar
Food preparation and serving related occupations	pink-collar
Building and grounds cleaning and maintenance occupations	pink-collar
Personal care and service occupations	pink-collar
Sales and related occupations	pink-collar
Office and administrative support occupations	white-collar
Farming, fishing, and forestry occupations	blue-collar
Construction and extraction occupations	blue-collar
Installation, maintenance, and repair occupations	blue-collar
Production occupations	blue-collar
Transportation and material moving occupations	blue-collar

The Great Lockdown and criminal activity: Evidence from Bihar, India

Rubén Poblete-Cazenave¹

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The COVID-19 pandemic has resulted in over 2 billion people in the world affected by lockdowns. This has significant socioeconomic implications, especially in areas such as crime, where police resources are diverted from crime prevention towards enforcing lockdowns. Also, mobility restrictions imposed by lockdowns might make it harder for criminals to find victims. The net effect of these opposite forces is unknown. This study analyzes the effect of lockdowns on criminal activity in the state of Bihar, India. A sharp regression discontinuity design is implemented harnessing the sudden introduction of a state-wide lockdown and novel high-frequency criminal case data. The results show that lockdown decreases aggregate crime by 44 percent. Negative large effects are observed in diverse types of crimes such as murder (61 percent), theft (63 percent), and crimes against women (64 percent), among others. This seems to be driven by the higher search costs faced by criminals. Finally, by exploiting geographic variation in terms of lockdowns' severity across districts, this study shows that relaxing lockdowns' initial restrictions increase crime, but the increment is lower in less restrictive lockdowns than in restrictive ones. While economically-motivated crimes increased, violent crimes were not impacted. This suggests that the economic downturn produced by the lockdown might be driving these effects. Policy recommendations are discussed.

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1 Introduction

The COVID-19 pandemic has brought the world to a standstill, threatening nations' economies and causing unprecedented human and socioeconomic losses. To contain the spread of the virus, governments around the world have introduced strict lockdown and shelter-at-home restrictions. As of the beginning of May, a third of the world's population was under lockdown. Until the threat of COVID-19 has been fully contained, lockdowns are likely to remain in place across the world. Understanding the consequences of these measures is therefore critical.¹

This paper studies the impact of lockdowns on criminal activity. Lockdowns have a direct impact on criminal activity, but its net effect is uncertain. On one side, they have resulted in a redirection of resources away from crime prevention and towards lockdown enforcement. In most countries, the police enforces and monitors compliance with these measures, which adds extra pressure on some already overburdened systems.² On the other hand, fewer people on the streets reduces the number of potential victims. This increases criminals' costs of offending, and could, therefore, reduce the incidence of crime. Studying the unintended consequences of lockdowns and their impact on criminal activity is important not only due to the huge socioeconomic burden of crime, but also to provide vital information to policymakers to make informed decisions on (i) the length and geographic coverage of lockdowns, (ii) how restrictive they should be, and (iii) the reallocation of resources to cope with potential shifts in criminal activity.

This study focuses on India, which is currently under the biggest lockdown in the world with nearly 1.3 billion people staying at home. Up-to-date information at criminal case-level is obtained from police station's First Information Reports (FIR) in the state of Bihar.³ This is the most granular data for criminal cases in India, and to the best of my knowledge, the first time it is being used. Over the course of 2020 up to May 27, more than 80,000 criminal cases were filed, containing detailed information on criminal charges and dates. We analyze aggregate crime as well as specific categories including murder, theft, robbery, burglary, kidnapping, rioting, crimes against women and crimes against public health. The latter is of special concern during the current pandemic.

Additionally, we use district-level data from the National Commission for Women (NCW) for all

¹Throughout the paper, lockdown and stay-at-home orders are used interchangeably.

²As the Polish police has pleaded: "Please stop all criminal activities until further notice". See <https://www.euronews.com/2020/03/20/please-stop-all-crime-polish-police-plea-amid-covid-19-workload>.

³Much of the analysis is based on the state of Bihar, which is the third most populous state in India with an estimate population of over 120 million people, similar to Japan or Mexico.

India, to complement the analysis on gender-based violence as some of these crimes might be particularly susceptible to stay-at-home orders. Particularly, lockdowns might increase domestic violence for a variety of reasons: perpetrators and victims confined within the same space, high levels of stress due to reduced job opportunities and financial distress, among others.

To estimate a causal effect of lockdowns on crime, a sharp regression discontinuity (RD) design using the date as the running variable. This is possible due to the high-frequency of the data and the fact that on March 22, Bihar's government announced a sudden lockdown with immediate effect. Also, based on the number of COVID-19 cases in each district, the Union government of India classified all districts in the country across three different categories where lockdowns would be implemented under different restriction levels. We exploit this additional geographic variation to examine whether the severity of the lockdowns has a differential impact on crime by estimating a model using police station-month fixed effects.

The results show that stay-at-home orders decrease aggregate crime by 44 percent. This effect is not only statistically significant but also economically relevant, and robust across different econometric specifications. Large effects are found for all the crime-categories studied, despite their diverse nature. There is a decrease of 63 percent in the number of thefts, 49 percent in burglaries, 56 percent in robberies, 61 percent in murders, 88 percent in kidnappings, 77 percent in rioting and 64 percent in crimes against women. As expected, only crimes against public health increased during the lockdown, by 143 percent. While there is a sharp decrease in crimes due to the lockdown, there is an upward trend after the beginning of the lockdown.

Regarding the impact of the severity of the lockdowns on crime, the study finds a lower increase in crime in less restrictive lockdowns compared with more restrictive ones. Particularly, violent crimes were not significantly impacted by the transition to the restriction zones, whereas other economically-motivated crimes were. This suggests that economic motives might be impacting lockdown-crime dynamics as lockdowns progress. Also, we find that the severity of the lockdown intensifies violence against women. This is confirmed by using police-level data as well as reported complaints received by the NCW. The only crimes that follow a different pattern are those against public health, in which more restrictions decrease the incidence of these crimes.

This study makes several contributions. From a public policy perspective, it provides policymakers with timely information about the unintended impact of lockdowns on criminal activity. This is crucial for

the introduction of effective crime-prevention policies and the better targeting of scarce police resources. An important implication of this study is that the large reduction in crime produced by the lockdown could allow authorities to free up police resources for pandemic-containment.

Also, regarding criminal activity, this study supports the implementation of less restrictive lockdowns, that allow the functioning of business and shops in a controlled manner. This could prevent economic factors to negatively affect crime. However, it should be noted that more restrictive lockdowns are effective in decreasing the incidence of crimes against public health. This could have important consequences for the containment of the virus.

From an academic standpoint, this study is the first to analyze the effect of lockdowns on a wide range of crimes by using criminal case-level data. It contributes to different strands of the literature. First, it adds to the academic literature studying the determinants of crime by analyzing how crime evolves in contexts of high restricted mobility (for perpetrators and potential victims). There are some studies analyzing contexts that share similarities with the present study. One common incapacitation policy is the use of curfews, where people are ordered to stay indoors during a specific period of time. The papers of [Kline \(2012\)](#) and [Carr and Doleac \(2018\)](#) analyze the impact of juvenile curfew on crime. While the former finds a decrease in violent and property crimes, the latter reports an increase in gun violence. The present paper extends this literature by examining mobility restrictions affecting the entirety of the population and their impact on a wide range of criminal cases.

This paper also relates to the literature on crime deterrence and police deployment. The most relevant studies to this paper's context are those analyzing the effects of terrorist attacks on crime, due to the high level of police deployment and people's avoidance of being in public places due to fear. Most articles offer evidence showing that police presence reduces crime ([Di Tella and Schargrodsky, 2004](#); [Gould and Stecklov, 2009](#); [Draca et al., 2011](#)). However, in lockdowns police resources are reallocated towards their enforcement and to applying penalties for non-compliance, while in the case of terrorist attacks, the police are attentive to criminal activity. This could have important implications for criminal behavior. In this regard, a recent study by [Carrillo et al. \(2018\)](#) is of particular interest as it shows that the displacing of policing resources to enforce policies non-related to criminal activities increases criminal activity. They analyze the case of driving restriction programs in Ecuador.

Finally, this paper contributes to the growing literature on gender-based violence. Previous studies have shown the effect of labor market outcomes on domestic violence ([Aizer, 2010](#); [Anderberg et al., 2016](#);

Bhalotra et al., 2020) as well as alcohol consumption (Luca et al., 2015; Khurana et al., 2019), conditional cash transfers (Bobonis et al., 2013), the presence of women in the police (Miller and Segal, 2019), among others. This paper focuses on the consequences of continuous confinement produced by stay-at-home orders on violence against women. This is particularly relevant in the case of India, where violence against women is prevalent and four rape cases reported every hour (Thomson Reuters Foundation 2018).

The paper is organized as follows. Section 2 describes the Indian context and governmental policies during the COVID-19 pandemic. Section 3 describes the types of crimes more likely to be affected by the COVID-19 containment measures. In section 4 we describe the data sources and descriptive statistics, while in 5 we provide details on the empirical strategy. The results are shown in section 6. Finally, we conclude and discuss the implications of the results in section 7.

2 Lockdown in Bihar and India

On Sunday 22 March, the state government of Bihar ordered a complete lockdown with immediate effect to prevent the spread of the COVID-19. This implied severe restrictions on the movement of individuals and the closure of all establishments, with the exception of those providing essential goods and services.

Days later, on March 24, the central government of India announced a complete nation-wide lockdown for (an initial) 21 days, resulting in more than 1.3 billion people staying at home. In an effort to ease the socio-economic consequences of the pandemic response measures, restrictions have been relaxed in COVID-19-less-affected districts since April 20. The central government classified districts in three types of zones: green, orange and red (the latter being the most restrictive) depending on the number of COVID-19 cases and propagation of the virus.⁴ Out of the 38 districts in Bihar, 27 were classified as green, 7 as orange and 4 as red zones.⁵ On May 3, the state government of Bihar ordered all green zones to be reclassified as orange in order to halt the transmission of the virus. This reclassification of districts came into effect on 4 May.⁶ The lockdown has been extended numerous times and currently it is still in place.

The role of the police has been crucial in enforcing lockdowns around the world. In India, the relatively low number of police officers to population has put the police under extraordinary pressure. This is of

⁴See appendix A.1 for more details on how zones were selected and the restrictions for each category.

⁵The initial list classified 170 districts as red, 207 districts as orange and 356 districts as green across whole of India. This list is in constant revision by the central government. In May 4, an updated list came into effect contained 130 red, 284 orange, and 219 green districts. These 130 districts cover nearly a third of the country's population.

⁶As per order of the central government announced on 1 May, states can classify areas under the three levels but only if they mean to increase restrictions.

particular concern in the case of Bihar, which has the lowest number of policemen per population in the country.⁷

3 Stay-at-home orders and criminal activity

The rational model of criminal behavior proposed by [Becker \(1968\)](#) suggests that the decision to engage in crime depends on the expected benefits and costs of committing the crime.⁸ The imposition of lockdowns impacts criminals' behavior by affecting their motives, means and/or opportunities. To be more specific, let p be the probability of getting caught, C the cost of being punished if caught, Y the benefit of committing a crime, S the costs incurred when offending, and F the police force devoted to fighting crime. Denote as U_{nc} the utility when the individual abstains from crime, $U_1 \equiv U(Y, S)$ the utility of committing a crime without an apprehension, and $U_2 \equiv U(Y, S, C)$ the utility when committing a crime that results in apprehension and punishment. Let $\frac{\partial U}{\partial Y} > 0$, $\frac{\partial U}{\partial S} < 0$, $\frac{\partial U}{\partial C} < 0$, $\frac{\partial p}{\partial F} > 0$. An individual engages in crime if $(1 - p(F)) \cdot U_1 + p(F) \cdot U_2 > U_{nc}$, that is,

$$(1 - p(F)) \cdot U(Y, S) + p(F) \cdot U(Y, S, C) > U_{nc} \quad (1)$$

The net effect of lockdowns on crime is uncertain. On one hand, it reduces crime by increasing the criminal's search costs (S) involved in committing a crime. Fewer people on the streets and for shorter lengths of time reduces the number of potential victims, and therefore the chances of a victim-criminal match. This reduces the expected utility of crime and will deter a criminal from offending if and only if the inequality in equation 1 flips sides.⁹ On the other hand, police deployment to enforce stay-at-home orders diverts crucial resources away from fighting crime. The reduction in F decreases the likelihood of capture (p) and therefore increases the expected utility of engaging in crime. Additionally, lockdowns could have an direct incapacitation effect on offenders. However, due to the law-breaking nature of criminals it is unlikely that they will abide with the law.¹⁰

When analyzing the impact of lockdowns on crime it is important to consider the nature of the

⁷According to Data on Police Organization 2019 Report, the number of police officer per 100,000 people in Bihar is 81, whereas for India this is 158. To put this into context, according to the Uniform Crime Reporting, for 2018 this number is 298 in the United States.

⁸For a review of the crime literature see for instance [Nagin \(2013\)](#), [Draca and Machin \(2015\)](#) and [Chalfin and McCrary \(2017\)](#).

⁹Also, fewer people on the streets imply fewer witnesses (W) which can increase crime by reducing the probability of getting caught $p(F, W)$, where $\frac{\partial p}{\partial W} > 0$.

¹⁰Note that offenders might be out of the streets due to fear of the virus. However, if criminal activity is their main (and usually only) source of income or if they are part of a gang/mafia, they might be forced to go on the streets.

crimes and the locations where they take place. Taking this into account would provide insights on the mechanisms affecting each particular crime. For instance, given that property crimes such as theft are economically motivated and occur in the streets, they are susceptible to changes in police deployment (F) and criminal-victim matching (S) produced by the lockdown, while crimes of passion such as murder might not be as affected by police deployment but only by the chances of criminal-victim matching.¹¹ In this regard, crimes against women such as domestic violence might be particularly affected by lockdowns, since the crime is committed indoors and perpetrators and victims are confined within the same space for longer periods of time. This implies in a double impact due to low F and low S . Note however, that due to the particular characteristics of lockdowns, reporting of this crime might be difficult for the same reasons just exposed.

Finally, depending on the duration of the lockdowns, additional channels through which lockdowns affect crime might emerge. If labor market conditions are severely affected by prolonged lockdowns, the utility individuals get from abstaining from crime (U_{nc}) will decrease, making crime a more attractive option (see equation 1). This would be the case if a high proportion of people are unemployed as a consequence of the lockdown.¹²

4 Data

The data on criminal cases is obtained from First Information Reports (FIR) made available by Bihar Police Department.¹³ The data contains criminal cases reported at police stations including the specific registration date and associated criminal charges (related to the Indian Penal code and/or particular laws). The data was scraped up to 27 May 2020. This is the most granular data possible for criminal cases in India.¹⁴

The information is retrieved at police-district level. We work with 41 police districts in Bihar, comprising 883 police stations, 80,600 criminal cases up to 26 May 2020.¹⁵ Criminal cases are categorized and aggregated at the police station-level for each day. Criminal charges are used to classify the cases in

¹¹For crimes involving entering a private property such as burglary, stay-at-home orders also increases search cost (S) in order to find non-occupied properties.

¹²For evidence of the effects of recessions on crime see for instance [Mocan and Bali \(2010\)](#) and [Bell et al. \(2018\)](#).

¹³The First Information Report is a written document prepared by the police when receiving an alleged commission of a cognizable offense. This report represents the first step in the whole criminal procedure. Data source: http://scr.bihar.gov.in/View_FIR.aspx.

¹⁴This information is available due to a mandate dictated by the Supreme Court of India in September 2016. Offenses of sensitive nature (sexual offenses, offenses pertaining to insurgency, terrorism and of that category, offenses under the Protection of Children from Sexual Offenses Act) are not reported.

¹⁵There are 44 reporting police-districts in Bihar. The district of Arariya, Bhabhua and Khagaria are dropped from the sample due to incomplete reporting during 2020. For January 2020, these three districts represent 4.5 percent of the total number of cases.

different categories. We use the most common crimes analyzed in the literature: murder, theft, robbery, burglary, kidnapping, rioting and additionally include crime against women and crimes against public health, which are of special concern during the pandemic.¹⁶

Table 1: Summary statistics

	(1)		(2)	
	No Lockdown		Lockdown	
	mean	sd	mean	sd
All crimes	0.693	(1.138)	0.502	(0.986)
Murder	0.009	(0.096)	0.008	(0.091)
Theft	0.273	(0.659)	0.232	(0.623)
Robbery	0.009	(0.097)	0.002	(0.050)
Burglary	0.0202	(0.149)	0.0141	(0.124)
Kidnapping	0.0315	(0.187)	0.009	(0.097)
Rioting	0.0473	(0.260)	0.0653	(0.312)
Against health	0.000	(0.017)	0.034	(0.210)
Against women	0.135	(0.427)	0.113	(0.401)
Police stations	898		898	
Crimes during the period	50,384		30,216	
Observations	72738		60166	

Notes: This table shows average daily crimes at police station level for different crime categories based on First Information Reports in Bihar. The sample covers 1 January 2020 to 27 May 2020. ‘No Lockdown’ covers from 1 January to 21 March 2020, while ‘Lockdown’ includes 22 March 2020 to 27 May 2020. Standard deviations are in parentheses.

Table 1 shows summary statistics for the 2020 criminal activity in Bihar separated by the lockdown period (starting 22 March 2020 onward) and no lockdown period (1 January to 21 March). Nearly 50,000 cases were reported in pre-lockdown period and around 30,000 during the lockdown. On average, each day 0.69 crimes were reported per police station pre-lockdown, this number decreases during the lockdown to 0.5 cases. Similar patterns occur for the other crimes apart from rioting and crimes against public health, which increase during the lockdown. The most prevalent crime are thefts followed by crimes against women,¹⁷ while violent crimes as murder and robbery are the least common.

As by law, certain crimes against women are not reported in the FIR data (see footnote ¹⁴), we complement the analysis using data from the National Commission for Women (NCW). This data con-

¹⁶Crime categories are based on the analysis of the National Crime Records Bureau. Murder (IPC 302), Theft (379-302), Robbery (392-394, 397, 398), Burglary (454-459, 460/380), Kidnapping (363-369), Rioting (143-145, 147-151), Crime against health (269-271), Crime against Women (313, 314, 354, 366, 498, 509, 375, 376, 304(b)), following Acts: Dowry; Domestic Violence, Immoral Trafficking, Indecent Representation).

¹⁷The most common charge for crimes against women is ‘Assault of criminal force to woman with intent to outrage her modesty’ (IPC 354). This comprises more than 70 percent of this type of crime.

tains up-to-date information for districts across India on the number of reported cases received by NCW. Complaints are made by phone, through online registration, emails, social media (such as WhatsApp) or directly in person. Note, however, that during the lockdown, only social media, email and online registrations are possible ways to file a complaint. The data covers the period from January 2017 up to end March 2020. For 2020, there are more than 6,500 reported cases for violence against women, with an average of 2.5 cases per month.¹⁸ While this data is aggregated per month, the geographic coverage across district in India allow analyzing whether more restrictive lockdowns have a higher impact on violence against women. To measure the severity of lockdown policies we use the three categories (red, orange, green zones) defined by the Union government of India. We obtain this data from <https://covidindia.org/>.

5 Empirical strategy

5.1 Regression Discontinuity Design

The goal of this study is to identify the impact of lockdowns on crime. One interesting feature for the analysis is that the day Bihar's government announced the lockdown it was not targeted at a special date nor advised beforehand. We regard this as an exogenous shock and exploit a discrete change in the 'lockdown-status' in the state of Bihar. Hence, by harnessing on the up-to-date high frequency data on criminal activity for Bihar, a sharp regression discontinuity (RD) design using the date as the running variable is employed.¹⁹ To eliminate persistent temporal effects, we demeaned the number of criminal cases by day-of-the-month (Lee and Lemieux, 2010), and then followed the standard RD specification (Imbens and Lemieux, 2008; Lee and Lemieux, 2010).²⁰ In particular, to study the effect of the lockdown on crime the following equation is estimated:

$$crime_{it} = \alpha + \beta \cdot lockdown_{it} + f(date_{it}) + \epsilon_{it}, \quad (2)$$

where $crime_{it}$ is the demeaned number of crimes at date t for police station i , $lockdown_{it}$ is a binary variable equal to one when the lockdown came into effect, and $date_{it}$ is the date measured in days from

¹⁸This data does not distinguish the nature of the case. However, based on NCW sources, the proportion of cases for 2020 are: Right to live with dignity is most common complaint with 29%, followed by domestic violence with 24%, Harassment 14% Molestation 7%, Rape 6%, and others.

¹⁹For a discussions when the running variable is time see (Lee and Lemieux, 2010; Hausman and Rapson, 2018). For other studies using time as running variables see Davis (2008); Anderson (2014); Doleac and Sanders (2015).

²⁰Results using the number of criminal cases do not affect significantly the results of the paper. The effects are larger in absolute term and significant.

the beginning of the lockdown and ϵ_{it} represents an idiosyncratic error. The parameter of interest β captures the causal impact of the lockdown on crime at the transition date. The identification of β comes from assuming that the underlying, potentially endogenous relationship between ϵ_{it} and the date is eliminated by the function $f(\cdot)$. This is, ϵ_{it} should not change discontinuously around the date in which the lockdown starts. Since the lockdown in Bihar started on a Sunday, we expand equation 2 to include day of the week fixed effect (τ_{dow}) to account for different crime patterns during different days (weekends might have different crime level than weekdays). Following [Imbens and Lemieux \(2008\)](#), our main specification considers a linear model with different slope in both sides at the transition date:

$$crime_{it} = \alpha + \beta_1 \cdot lockdown_{it} + \beta_2 \cdot date_{it} + \beta_3 \cdot lockdown_{it} \cdot date_{it} + \tau_{dow} + \epsilon_{it} \quad (3)$$

We use a uniform kernel ([Imbens and Lemieux, 2008](#)) and a bandwidth of 21 days on both sides of the lockdown threshold.²¹ Hence, dates between March 2 until April 12 are included in the estimation. We perform a wide variety of robustness checks, such as the use of different bandwidths, other functional forms for $f(\cdot)$ and placebo tests analyzing other dates for ‘fake lockdowns’.

One relevant concern for statistical inference is the fact that ϵ_{it} can be correlated over time and police-stations levels. We therefore cluster the standard errors along these two dimensions by following the methodology suggested by [Cameron et al. \(2012\)](#). This allows accounting for common variation in crime at the police station-level and also across days.

5.2 Fixed-Effect Estimations

The previous approach provides a local average treatment effect of lockdowns on crime at the transition date. However, the effect of lockdowns on crime can vary throughout time and also by the type of restrictions imposed. In order to capture any differential effects along these margins, a fixed-effects approach is followed. To identify the effect of different types of lockdowns on crime, we exploit time and geographic variation across districts in Bihar. We use the classifications given by the Union government of India to determine whether crime rates differ across districts with different levels of lockdown restrictions. We use the following specification:

$$crime_{it} = \alpha + \beta_1 \cdot lockdown_{it} + \beta_2 \cdot red_{it} + \beta_3 \cdot orange_{it} + \beta_4 \cdot green_{it} + \tau_{dow} + \lambda_{month,PS} + \epsilon_{it}, \quad (4)$$

²¹This 21 days coincide with the initial proposed duration of the lockdown.

where $lockdown_{it}$ is a binary variable equal to one from the start of the lockdown onward. The variable red_{it} is also a binary variable equal to one if the police station i belongs to a district classified as a ‘Red Zone’ at day t , otherwise it is zero. The variables orange and green follow the same logic.²²

We include police station-month specific fixed-effect to control for different time trends for each police station. Therefore, the *initial* effect of the lockdown on crime (β_1) is identified by comparing crimes rates when (i) the initial lockdown is in place versus (ii) when there is no lockdown, this within a month in a given police station.²³ The other parameters are capture in a similar manner.

Violence against women - NCW data. To study the effect of lockdowns on violence against women using the NCW data, we follow a similar fixed-effect approach as in equation 4. However, since the data is monthly, variables $\{lockdown_{it}, red_{it}, orange_{it}, green_{it}\}$ are defined as a proportion of the month were the condition associated with the variable is satisfied. Thus, let var_{it} be any of the previous variables, then if for a district i the condition associated to var_{it} is ‘switched on’ at day d_1 of month m_1 , then $var_{im_1} = (\#m_1 - d_1 + 1)/\#m_1$, where $\#m_1$ denotes the numbers of days in month m_1 , and if the condition is ‘switched off’ at day d_2 of month m_2 then $var_{im_2} = (d_2)/\#m_2$. var_{it} is equal to one for all months t between m_1 and m_2 . For instance, $lockdown_{it}$ is equal to 0 in February 2020, $(31-22 + 1)/31$ in March 2020 and 1 onward.

6 Results

Figure 1 shows the RD design for estimating the effect of lockdown on crime. The scatter points show the daily averages of the residuals of the total number of crimes after controlling for day-of-the-month effects. The solid lines are the predicted values for these residuals based on a local linear regression based on 3 and using a 21-days bandwidth to match the main RD specification. The horizontal axis denotes the number of days from the beginning of the lockdown (specified as day ‘0’). There is a sharp decrease of nearly 30 percent in crime at the moment of the imposition of the lockdown. An upward trend after the imposition of the lockdown suggests an increase in crime as the lockdown progresses.

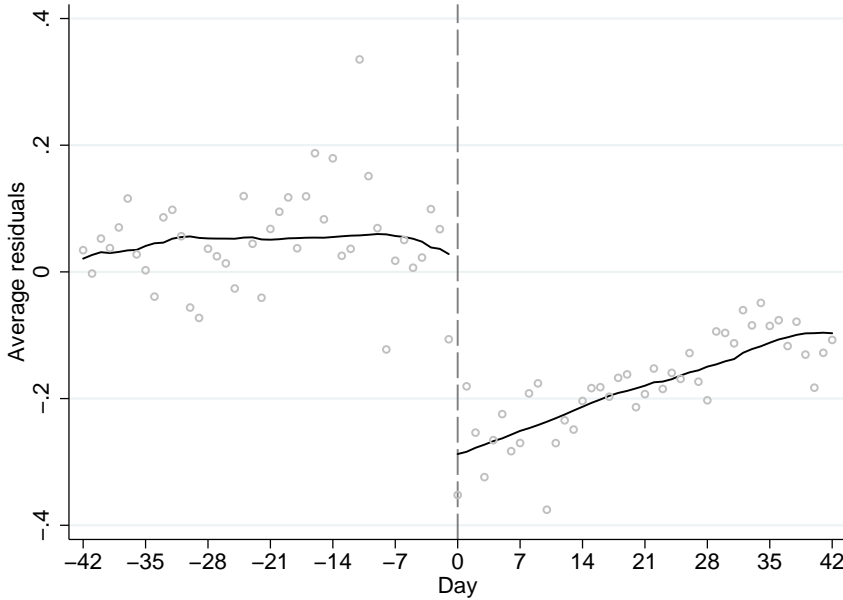
Table 2 shows the main results for the RD as well as other RD estimates for different specifications.

Column 1 shows the estimates for the main specification. According to this, the imposition of the

²²To be more specific, the variable lockdown is equal to one from 22 March until the end of the sample. From 20 April onward, police stations are assigned to be red, orange or green for 14 days and these are re-classified as either red or orange from 4 May onward. See section 2 for more details on these dates.

²³The high frequency of the data and the fact that the lockdown-status changes for districts/police stations within a month are important in identifying the parameters.

Figure 1: Daily estimates of local linear regression - All Crimes



Notes: This figure shows in solid lines the predicted values for the total number of crimes (demeaned by day-of-the-month) based on the following local linear regression $crime_{it} = \alpha + \beta_1 \cdot lockdown_{it} + \beta_2 \cdot date_{it} + \beta_3 \cdot lockdown_{it} \cdot date_{it}$. 'Day' is the number of days since the start of the lockdown. Day 0 denotes when the lockdown starts in Bihar (22 March). The scatter plot is the daily average of the total number of crime demeaned by day-of-the-month.

Table 2: RD Estimates of the effects of lockdowns on crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Quadratic	Bandwidth 14 days	Bandwidth 28 days	Placebo 22 Mar 2019	Placebo 22 Jan 2020	Placebo 22 Feb 2020
Lockdown	-0.307 (0.031)***	-0.232 (0.052)***	-0.256 (0.042)***	-0.350 (0.036)***	0.061 (0.040)	0.041 (0.043)	-0.028 (0.033)
Date	-0.005 (0.001)***	-0.021 (0.012)*	-0.011 (0.006)*	-0.000 (0.001)	0.015 (0.002)***	-0.001 (0.003)	-0.001 (0.002)
Date × Lockdown	0.011 (0.002)***	0.022 (0.014)	0.014 (0.007)**	0.006 (0.002)***	-0.043 (0.003)***	0.004 (0.004)	0.009 (0.003)***
Observations	37,716	37,716	25,144	50,288	37,716	37,716	37,716
Pre-lockdown Mean	0.69	0.69	0.69	0.69	0.71	0.66	0.67
Share of Mean	-0.44	-0.33	-0.37	-0.50	0.09	0.06	-0.04

Notes: This table shows estimates of the effect of lockdown on crime. The baseline specification shows the estimates based on the regression discontinuity model as shown in equation 3. The other columns show estimates for other specifications baseline as specified in the column title. The sample contains dates within 21 days of the beginning of the lockdown, unless specified otherwise. Observations are daily at police station level. Parentheses show clustered standard errors that are robust to within day and within police station serial correlation following Cameron et al. (2012). All regressions include day-of-the-week fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

lockdown decreases aggregate crime by 31 percentage points. This effect is not only statistically significant but also economically relevant. This impact represents a large 44 percent reduction of crimes. The

negative impact of lockdown on aggregate crime is quite robust across different econometric specifications: the use of (different) quadratic trends on both sides on the transition date,²⁴ and the use of different bandwidths.²⁵ All the estimates are significant at 1 percent significance level. The magnitude of the estimates ranges from 24 to 35 percentage points, implying a decrease in crime produced by the lockdown of 34 to 51 percent depending on the specifications. Columns (5) to (7) present estimates when using the baseline specification on a different ‘fake lockdown’ date as a placebo. To see whether specific temporal effects (not related to the lockdown) are driving the result, we use the same date for the previous year and the same day of the lockdown but for the two month preceding the lockdown. The point estimates are considerably lower (in absolute value) and in two cases the sign is positive. This suggests that the decrease in crime observed during the real lockdown is produced by the policy itself rather than the transition date.

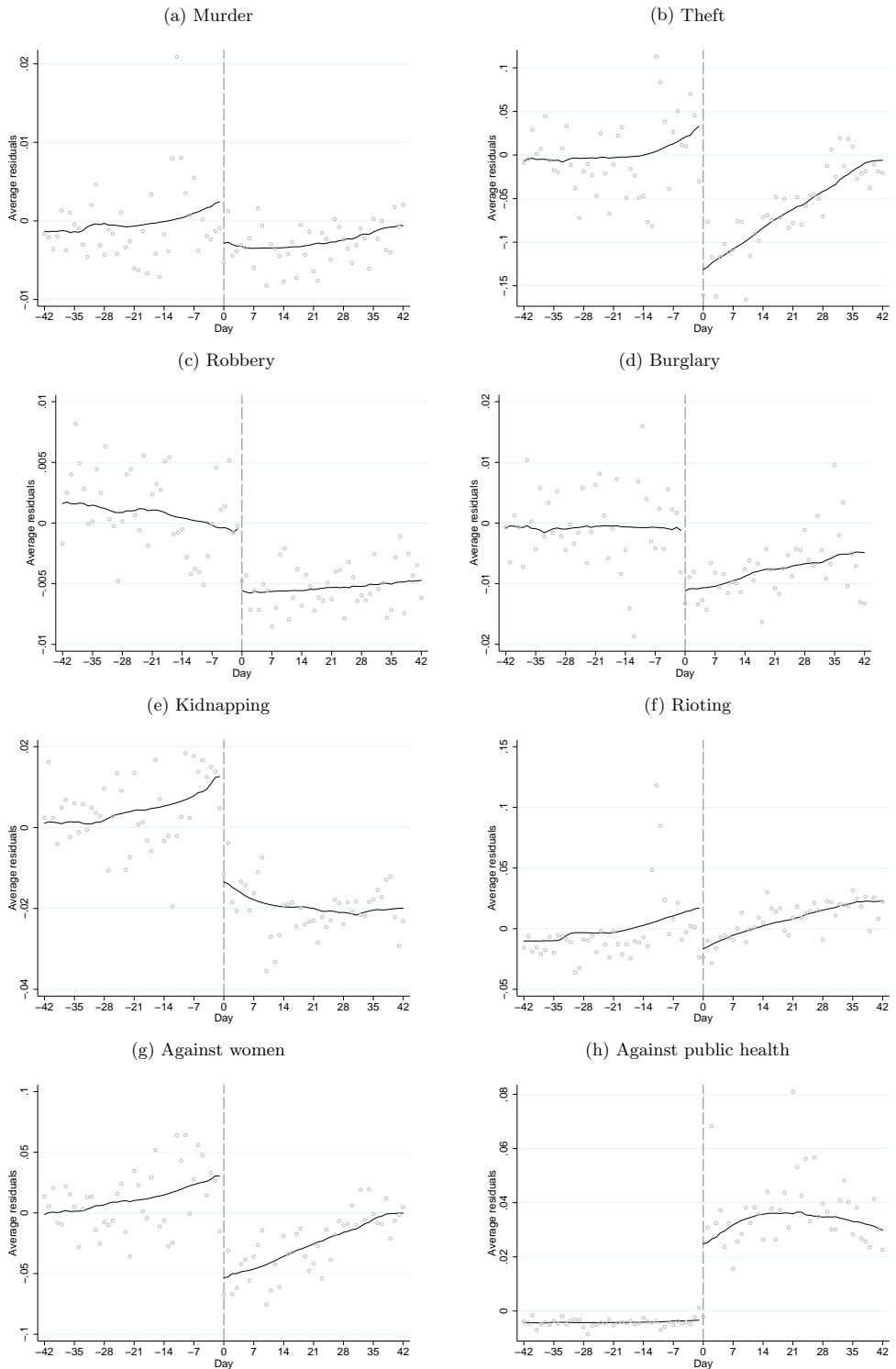
Lockdown’s impact on crime categories.

Regarding the impact of lockdowns on each crime category, figure 2 shows the same visual analysis as before. The figure suggests that lockdowns reduce criminal activity across the board, despite the diversity of the crimes in terms of motives and presumably the location of the incidents. While for all crimes there is a change in levels after the lockdown, in the case of theft, rioting and crimes against women, the steep upward trend after the lockdown suggests that the incidence of these crimes are reaching the pre-lockdown levels. In the case of crimes against public health, there is a large discontinuous jump. This reveals that not all individuals are complying with the lockdown and that the police is enforcing the stay-at-home order and imposing penalties for non-compliers.

²⁴Gelman and Imbens (2019) argued that including cubic or higher-order polynomial terms in the RD design can be misleading, hence linear and quadratic functions are used.

²⁵The 28 days bandwidth includes dates between 24 February until 19 April, just before relaxed lockdown measures came into effect.

Figure 2: Daily estimates of local linear regressions by crime categories



Notes: This figure shows in solid lines the predicted values for each crime type (demeaned by day-of-the-month) based on the following local linear regression $crime_{it} = \alpha + \beta_1 \cdot lockdown_{it} + \beta_2 \cdot date_{it} + \beta_3 \cdot lockdown_{it} \cdot date_{it}$. 'Day' is the number of days since the start of the lockdown. The scatter plot is the daily average number of crime for each crime category demeaned by day-of-the-month.

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Table 3: Estimates of the effects of lockdowns on crime by category of crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Crimes	Murder	Theft	Robbery	Burglary	Kidnapping	Rioting	Against Women	Against Health	NCW
Panel A: RD										
Lockdown	-0.307	-0.006	-0.171	-0.005	-0.010	-0.028	-0.036	-0.087	0.033	
	(0.031)***	(0.002)**	(0.017)***	(0.001)***	(0.003)***	(0.004)***	(0.012)***	(0.011)***	(0.007)***	
Pre-lockdown Mean	0.69	0.01	0.27	0.01	0.02	0.03	0.05	0.14	0.00	
Share of Mean	-0.44	-0.61	-0.63	-0.56	-0.49	-0.88	-0.77	-0.64	143.01	
Panel B: FE										
Lockdown	-0.324	-0.003	-0.114	-0.006	-0.010	-0.019	-0.016	-0.064	0.033	-1.224
	(0.017)***	(0.001)**	(0.009)***	(0.001)***	(0.002)***	(0.002)***	(0.003)***	(0.006)***	(0.003)***	(0.268)***
Red Zone	0.130	0.001	0.089	-0.001	0.009	0.009	0.027	0.046	-0.022	3.907
	(0.026)***	(0.002)	(0.015)***	(0.001)	(0.003)***	(0.003)***	(0.012)**	(0.010)***	(0.008)***	(0.693)***
Orange Zone	0.110	0.001	0.057	-0.001	0.007	0.008	0.010	0.025	-0.009	0.012
	(0.019)***	(0.002)	(0.011)***	(0.001)	(0.003)***	(0.002)***	(0.006)*	(0.008)***	(0.005)*	(0.284)
Green Zone	0.104	0.001	0.062	0.001	0.003	0.004	0.006	0.035	-0.005	-0.630
	(0.013)***	(0.001)	(0.009)***	(0.001)	(0.002)	(0.001)***	(0.005)	(0.006)***	(0.004)	(0.0476)

Notes: Panel A shows RD estimates from equation 3 for different types of crimes. The dependent variable is the number of crimes demeaned by day-of-month. The sample contains dates within 21 days of the beginning of the lockdown. Observations are daily at police station level. Parentheses show clustered standard errors that are robust to within day and within police station serial correlation following Cameron et al. (2012). All regressions include day-of-the-week fixed effects. Observation: 37,716.

Panel B shows the estimates of a fixed-effects regression. Lockdown is defined as one when the lockdown starts onward. Red zone (Orange and Green) is equal to one if in a given day the district where the police station belongs is classified as Red (Orange or Green) by the Union or state government. All regressions include day-of-the-week fixed effects and also police station-month fixed effects. For columns (1)-(9) Observations: 132,904.

In the last column are the estimates for crime against women using the data from National Commission of Women (NCW). Variables lockdown (Red, Green and Orange Zones) are between 0 and 1, and represents the share within a month where the condition associated with the variable is satisfied. Observations: 22,827. For more details see section 5.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Panel A in table 3 shows the results associated with the RD estimation for each crime-type. There are large significant effects of the lockdown on all crime categories. For violent crimes such as murder and robbery, the point estimates are -0.006 and -0.005, respectively, implying a large reduction of 61 and 56 percent, respectively (see third row panel A). Even though the incidence of these crimes is low compared to others, they impose a high cost to society. In the case of the most common type of crime, theft, there is also a large reduction of 63 percent. Burglary, which involves breaking into properties, decreased by 49 percent. The largest negative impacts of the lockdown are on kidnapping (88 percent) and rioting (77 percent), both of which occur in the streets. Crimes against public health increased by 143 percent due to the lockdown. Additionally, the results show a 64 percent reduction in violence against women due to the lockdown. This is mainly driven by a reduction in assaults to women.

6.1 Severity of the lockdown on crime

One particularly relevant question is whether the severity of lockdowns have a differential impact on criminal activity. Panel B in table 3 shows the results from estimating the model in equation 4. The first row shows the estimates of the impact of the lockdown on crime. The results are in line with the findings from the RD estimates in panel A, despite the fact that the RD and the FE models capture different parameters.

For almost all crimes, the estimates associated with the restrictions zones have the opposite sign of the parameters related with the lockdown. This suggests a shift in criminal patterns produced by the implementation of the restrictions zones. It can be noted also that, irrespective of the type of crime, the effects of the initial lockdown on crime are larger (in absolute terms) than the ones produced by the introduction of the restriction zones. This makes sense given the asymmetry of the implemented measures. The initial lockdown was introduced in full force and was highly restrictive, while the new restriction zones (red, orange, green) relaxed certain previous restrictions but kept some constraints in place. Moreover, the initial context in which each policy was introduced (no lockdown versus lockdown), could drive different behavioral responses in criminals and everyday citizens.

Considering the effects of the restriction zones on aggregate crime (column 1), it is interesting to note that more restrictive lockdowns (red zone) produce a larger increase in crime compared to less restrictive zones (orange and green). However, the point estimates are not statistically significantly different from each other. Similar patterns emerge for all other crimes except violent crimes. Indeed, the transition

from a strict lockdown to any type of restriction zone did not affect murder and robbery. These results contrast with the findings for property crimes such as theft and burglary, suggesting that economic incentives might be an important reason for the increment in these crimes.²⁶

One of the most important differences across restriction zones is the functioning of certain shops and commerce, which were allowed in green and orange zones, but not in red ones. Hence, within a month and police station area, the economic situation can experience a dramatic downturn depending on the assigned restriction zone.²⁷ Hence, more restrictive zones could be facing worst economic conditions than less restrictive zones, implying another potential channel affecting criminal activity, that is not present in the very short-term (see section 3). This could also explain the significant increase in rioting in more restrictive zones compared to less restrictive ones.

In the case of crimes against women, the transition from lockdown to any of the three restriction zones produces an increment in crimes against women. More restrictive zones (red zones) increase the number of cases compared to less restrictive zones (Green zones). The results using data from NCW for all districts in India are shown in the last column of table 3. The initial lockdown decreased violence against women by 44 percent (with respect to the pre-lockdown level). However, in red zones, these crimes increased in 140 percent (pre-lockdown level), this impact outweighs the effects of the lockdown. The other zones do not seem to affect the number of reported cases. However, if anything, less restrictive zones decrease violence against women. These results are in line with the idea that more restrictions to people's mobility and higher levels of confinement could negatively impact violence against women. This, despite that it might be more difficult for victims to seek help in restrictive zones.

Overall, in terms of criminal activity, there seems to be some benefits of imposing less restrictive lockdowns as opposed to more restrictive ones. However, highly restrictive lockdowns are more effective in curbing crimes against public health. In turn, less restrictive lockdowns do not seem to affect people's propensity to commit crimes against health.

²⁶Note that if individuals are forced to engage in criminal activity because of economic motives (a decrease in U_{nc} in equation 1), they are more likely to be involved in non-violent crimes.

²⁷Even more if we consider the fragile state of the economy when restrictions zones were implemented - after 28 consecutive days of strict lockdown. Indeed, the Centre for Monitoring Indian Economy (CMIE) estimates that India's unemployment rate soared to over 20 percent in April, and for Bihar this is 46.6 percent.

7 Discussion

Lockdowns and social distancing orders have been the main policies deployed to contain the COVID-19 outbreak. In this study, we analyze the impact lockdowns have on criminal activity across a wide range of crime categories and its public policy implications. There are two main immediate and opposite channels of why lockdowns impact crime: (i) diversion of police resources to enforce lockdowns and (ii) the reduction in the number of people in the streets, which increases criminals' costs of finding victims. The findings reveal large negative effects of lockdowns in aggregate criminal activity of 44 percent. This is also true across crime categories, regardless of their nature and the settings where crimes are committed. These crimes span from murders, thefts, burglaries, kidnapping, robberies, rioting to crimes against women. Additionally, this evidence suggests that the main channel at play is the higher search costs that lockdowns impose on criminals. An important implication is that the large reduction in crime allows the police to free up resources for pandemic-containment.

The main estimates based on an RD design capture the immediate effects of lockdown on crime. However, lockdowns could impact crime through other channels in the medium and long-term. A fixed-effects model is used to capture the effect of the initial lockdown as well as its transition towards three different stay-at-home orders under diverse restriction measures. While the initial lockdown decreases crime, the subsequent relaxing of restrictions via the introduction of red, orange and green zones led to an increase in criminal activity. Notably, following the transition to the restriction zones, violent crimes were not significantly impacted, whereas other economically-motivated crimes were.

A key consideration is the effect that strict and prolonged lockdown measures have on economic activity, unemployment and individuals' financial outcomes. As the literature has shown, this has important consequences for criminal activity. Indeed, when comparing the three types of restrictions zones (introduced 28 days after the initial lockdown), the study finds that crime increased more in high-restriction areas compared to low-restriction ones. In this sense, economic motives might be impacting lockdown-crime dynamics as lockdowns progress. High-restriction zones have potentially been more severely impacted by the lockdown due to business closures and job losses. Further research in this area will be required to understand the full socioeconomic impact of lockdowns in the medium and long term.

One potential concern in this study is that a high proportion of crimes go unreported due to forced confinement. This is less likely to be the case for crimes of serious nature such as murder and robbery, where reporting is usually timely and accurate. This study finds that these crimes also decrease due

to the lockdown, therefore suggesting that under-reporting is not a leading factor for these types of crime. In contrast, already under-reported crimes such as those against women might be further affected by the lockdown. This is overcome by running the analysis on two different data sources (Police First Information Reports and National Commission for Women), which shows similar results.

Finally, in terms of criminal activity, this paper argues for the introduction of less restrictive lockdowns. When designing lockdown policies, policymakers should pay special attention to the role that economic factors have in driving crime dynamics in the medium term. If prolonged and strict lockdowns are imposed, targeted financial support packages could be offered to those under high financial distress to deter their involvement in criminal activity. Similarly, resources should be allocated and support provided to tackle crimes against women in high-restriction zones.

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A Supplementary material

A.1 Restriction zones

The districts' classification is done as follows. Red zones are based on either one of the following rules:

(i) Highest case load districts contributing to more than 80% of cases in India or (ii) Highest case load districts contributing to more than 80% of cases for each state in India or (iii) Districts with doubling rate less than 4 days (calculated every Monday for last 7 days, to be determined by the state government).

If there is not new confirmed cases for the last 14 days a Red Zone is now defined as Orange Zone. If an Orange Zone has no new confirmed cases for the last 14 days, then it is defined as Green zone.

Activities banned in India irrespective of the zone classification: Among the most relevant are travel by air, rail, metro and inter-State movement by road; schools, colleges, and educational centers; Hotels and restaurants; Also, all places of large public gatherings, such as cinema halls, malls, gymnasiums, sports complexes are closed as well as religious places. **Red zones:** In the initial phase, no activity will be permitted, and it shall remain totally sealed for to and fro movement of people and vehicles. A door-door screening is conducted in every household in the area to search for suspected patients. Essential goods are delivered to the doorstep of every individual. **Orange zones:** restricted activities such as limited public transport and agriculture-based micro small and medium enterprises are allowed. All under strict maintenance of social distancing. **Green zones:** Limited movement of people linked to essential services and busines. Opening of liquor shops and other essential items contributing to state's revenue. Plus all from Orange zones. For more information see <https://covidindia.org/zone-restrictions/#hotspot-zones>.

Twin peaks: Covid-19 and the labor market¹

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This paper develops a choice-theoretic equilibrium model of the labor market in the presence of a pandemic. It includes heterogeneity in productivity, age and the ability to work at home. Worker and firm behavior changes in the presence of the virus, which itself has equilibrium consequences for the infection rate. The model is calibrated to the UK and counterfactual lockdown measures are evaluated. We find a different response in both the evolution of the virus and the labor market with different degrees of severity of lockdown. We use these insights to make a labor market policy prescription to be used in conjunction with lockdown measures. Finally we find that, while the pandemic and ensuing policies impact the majority of the population negatively, consistent with recent studies, the costs are not borne equally. While the old face the highest health risks, it is the young low wage workers who suffer the most income and employment risk.

¹ The usual disclaimers apply.

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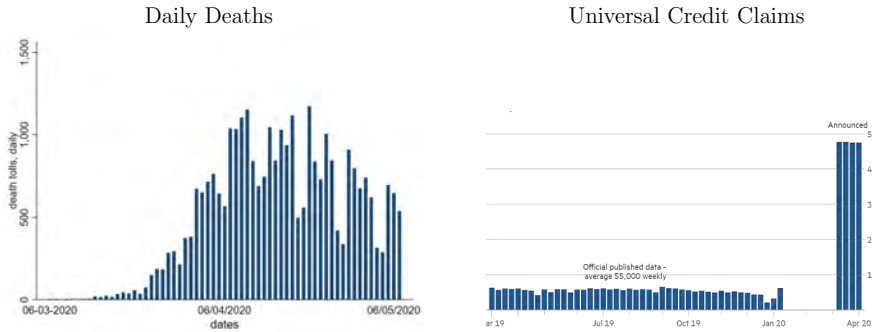
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1 Introduction

The COVID-19 outbreak has posed significant global challenges to public health and the economy. Since the first cases of infection reported in China in January 2020, there have been more than 7 million cases reported worldwide and at the time of writing, it has killed more than 400 thousand people. In the United Kingdom (UK), this virus has caused the death of more than 40 thousand people, with a daily peak of 1100 deaths suffered on April 21, 2020 (Figure 1). Economically, the FTSE 100 fell by 25% in the first three months of 2020, the largest quarterly fall in over three decades. Workers in the economy were particularly hard hit, with the Department of Work and Pensions processing more than five times the typical level of benefit claimants (see the second panel of Figure 1). Public lockdown policy, aimed at reducing the spread of the infection and ultimately saving lives, further exacerbates the economic costs associated with the pandemic.

This paper merges two workhorse models from epidemiology and economics to garner a deeper understanding of the interaction between the health and economic costs associated with the pandemic. Using the UK as a case study, we examine the implications of different lockdown policies on fatalities and the economy. Finally, we study active labor market policy that can run in conjunction with a lockdown that we argue will mitigate the economic costs.

Figure 1: The UK’s Health and Economic Cost of Covid-19



Source: UK NHS (See <https://coronavirus.data.gov.uk/>)

Source: UK Department for Work and Pensions

We analyse lockdown policies of differing durations. Unsurprisingly, we find that longer lockdowns will save more lives, while causing greater harm to the economy. However, the disease and labor market dynamics can contrast quite markedly across these differing durations. In terms of the labor market, when locked down, a worker-firm pair’s production falls. A longer lockdown makes it more expensive for firms to hold onto their employees. Consequently, we see a larger number of layoffs at the start of lockdown and a greater adjustment in worker-firm allocation throughout its duration. This results in lower output losses per

period during the lockdown, as the market has adjusted to the new *normal*. However, it also comes with a much slower recovery. In contrast, if the lockdown is short, firms hoard their workers in anticipation of the policy's conclusion, thereby taking short term losses during the economic lockdown. This motivates our primary policy prescription — one that allows reallocation of workers during the lockdown to mitigate economic losses throughout its duration. This approach preserves the match capital before lockdown, while simultaneously allowing for a faster recovery post lockdown. The specific policy we discuss is a furlough worker scheme, in which furloughed workers can look for new employment without foregoing the government paid furloughed wage.

Our model incorporates the SIR model of infectious diseases (Kermack and McKendrick (1927)) with the Diamond-Mortensen-Pissarides (DMP) model of the labor market (Diamond (1982), Pissarides (1985) and Mortensen and Pissarides (1994)). Fundamentally it is through these two classes of models that we can simultaneously examine the tradeoff in the health and economic cost of the pandemic. In order to understand the particularities of the Covid-19 pandemic we add three sources of heterogeneity not present in the prototypical versions of either class of model. Looking at any country the most striking feature regarding the composition of fatalities is age — Covid-19 is far more dangerous for the old than the young. Consequently, we incorporate ageing into the model. From the epidemiology perspective that means higher mortality rates for the old. Using data on fatality rates we calibrate a mortality rate for the over 65s to be twenty times larger than for those under 65s. From a labor market perspective that means retirement. A second feature of the Covid pandemic that is becoming clear is economic losses are not borne equally by workers. Those in low wage jobs face far greater income and employment risk than those in high wage jobs, (for the UK context see Adams-Prassl et al. (2020)). To this end we introduce wage dispersion into the model through an exogenous productivity distribution.

The final refinement we make is in order to link the two classes of models directly, other than through general equilibrium effects. To this end we introduce a production function that depends on, in addition to the inherent productivity of the match, the fraction of tasks that can be performed at home. While spending more time working away from home can increase total production, in a pandemic it will also increase a worker's exposure to the virus. Susceptible workers who are very productive from home, thereby foregoing little production and little of their wage, will choose to do so when the infection rate is high, slowing the spread of the pandemic. However, not all workers are afforded this luxury and as will be shown these less *lucky* workers tend to be in low paid work. Further, while workers, even in the absence of lockdown policy, will work more at home, they will do so out of self interest. When making this decision however, they do not internalize the negative externality of becoming infected on increasing the infection rate for society as a whole. This market failure additionally motivates the need for government intervention in locking down a section of the economy.

Related literature. Before the Covid-19 pandemic there existed a small theoretical

literature which merged economic behavior to epidemiology models. In a standard model of disease transmission the ‘*basic reproduction rate*’ is a constant — that is the average number of people one will infect given that the rest of the population is susceptible. In some sense the theoretical economic literature attempts to endogenize this rate. For a variety of mechanisms and diseases see, Kremer (1996), Quercioli and Smith (2006), Toxvaerd (2019, 2020) and Galeotti and Rogers (2013). In the context of our model the reproduction number depends on the decisions of how much to work away from home made by the susceptible employed. This paper is quantitative in nature and incorporates heterogeneity in many dimensions. Again, there is a small literature before this pandemic on calibrating and simulating a quantitative model of economic agents in an epidemiological framework. For the HIV virus see Greenwood et al. (2017, 2019) and Chan et al. (2016) and for Bird-flu (and now Covid) Keppo et al. (2020).

Since the outbreak of the Covid-19 pandemic there is a large and expanding number of papers building on the work of the aforementioned authors. That said, to our knowledge there is only Kapická and Rupert (2020) that also explore how a frictional labor market interacts with a pandemic. However, the focus and exposition of their paper is quite different. A worker’s health status segments the labor market and is the only source of heterogeneity. Interestingly there are papers that have leaned on the two building blocks of our model to understand disease spread, see Farboodi et al. (2020) and Garibaldi et al. (2020). But neither paper explicitly models the labor market. More broadly, there are a number of quantitative models that evaluate the economic and health tradeoffs of the pandemic and policies. Eichenbaum et al. (2020) merge the SIR model with a neo-classical representative agent model. We argue that heterogeneity is an important factor in the pandemic and our model allows for health and economic costs to vary by age, wage and occupation. Kaplan et al. (2020) account for dispersion in occupation and assets and Brotherhood et al. (2020), Favero et al. (2020) and Glover et al. (2020) use a multi-risk SIR model to account for differential mortality by age.

The rest of the paper proceeds as follows. In section 2 we setup our baseline model of the labor market and the pandemic. In section 3 we explain the role of lockdown policy. The model is calibrated to data and policy simulations are run in section 4. Section 5 concludes.

2 The baseline model

The Environment

Time is continuous and initially the economy is populated by a unit mass of individuals who are risk neutral, either young or old and discount the future at a constant rate r . Young individuals are part of the labor force and age stochastically at a Poisson rate η . A constant exogenous flow ψ of young individuals are born into unemployment. Given their age and

health status workers are ex ante homogeneous and if young are ex post heterogeneous in their employment status. They can be either employed and vary in their wage w or unemployed, sustaining themselves with an exogenous flow b_u . We do not distinguish between the unemployed and the inactive and will therefore use the terms *not employed* and *unemployed* interchangeably. Old individuals are retired, they sustain themselves with exogenous flow b_o and die stochastically of natural causes at Poisson rate χ .¹ In addition to age and labor force status individuals are characterized by a health state, h , which can be either susceptible $h = s$, infected $h = i$, or recovered $h = r$.

Production

A match between a worker and a firm is characterized by two indices. A productivity index x and a technology index α , where $x, \alpha \in [0, 1]$. The variable α describes the efficiency of home working relative to working away from home. The function $h(\alpha)$ describes the measure of tasks associated with a job that can be performed at home, where $h : [0, 1] \rightarrow [0, 1]$ and $h'(\alpha) > 0$. The function $g(x)$ describes the total potential output of the worker-firm pair, where $g'(x) > 0$ and $g : [0, 1] \rightarrow \mathbb{R}^+$. We assume an ϵ cost in performing a task away from home. So any task that can be completed at home will be. Total output of a match is given by $p(\alpha, x, m)$ where $m \in \{0, 1\}$, taking the value 0 if a worker exclusively works from home and one if they ever work away from home.

$$p(\alpha, x, 0) = g(x)h(\alpha) \quad \text{and} \quad p(\alpha, x, 1) = g(x) \quad (1)$$

The functions $g(\cdot)$ and $h(\cdot)$ will be parameterized later but notice that a worker leaving their house for work will produce an amount entirely dependent on x and output is always at least as high by working outside of the household, $p(\alpha, x, 1) \geq p(\alpha, x, 0)$. The indices α and x are drawn from a joint distribution $f(\alpha, x)$ at the time of worker-firm meeting and are fixed for the duration of the match. We allow for dependence between α and x in the distribution f and without loss of generality we assume that both have uniform marginal distributions on $[0, 1]$.

Health status

Individuals transit between three health states h : susceptible (s), infected (i) and recovered (r) according to the standard SIR epidemiology model, with one modification. Susceptible agents who do not leave the home to work contract the disease with a Poisson rate $\lambda_0 \ell_{it}$ where $\lambda_0 > 0$ is an exogenous fixed parameter and ℓ_{it} is the share of the population who are infected at time t . We depart from the standard model by assuming that if a susceptible individual goes to work outside of their home they increase their rate of infection and become

¹To fix the initial population to one, the parameter ψ is set accordingly as $\psi := \frac{\eta\chi}{\eta+\chi}$.

infected at an increased Poisson intensity $(\lambda_0 + \lambda_1)\ell_{it}$, where $\lambda_1 > 0$.² This introduces a clear trade-off for the worker, by working away from home their production will increase, and in turn so will their wage. However, they do so by increasing the likelihood of contracting the disease. Further, while a worker's decision will internalize the individual cost of working away from home it does not internalize the cost to society. By becoming infected the share of the infected population ℓ_{it} will increase and so will the rate of infection at which susceptible workers of any age and employment status catch the disease.

Once infected, individuals will either recover from the disease at Poisson rate ρ and transition to the recovered state or they pass away from the disease at rate $\gamma_a(\ell_{it})$. We allow the mortality of the disease to vary with both an individual's age and the share of the population infected. We allow variation in age as data on recorded mortality rates differ starkly across age groups and we allow the death rate to vary with the infection rate as a proxy for capacity constraints in intensive care units. Further, in our model being infected means a worker is not able to either look for employment if out of work or produce output if in work. Finally, being recovered is an absorbing health status.³

The labor market

The labor market is subject to search frictions. Unemployed and healthy workers can costlessly search for a job. Firms post vacancies at flow cost κ to attract potential applicants. The total measure of vacancies posted is determined by a free entry condition. On the worker's side, only the young, non-employed and non-infected can search for work. Searching workers, $s_t := u_{st} + u_{rt}$, where u_{st} (u_{rt}) is the measure of susceptible (recovered) unemployed workers at time t , and unfilled vacancy, v_t , meet at a rate determined by a constant returns to scale meeting function $m(s_t, v_t)$. This implies a job finding rate for workers of ϕ_t and a worker finding rate of ϕ_t^f for firms,

$$\phi_t = \frac{m(s_t, v_t)}{s_t} \quad \text{and} \quad \phi_t^f = \frac{m(s_t, v_t)}{v_t} = \phi \frac{s_t}{v_t} \quad (2)$$

After meeting, the worker and firm draw α and x from the joint distribution f . There is no private information and the values of α , x and the health status of the worker will determine whether the meeting results in a match. Matches exogenously separate at a constant exogenous Poisson rate δ .

²In the model workers will not run into infected colleagues at their place of work. We think of this increased risk through travelling to work and increased exposure to other members of society while at their place of work.

³At the time of writing, there is little evidence regarding antibody immunity or lack thereof. We take the stance that those who have recovered from the virus can not contract it again. Note, the model could easily accommodate a Poisson rate from recovery back to susceptibility and depending on the epidemiological evidence we may change this in future work.

Contracting space

The joint surplus generated from a match is shared between worker and firm according to a Nash bargaining protocol. In a first step a contract is written to account for time devoted to working from home by maximizing joint surplus. Let $m \in \{0, 1\}$ be an indicator to denote if work is only performed at home, $m = 0$, or away from home, $m = 1$, respectively. Wage is determined to split the surplus according to the standard Nash sharing rule, where worker receives a share $\beta \in (0, 1)$ of the total surplus and the firm $(1 - \beta)$.

We denote the value functions of matched workers and firms as $W_{ht}(w, \alpha, x, m)$ and $J_{ht}(w, \alpha, x, m)$, where W is the value of being employed and J the value of a filled vacancy for the firm in a match with a worker of health status $h \in \{s, i, r\}$, with job characteristics (α, x) under a contract (w, m) at time t . Let U_{ht} be the value of being unemployed for a worker with health status $h \in \{s, i, r\}$ and V_t be the value of an open vacancy. We assume that the joint surplus of a match can be written independent of the wage and is given by equation (3), (which is verified ex-post)

$$S_{ht}(\alpha, x, m) = W_{ht}(w, \alpha, x, m) - U_{ht} + J_{ht}(w, \alpha, x, m) - V_t \quad (3)$$

Thus when a worker and firm meet they decide jointly on the working arrangements and choose m according to

$$\arg \max_{m \in \{0, 1\}} \{S_{ht}(\alpha, x, m)\} := S_{ht}(\alpha, x).$$

Since there is an ϵ cost associated with working outside the home we break the indifference by assuming if the surpluses are equal a worker works exclusively from home. We can define the set of feasible matches as the values of h , α and x that generate non-negative joint surplus, $S_{ht}(\alpha, x) \geq 0$.

Finally, after negotiating a wage and work environment both parties must comply to their contractual agreement for a stochastic length of time. We assume that if there is a change in the health status of the worker the pair can costlessly change the agreement of working at or away from home, but not their wage agreement. Otherwise they can only adjust the hours of work or wages when they re-negotiate, which happens at an exogenous Poisson rate ν . After the re-negotiation shock they may also decide to separate if the joint surplus is negative. This rigidity models in a reduced form way the inability of UK firms to layoff workers immediately after changes in policy or worker's changing health status.

Vacancy creation

Vacant jobs make contact with unemployed workers at a rate ϕ_t^f . We assume free entry such that potential firms continue to post vacancies until the presented discounted expected value of doing so is zero. The value of posting a vacancy is given by

$$rV_t = -\kappa + \phi_t^f(1 - \beta) \left(\frac{u_{st}}{u_{st} + u_{rt}} \int \int \max\{S_{st}(\alpha, x, 0), S_{st}(\alpha, x, 1), 0\} dF^2(\alpha, x) + \frac{u_{rt}}{u_{st} + u_{rt}} \int \int \max\{S_{rt}(\alpha, x), 0\} dF^2(\alpha, x) \right) \quad (4)$$

where κ is the flow cost incurred when posting a vacancy. Thus the equilibrium aggregate number of vacancies are determined by setting the left hand side of equation (4) to zero.

Equilibrium and solving the model

The model structure allows all decisions, whether a worker-firm match is feasible and if so whether the worker should work in or away from the household, to be a function of the joint surplus of a match. This property is shown by specifying and solving the value functions in Appendix A.1. In addition one must compute the allocation of workers across demographic, health and economic status. These follow the dynamics in Appendix A.2. We assume the economy starts from a unique steady-state in which the whole population is susceptible and deviate with a *small* initial seed mass in which the probability of infection is constant across employment state. The final equilibrium object to pin down is the number of vacancies posted by firms, which given worker allocations and surpluses uniquely solves equation (4). Details of how these objects are computationally solved are provided in Appendix A.3.

3 Economy under lockdown

Lockdown is modeled as an exogenous and random share $\pi \in [0, 1]$ of the economy prevented from operating away from home (e.g. an office). Workers in these locked jobs are mandated to only work at home. Thus if the policy binds, a match of production index α will see their production fall by a share $(1 - h(\alpha))$. New jobs can either be in the ‘*locked*’, (with probability π), or ‘*unlocked*’ sector, (with probability $(1 - \pi)$). This draw is made at the time of worker-firm meeting and is assumed orthogonal to α and x .⁴

We model lockdown as slowing the rate of transmission through two mechanisms. Firstly, fewer people work away from their home. This reduces the number of people who contract the disease at their place of work. Those working at home have a Poisson rate of becoming infected which is $\lambda_1 \ell_{it}$ less than those working away from home. The second mechanism is through social distancing. While not explicitly modeled, a lockdown on bars and restaurants

⁴In future work, when survey data can be easily analyzed it would be interesting to assume two conditional distributions for $f(\cdot)$. This would allow one to evaluate economic costs from targeted lockdowns.

for example will reduce the number of social interactions in the economy. The parameter λ_0 governs the latent transmission rate irrespective of working decisions. Since lockdown will also reduce this we assume this parameter in lockdown is given by

$$\lambda_0^L := (1 - \zeta\pi)\lambda_0.$$

$\zeta \in [0, 1]$ governs the potential effectiveness of the lockdown. For example, if the government took the extreme action of shutting down the entire economy the Poisson rate of infection for a susceptible individual would be given by $(1 - \zeta)\lambda_0\ell_{it}$. The final amendment to the model is that lockdown is not permanent. While lockdown arrives as an unanticipated shock, agents assume it ends at an exogenous Poisson rate Λ after which the economy returns to the status quo. Modeling lockdown policy introduces an additional state variable for a worker-firm pair. That is, whether or not the job is ‘*locked*’ or ‘*unlocked*’, otherwise the model retains the same structure. In order to avoid repetition, we relegate the exposition and solution of the model to a complementary online appendix.

4 Quantitative results

The goal of this section is to examine the likely effects of lockdown policy on the safety of workers and the performance of the economy as a whole. Rather than being explicit about a social welfare function we simply demonstrate the tradeoff between the likely number of fatalities from the epidemic and the stress to the economy caused by lockdown policy. It is necessary to begin with two home truths. Firstly, a *laissez faire* approach, in the presence of the pandemic, will cause an economic downturn. That is to say, because of endogenous responses in the model, even in the absence of economic policy there will be economic losses and they are likely to be large. In particular, we find cumulative output losses to be around 2.4% of the pre-pandemic level under the *laissez faire* approach over 5-year horizon. Secondly, in the absence of a vaccine, the infection exists indefinitely, irrespective of how draconian a lockdown policy may be. In fact because we model new entrants into the labor market as susceptible, in the long run the pandemic will repeat itself in dampening cycles in perpetuity. Since these cycles materialize at approximately a twenty year frequency, we abstract from these in our discussion of policy and assume by the time of the next cycle a vaccine has been developed. Consequently, all discussion will relate to the ongoing wave of the pandemic. As a preview of our results we summarize these points and other findings in the list below.

1. Lockdown will not rid us of the virus. For that a vaccine needs to be found.
2. Lockdown is not the only source of economic stress. The economy will suffer from a *laissez-faire* approach.

3. Lockdown policy can mitigate the loss of life in this wave but to be effective in saving lives it will have to be implemented for a considerable length of time.
4. The economic costs of lockdown are not borne uniformly across the cross-section of workers: those at the lower-end of the wage distribution are affected disproportionately more.
5. Given the response of the labor market to different lockdown measures and the heterogeneity in economic costs — we make a policy prescription to be run in conjunction with lockdown to mitigate economic losses.

4.1 Parameterization

To proceed, we begin by specifying functional forms for the matching function $m(s_t, v_t)$, the functions entering production, $g(x)$ and $h(\alpha)$, the distribution of job's characteristics, $f(x, \alpha)$, and the death rates for young and old individuals, $\gamma_o(\ell_{it})$ and $\gamma_y(\ell_{it})$. We use a standard Cobb-Douglas function to model contacts between vacancies v and searchers s

$$m(s_t, v_t) = s_t^{1-\xi} v_t^\xi,$$

where $\xi \in (0, 1)$ denotes the elasticity of contact with respect to the stock of open vacancies. This matching function implies

$$\phi_t^f = \frac{m(s_t, v_t)}{v_t} = \theta_t^{\xi-1} \quad \text{and} \quad \phi_t = \frac{m(s_t, v_t)}{s_t} = \theta_t \phi_t^f.$$

The variable θ_t denotes the labor market tightness, defined as $\theta_t := v_t/s_t$. We specify the total potential output of a worker-firm pair of index x as the inverse of a log-normal distribution with underlying mean μ_x and variance σ_x^2 ,

$$g(x) = \exp(\mu_x + \sigma_x \Phi^{-1}(x))$$

where $\Phi^{-1}(\cdot)$ denotes the inverse cumulative distribution function of a standard normal distribution. To describe the proportion of job tasks that can be performed at home, we assume $h(\alpha)$ to be an inverted Beta distribution,

$$h(\alpha) = \frac{\alpha^{\beta_1-1} (\alpha+1)^{-\beta_1-\beta_2}}{\mathcal{B}(\beta_1, \beta_2)}$$

where $\beta_1, \beta_2 \geq 1$ are the parameters of the beta distribution and \mathcal{B} denotes the Beta function. To model correlation between job productivity x and home efficiency α , we choose the function $f(\alpha, x)$ to be a Gaussian copula with correlation parameter $\rho_{\alpha, x}$. Finally, we assume the death rates for old and young individuals are independent of the stock of infected, and we set them equal to

$$\gamma_o(\ell_{it}) = \gamma_o \quad \text{and} \quad \gamma_y(\ell_{it}) = \gamma_y.$$

4.2 Calibration

The model is calibrated at a weekly frequency for the pre-epidemic period and simulations are run at a daily frequency. The first three blocks of Table 1 report parameters values for demographic, labor market and technology and the moments used to calibrate them. The interest rate r is set to have an annual return of 5%. Workers spend on average 40 years in the labor market, and 15 years in retirement. These values pin down ageing rate η and death rate χ .

We set the re-negotiation rate to match two weeks of advance notice and fix $\nu = 0.5$.⁵ We set the income flow for unemployed workers to 65% of the average wage as reported for the UK in 2019 by the OECD. The income flow for retired workers to 75% of the average wage, to match the ratio between equalized disposable income of retired and non-retired HH (ONS). The bargaining power, β , is calibrated to match a value for labor share equal to 54.63% (UK national accounts 2016Q3). The matching elasticity, ξ is calibrated to match the estimated value of 0.35 in Turrell et al. (2018). The exogenous job destruction rate, δ , is calibrated to match a monthly separation rate of 4% reported in Postel-Vinay and Sepahsalari (2019).⁶ Finally, we calibrate the cost of posting of vacancy, κ , to match the employment rate in the last quarter of 2019 (ONS).

We are left with five parameters, governing productivity and home-working efficiency. We calibrate the parameters in the output technology μ_x and σ_x to match an average weekly earnings of 545 GBP (ONS Weekly Earnings Survey, February 2020) and an average stock of vacancy per population in the last quarter of 2019 of 1.19% (ONS - Vacancy Survey).⁷ Conditional on all other parameters, including the meeting function, the number of matches from a stock of vacancies is governed by the proportion of meetings that result in matches. This proportion is driven by the degree of dispersion in the job sampling distribution.⁸ While we choose the parameters in the inverted beta distribution, β_1 and β_2 to match average and standard deviation of home-working hours before the pandemic. These data are taken from January-December 2019 from the Annual Population Survey (APS) and presented in Appendix A.4, panel a. Finally, we calibrate the copula parameter, $\rho_{\alpha,x}$, to match the

⁵The statutory redundancy notice period in the UK is in practice a function of the length of time one has been in their job. Those employed for under a month can be laid off without notice. For those employed between one month and two years, one week notice is required. Then for each additional year a further weeks notice is required, capped at twelve weeks.

⁶Recall, we do not distinguish between the young and inactive and unemployed so take the sum of the separation rates to unemployment and inactivity at the end of their sample.

⁷Expressions for wages in our model are deferred to the online appendix.

⁸To see this, imagine there were no dispersion in productivity. All worker-firm meetings will result in matches as the worker or firm have no incentive to wait and find a better match.

Table 1: Calibrated Parameters

Parameters	Description	Value	Source/Target
<i>Demographics</i>			
r	Discount rate	0.00098641	Annual return: 5% annual
η	Ageing rate	0.00048077	40 years in the labor market: 25-65 y.o.
χ	Death rate	0.00128210	15 years of retirement: 65-80 y.o.
ψ	Birth rate	0.00034965	Pre-epidemic population=1
<i>Labor market</i>			
ν	Re-negotiation rate	0.5	Two weeks advance notice
b_r	Retirement income flow	406.02	Equivalized disposable income: retired/non-retired HH=75% (ONS)
b_u	Unemployment income flow	354.25	Average replacement rate=65% (OECD)
ξ	Matching elasticity	0.35	Turrell et al. (2018)
β	Bargaining power	0.0988	Labor share=54.63% (ONS)
δ	Job destruction rate	0.010205	Monthly job separation=4% Postel-Vinay and Sepahsalari (2019)
κ	Vacancy cost	60763	Employment rate=76% (ONS)
<i>Technology</i>			
β_1	Home-working efficiency	0.0510	Average home-working hours: $E[h]=11.55\%$ (APS)
β_2	Home-working efficiency	3.3780	St.Dev. home-working hours: $std[h]=9.99\%$ (APS)
μ_x	Output technology	4.1997	Average weekly earnings: $E[w]=545$ (ONS)
σ_x	Output technology	1.5252	Vacancy per population=1.19% (ONS)
$\rho_{\alpha,x}$	Copula parameter	0.9578	Corr. log weekly earnings and home-working hours: $corr[\log w, h]=0.713$ (APS)
<i>Epidemic dynamics</i>			
λ_0	Infection rate, basic	1.6759	Basic reproduction rate: $R_0 = 2.4$, Ferguson et al. (2020)
λ_1	Infection rate, at work	0.0728	Infection at work: 0.024, Riccardo et al. (2020)
γ_y	Death rate, young	0.00225	Case fatality ratio: death/cases 0.32% Verity et al. (2020)
γ_o	Death rate, old	0.04795	Case fatality ratio: death/cases 6.4% Verity et al. (2020)
ρ_y	Recovery rate, young	0.7	Average recovery period: ten days, Ferguson et al. (2020)
ρ_o	Recovery rate, old	0.7	Average recovery period: ten days, Ferguson et al. (2020)
<i>Practicalities</i>			
	Initial seed mass	10^{-9}	
	First death	$1/66/10^6$	
	Burnin period	24 days	Time between first death and lockdown in the UK.
<i>Lockdown</i>			
π	Share of economy on lockdown	0.63	Change in visits to 'workplace', Google location data
ζ	Social distancing parameter	0.67	Change in visits to 'retail and recreation', Google location data

correlation between number of hours and average log weekly earnings (see Appendix A.4, panel b)

Turning to the parameters of the SIR model, we follow Ferguson et al. (2020) and calibrate λ_0 and λ_1 to match an average basic reproduction rate of 2.4 at the eve of the epidemic breakthrough. From the context of the model this is the reproduction rate when the entire population is susceptible without any endogenous changes to the working environment. From the perspective of the data, this comes from the early estimates in Wuhan, again when the

population was close to fully susceptible.⁹ To disentangle the value of λ_0 from λ_1 we calibrate λ_1 to match the number of individuals who contracted the virus at their place of work. Riccardo et al. (2020) estimate this number in Italy as being at 2.4%. We calibrate death rates of young and old, γ_y and γ_o to match case fatality ratio in their age categories Verity et al. (2020)., Finally, we fix the average recovery period to 10 days following Ferguson et al. (2020).

4.3 Counterfactual experiments

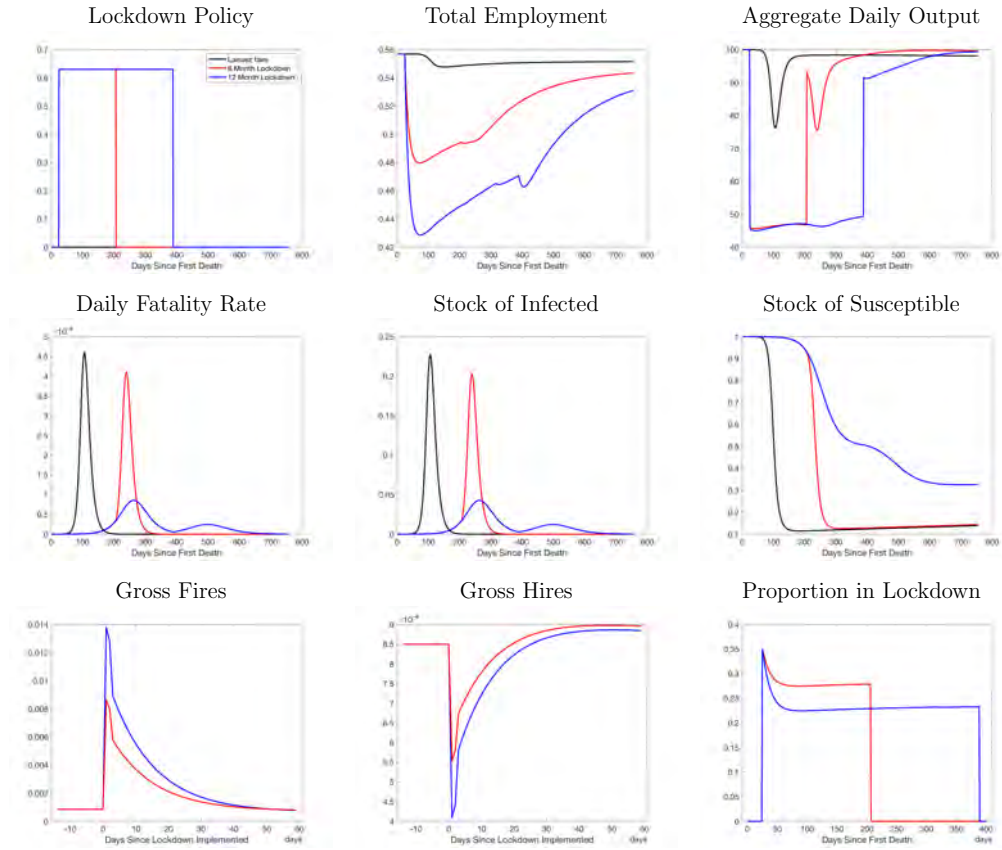
We keep the severity of a lockdown (π) fixed and vary the duration (Λ). The specifics of the policy simulation are represented in the final block of Table 1. We begin with very few infected people and assume all employment states are equally likely to be infected at time zero. The economy is simulated and we assume lockdown arrives as an unanticipated shock 24 days after the first registered death, to mirror the experience of the UK. Since there are a continuum of workers in the model we interpret the first death as the number of deaths exceeding one divided by the UK's population. The proportion of the economy locked down π and the impact this has on social distancing ζ are calibrated from Google user's location data. The proportion of jobs locked down is taken from the change in visits to the user's workplace which dropped by 63% post lockdown. The impact this had on social distancing is taken from the change in visits to a 'social' sector that was largely locked down, retail and recreation. This includes retail outlets, shopping centers, museums etc. but omits grocery stores and other more essential services that were not placed on lockdown.

Health costs. We begin by looking at the health costs of the pandemic associated with a six and twelve month lockdown period. The lockdown policy is shown in the first panel of Figure 2 and the associated health costs in the second row. Both lockdown policies are able to suppress the pandemic to some extent and will result in fewer total deaths than doing nothing shown in black. The six month lockdown suppresses the virus during lockdown but is lifted before the peak and results in many more lives lost following the lifting of restrictions. By contrast the twelve month lockdown appears to break the back of the pandemic. However, because of the tightness of the restrictions there are still many susceptible individuals in the economy, below the level needed for herd immunity. Hence after the lifting of the restrictions a second wave of the virus sweeps through the population.¹⁰

⁹Estimates from Riou and Althaus (2020) and Li et al. (2020) put the number somewhere between 2.0 and 2.6

¹⁰A less strict lockdown policy as measured by π could actually lower the fatality rates in this illustrative example. For the case of the six month policy, the peak would come sooner and could potentially be dampened with more early exposure. Similarly, if calibrated perfectly, the twelve month lockdown with a lesser π would have a larger initial wave but could avoid the second wave by reducing the number of susceptible people still in the economy.

Figure 2: Dynamics of the Pandemic and Economy



Economic cost. As well as variation in the health costs associated with different lockdown policies there are also large variations in the economic consequences. As has been discussed no policy intervention is not costless from an economic point of view. Work days are lost because of illness and the increased exposure to health risks reduce the value of jobs and thus the level of vacancy posting reduces. Lockdown policy will inevitably confound these losses. Primarily because it directly reduces potential output, forcing a share of jobs in the economy to limit production to inside the worker’s home. Clearly, the longer the economy is restricted, the larger these losses are going to be. However the losses are also

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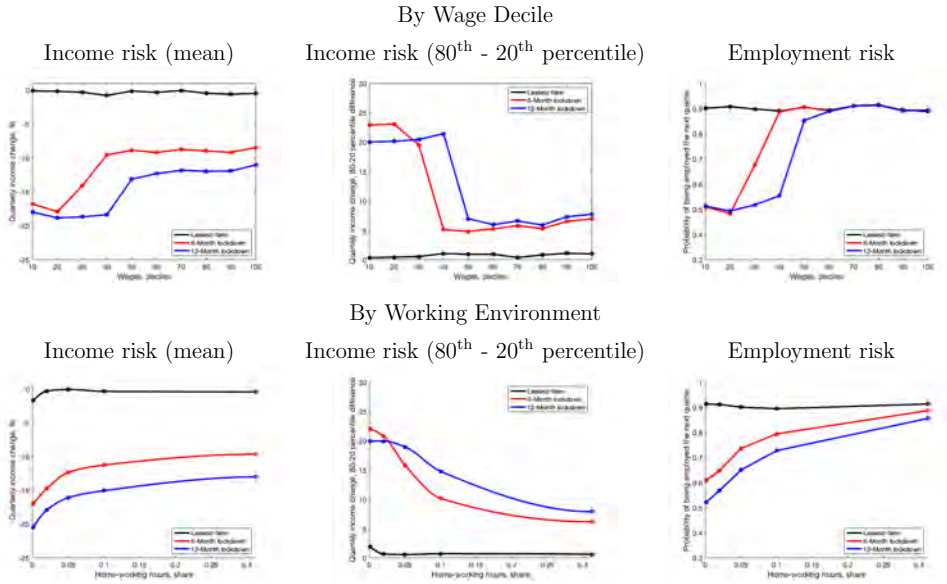
intrinsically linked to the workings of the labor market. This can be seen in the first row of Figure 2. The shorter lockdown has a much smaller initial fall in employment. Since firms know the lockdown is relatively short, firms opt to hoard their workforce. Even in the face of a considerable drop in production, firms prefer this choice over incurring hiring costs in the future; they keep their workers on the payroll and take the short term losses. This labor hoarding has advantages and disadvantages to the economy. On the positive side, it makes for a speedier recovery when lockdown ends. As can be seen in the figure, daily output returns to pre-crisis levels quicker for the shorter lockdown. Since many more matches are held together through the pandemic they are well suited to the *normal* environment post lockdown. However, during the lockdown production is likely to stay low as the labor market does not readjust to the changing environment.

Labor adjustment. To better understand the different labor market response to the different durations of lockdown, the final row of Figure 2 plots the response in gross hiring and firing following implementation. As discussed, the more severe lockdown results in many more layoffs as hoarding labor for prosperous times to come becomes far more expensive. At the same time there is also a large initial fall in hiring as many matches are locked and will not hire unless they are extremely productive or efficient in working from home. After an initial fall, the level of hiring rises steadily under both regimes. This is in part due to a larger pool of unemployed following the large rise in layoffs and in part because of workers' falling outside option — the deteriorating state of the economy makes them less discerning in which matches to accept. In fact, because of the enormous misallocation shock to the economy, hiring levels under both policy options eventually exceed the level of hiring pre-lockdown. The final panel shows the direction that reallocation takes. Initially the share of workers subject to lockdown is the same as the proportion of the economy under lockdown. However, following layoffs based predominantly in locked sectors, in addition to new hires going into matches that are unlocked, there is a decline in the fraction of the economy locked down.

Heterogeneous effects. Figure 3 depicts the effect of the short and long duration lockdown policies, in addition to a laissez-faire approach, on measures of income and employment risk for a simulated panel of workers. To study the effect on income, we look at total income of a worker in the first quarter of lockdown relative to the last prior to its commencement. Our measure of employment risk is the probability that a worker, who is employed at the time of lockdown's commencement, remains employed in the next quarter.

Quarterly income is computed as the integral of all earnings over a quarter, both labor, and if unemployed, home production. For a susceptible worker, who form almost the entire population at the implementation of lockdown, see Figure 2, the surplus of a match will fall. This is true irrespective of lockdown status as there is an increased probability of match disruption, through the worker getting infected. For those in locked professions this fall in

Figure 3: Heterogeneous effects of policies on the worker cross-section



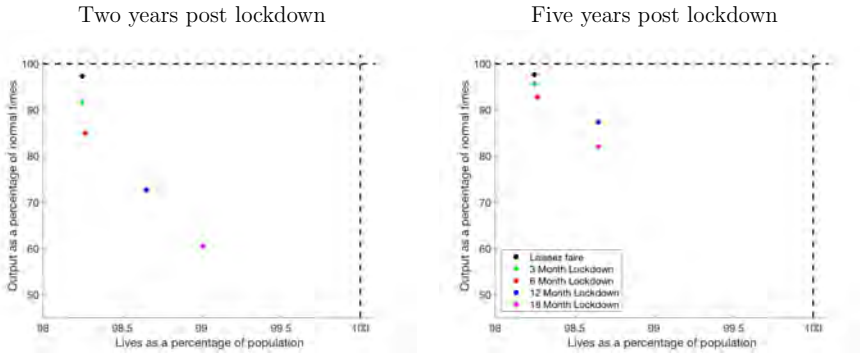
Notes: 20,000 workers are simulated over two quarters either side of the implementation of lockdown. Included in the sample presented in the figure are those who were employed at lockdown and were active in the labor market (neither retired nor newly entered) for the 90 days prior and subsequent to lockdown. Leaving a reduced sample of 10,864.

surplus and hence wages is confounded further as output will fall considerably.¹¹ In unlocked professions the change in wage is ambiguous and will vary from match to match. On the one hand, the surplus falls through increased disruption. On the other, to compensate the increased risk exposure the worker will take a larger share of the output. In addition to wage changes on the job the other source of income risk are endogenous separations. If the surplus falls below zero a worker and firm match separates. A terse glance at Figure 3 reveals this second mechanism is the primary driver in increased income risk.

Comparing mean income falls with employment probabilities by either wage or work environment show the same workers are losing out in both. Inspection of Figure 3 reveals the aggregate implications of these different mechanisms for workers across the distribution of wages and working environment. The first column shows the average change in quarterly

¹¹For a worker in a match (α, x) who if unlocked would leave the home for work will see a proportional fall in output of $(1 - h(\alpha))$. On average that corresponds to an almost 90% fall in output.

Figure 4: Policy Possibility Frontier



income. While lockdown policy is ubiquitous in its impact those that spend little time working at home or are low wage workers suffer a lot more. As discussed, looking at the third column it is easy to see why. These are the workers who are being laid off and consequently suffer large losses in income. For sufficiently well paid workers there is no increase in employment risk with lockdown. This cutoff increases as the severity of the lockdown increases. Finally, in addition to increased employment risk and lower income, the risk (measured as the dispersion of income changes) also increases. This is felt hardest by those with the least ability to insure against it, the lowest paid.

Evaluating policy options. Rather than being explicit about a social welfare function we follow Kaplan et al. (2020) and define a policy possibility frontier. This function is useful for policymakers as it plots the feasible outcomes, lives saved and economic consequences of different lockdown policies. Taking two and five year horizons, Figure 4 plots differing durations of lockdown on this health-economic space. One can see the clear tradeoff between the two metrics; a judgment on how draconian a policy a government wishes to implement will depend on its specific welfare function. Given insights from the quantitative model we instead discuss how to give policymakers a better menu of outcomes. That is: what labor market policy used in conjunction with lockdown could shift the frontier in a north easterly direction. In particular we consider the ‘Coronavirus Job Retention Scheme’ implemented by the UK government.

The key findings that drive our policy discussion are the following. First, during a short lockdown, there is a large degree of labor hoarding, which speeds-up the economic recovery when the restrictions are lifted. Second, this labor hoarding suppresses economic activity during the lockdown. Third, young workers on a low wage are those harmed the most economically from the lockdown. These three results speak directly to the efficacy of the

furlough aspect of the UK Government's Scheme.

The furlough scheme implemented paid workers 80% of their monthly salaries, capped at 2,500 pounds per month. The policy eventually allowed workers to seek alternative employment while furloughed and expanded to the self-employed as well. The impulse response functions in Figure 2 illustrate why this policy would mitigate economic costs associated with a lockdown. Allowing worker-firm pairs to temporarily separate without breaking their employment ties will foster a quick recovery following the end of lockdown, as with the short lockdown exercise. Crucially however allowing workers to seek alternative employment in the short run allows for greater production during lockdown — either in the unlocked sectors, which are likely vital, or in locked sectors that do not rely so much on working outside of the home.

A similar conceptual point is made by Fujita et al. (2020) and Costa-Dias et al. (2020) whom lobbied the government to switch track and allow furloughed workers to seek other alternative temporary employment. Finally, a large component of the negative income risk brought on by the pandemic was employment risk and this is particularly felt by low wage workers. By taking the wage burden away from the firm, the government can insure against this risk. If policymaker also cared about inequality this would further improve outcomes. This mechanism is discussed by Blundell et al. (2020). In this paper we regard our policy prescription as a proof of concept. Future quantitative work to get a handle on just how useful such a policy could be extremely fruitful. To do this one would have to explicitly model a labor search model with *job memory* with an epidemiology model.¹²

5 Conclusion

This paper combines two workhorse models from labor economics and epidemiology to create a choice theoretic model of disease transmission and a frictional labor market. Worker-firm decisions about whether to work from home and firm's vacancy decisions are consequential for the state of the economy and crucial for the infection rate. Understanding the co-movement of the pandemic and labor market is crucial for policymakers especially when deciding on lockdown policies. We show that the response of both differ starkly given the length of the lockdown imposed. Finally, we use insights garnered from the quantitative model to support the UK government's 'Coronavirus Job Retention Scheme'.

¹²Labor search models with such a feature include for example Fujita and Moscarini (2017), Carrillo-Tudela and Smith (2017) or Bradley and Gottfries (2018).

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A Appendix

A.1 Surplus functions of baseline model

The demography of the model has workers moving from working age to retiring to death and the health dynamics from susceptible, to infected, to recovered, conditional on survival. We present the value functions in the same order the model is solved. Starting with terminal conditions and working backwards.

Retired workers

We begin with a retired individual who has recovered from the illness. The index t encapsulates all potential aggregate state variables that vary with time. The discounted value is the sum of the flow value worker's get after retiring b_o and the option value of death, which occurs at Poisson rate χ .

$$rR_{rt} = b_o + \chi(0 - R_{rt}) + \dot{R}_{rt}$$

It can be seen that this value function is independent of time and can be rewritten dropping the time subscript as

$$R_r = \frac{b_o}{r + \chi}.$$

Retired agents who are currently infected have an increased death probability of $\gamma_o(\ell_{it})$ which varies with time through the evolution of the proportion of sick people. Additionally, they can recover from their illness at a rate ρ_o .

$$\begin{aligned} rR_{it} &= b_o + (\chi + \gamma_o(\ell_{it}))(0 - R_{it}) + \rho_o(R_r - R_{it}) + \dot{R}_{it} \\ (r + \chi + \gamma_o(\ell_{it}) + \rho_o)R_{it} &= \frac{r + \chi + \rho_o}{r + \chi}b_o + \dot{R}_{it} \end{aligned}$$

Finally, retired agents who are susceptible again die at the reduced rate χ but they can also become infected which again depends on the proportion of the population with the infection at time t .

$$\begin{aligned} rR_{st} &= b_o + \chi(0 - R_{st}) + \lambda_o \ell_{it}(R_{it} - R_{st}) + \dot{R}_{st} \\ (r + \chi + \lambda_o \ell_{it})R_{st} &= b_o + \lambda_o \ell_{it}R_{it} + \dot{R}_{st} \end{aligned}$$

Recovered young individuals

The value of being unemployed for a recovered individual is the sum of four terms. (i) The flow benefit b_u they get from being out of work. This encapsulates both pecuniary and non-pecuniary benefits including for example the value of leisure time. (ii) The option value of finding a job, from which if the surplus is positive they will get a fraction β of. Offers arrive at an endogenous rate ϕ_t to be determined later. (iii) The option value associated with retirement which occurs at exogenous rate η . (iv) The continuation value from dynamic changes to the offer arrival rate and infection rate. These four terms are represented in the Bellman equation below.

$$rU_{rt} = b_u + \phi_t \beta \int \int \max\{S_{rt}(\alpha, x, 1), S_{rt}(\alpha, x, 0), 0\} d^2 F(\alpha, x) + \eta(R_{rt} - U_{rt}) + \dot{U}_{rt}$$

The value of being employed in a job of match (α, x) for a recovered individual in a contract (w, m) is given below. Where $w \in \mathbb{R}$ is the contractually agreed wage and $m \in \{0, 1\}$, taking the value one if the worker leaves their abode to work and zero otherwise.

$$rW_{rt}(w, \alpha, x, m) = w + \delta(U_{rt} - W_{rt}(w, \alpha, x, m)) + \eta(R_{rt} - W_{rt}(w, \alpha, x, m)) + \nu(\max\{\beta S_{rt}(\alpha, x, 1), \beta S_{rt}(\alpha, x, 0), 0\} + U_{rt} - W_{rt}(w, \alpha, x, m)) + \dot{W}_{rt}(w, \alpha, x, m)$$

Value of filled vacancy. The value of an employer in a match (α, x) with a recovered individual and contract (w, m) is equal to

$$rJ_{rt}(w, \alpha, x, m) = p(\alpha, x, m) - w + (\delta + \eta)(V_t - J_{rt}(w, \alpha, x, m)) + \nu((1 - \beta) \max\{S_{rt}(\alpha, x, 1), S_{rt}(\alpha, x, 0), 0\} + V_t - J_{rt}(w, \alpha, x, m)) + \dot{J}_{rt}(w, \alpha, x, m).$$

The flow value the firm receives is the production of the match, which will depends on whether the worker leaves their home ($m = 1$) or not ($m = 0$), net of the worker's wage w . From the firm's perspective whether a worker leaves to unemployment or to retirement is immaterial to them. Otherwise the option values are as in the case of the employed worker.

Value of surplus. Imposing free entry, $V_t = 0$, the surplus value for a match (α, x) in a contract (w, m) is derived by substituting the above expressions into equation (3).

$$(r + \delta + \eta)S_{rt}(\alpha, x, m) = p(\alpha, x, m) - b_u - \phi_t \beta \int \int \max\{S_{rt}(\alpha, x, 1), S_{rt}(\alpha, x, 0), 0\} d^2 F(\alpha, x) + \nu(\max\{S_{rt}(\alpha, x, 1), S_{rt}(\alpha, x, 0), 0\} - S_{rt}(\alpha, x, m)) + \dot{S}_{rt}(\alpha, x, m)$$

Since $p(\alpha, x, 1) \geq p(\alpha, x, 0)$, it is easy to show that $S_{rt}(\alpha, x, 1) \geq S_{rt}(\alpha, x, 0)$. In fact:

$$S_{rt}(\alpha, x, 1) - S_{rt}(\alpha, x, 0) = \frac{(1 - h(\alpha))g(x)}{r + \delta + \eta + \nu} \geq 0.$$

Therefore for brevity of notation we set $S_{rt}(\alpha, x) = S_{rt}(\alpha, x, 1)$, $J_{rt}(w, \alpha, x) = J_{rt}(w, \alpha, x, 1)$ and $W_{rt}(w, \alpha, x) = W_{rt}(w, \alpha, x, 1)$.

Infected young individuals

Infected unemployed are too ill to search for a job. Their value functions is equal to:

$$rU_{it} = b_u + \rho_y (U_{rt} - U_{it}) + \gamma_{0y}(\ell_{it})(0 - U_{it}) + \eta(R_{it} - U_{it}) + \dot{U}_{it}.$$

In addition to the flow value associated with any unemployment their option values consist of recovering and becoming unemployed and recovered, passing away in which case they get nothing, and retiring. Infected individuals are too ill to work, but receive a sick pay w , and they return to their job upon recovery. The value for the employed infected is equal to

$$\begin{aligned} rW_{it}(w, \alpha, x) = & w + \rho_y (W_{rt}(w, \alpha, x) - W_{it}(w, \alpha, x)) \\ & + \gamma_{0y}(\ell_{it})(0 - W_{it}(w, \alpha, x)) + \delta (U_{it} - W_{it}(w, \alpha, x)) + \eta (R_{it} - W_{it}(w, \alpha, x)) \\ & + \nu (\beta \max\{S_{it}(\alpha, x), 0\} + U_{it} - W_{it}(w, \alpha, x)) + \dot{W}_{it}(w, \alpha, x) \end{aligned}$$

Other than sick pay, the value of employed infected accounts for the option value of recovering and go back to work, of passing away because of the infection, of exogenously separating, in which case they become unemployed infected, of retiring, and of renegotiating the terms of the contract, which can lead to match destruction.

Value of filled job. Employers in a match with infected employee produce nothing and are forced to a mandatory sick payment w to the worker. Their value is equal to:

$$\begin{aligned} rJ_{it}(w, \alpha, x) = & -w + \rho_y (J_{rt}(w, \alpha, x) - J_{it}(w, \alpha, x)) + (\gamma_{0y}(\ell_{it}) + \delta + \eta)(V_t - J_{it}(w, \alpha, x)) \\ & + \nu ((1 - \beta) \max\{S_{it}(\alpha, x), 0\} + V_t - J_{it}(w, \alpha, x)) + \dot{J}_{it}(w, \alpha, x) \end{aligned}$$

Employers have to option of renegotiating the terms of the contract at rate ν , which could lead to match destruction. A match can also destroy because of exogenous separation, occurring at rate δ , or because of employee death, which occurs at a rate $\gamma_{0y}(\ell_{it})$. The match starts producing again upon worker recovery, occurring at rate ρ_y .

Value of surplus. Given free entry, $V_t = 0$, the surplus of a match between an employed and a sick employee can be written as follows:

$$(r + \delta + \eta + \rho_y + \nu + \gamma_{0y}(\ell_{it})) S_{it}(\alpha, x) = -b_u + \rho_y S_{rt}(\alpha, x) + \nu \max\{S_{it}(\alpha, x), 0\} + \dot{S}_{it}(\alpha, x)$$

Notice that - even when the employee is infected - the match surplus could be positive, as long as the continuation value is larger than the unemployment flow. In this case, the match won't cease to exist, the employer will transfer a sick pay to the employee and wait till her recovery.

Susceptible young individuals

Susceptible individuals face risk of infection. The infection rate is function of the share of infected people in the economy, ℓ_{it} , and it depends on the employment status: it is equal to $\lambda_{0y}\ell_{it}$ for unemployed workers. Susceptible unemployed have the following value:

$$(r + \lambda_{0y}\ell_{it} + \eta)U_{st} = b_u + \phi_t\beta \int \int \max\{S_{st}(\alpha, x, 1), S_{st}(\alpha, x, 0), 0\}d^2F(\alpha, x) + \lambda_{0y}\ell_{it}U_{it} + \eta R_{st} + \dot{U}_{st}$$

which depends on the unemployment flow plus the option value of finding a jobs, getting infected unemployed, and retiring as susceptible. Susceptible employed differ by their job characteristics (α, x) and their contractual arrangements, (w, m) , which in turns determine their rate of contagion. Employees working only from home ($m = 0$) get infected at the same rate of unemployed workers while employees working away from home get infected at a larger rate, equal to $(\lambda_{0y} + \lambda_{1y})\ell_{it}$, where λ_{1y} governs the rate of contagion at work. The value of employment for susceptible workers reflects these differences and it is equal to:

$$(r + \delta + \nu + \lambda_{0y}\ell_{it} + \eta)W_{st}(w, \alpha, x, 0) = w + (\delta + \nu)U_{st} + \lambda_{0y}\ell_{it}W_{it}(w, \alpha, x) + \eta R_{st} + \nu\beta \max\{S_{st}(\alpha, x, 0), S_{st}(\alpha, x, 1), 0\} + \dot{W}_{st}(w, \alpha, x, 0)$$

if $m = 0$, and equal to:

$$(r + \delta + \nu + (\lambda_{0y} + \lambda_{1y})\ell_{it} + \eta)W_{st}(w, \alpha, x, 1) = w + (\delta + \nu)U_{st} + (\lambda_{0y} + \lambda_{1y})\ell_{it}W_{it}(w, \alpha, x) + \eta R_{st} + \nu\beta \max\{S_{st}(\alpha, x, 0), S_{st}(\alpha, x, 1), 0\} + \dot{W}_{st}(w, \alpha, x, 1)$$

if $m = 1$. Except for the infection rates, employees with different home-working arrangement have similar value of employment: their matches are exogenously destroyed at a rate δ , they retire at a rate η and renegotiate their contract a rate ν .

Value of filled job. An employer (α, x) matched with a susceptible employee produces $p(\alpha, x, 0)$ if the employee works only from home or $p(\alpha, x, 1)$ if the employees works away from home. Imposing free entry, $V_t = 0$, the value of an employer matched with a susceptible employee is equal to:

$$(r + \delta + \eta + \lambda_{0y}\ell_{it} + \nu)J_{st}(w, \alpha, x, 0) = p(\alpha, x, 0) - w + \lambda_{0y}\ell_{it}J_{it}(w, \alpha, x) + \nu(1 - \beta) \max\{S_{st}(\alpha, x, 0), S_{st}(\alpha, x, 1), 0\} + \dot{J}_{st}(w, \alpha, x, 0)$$

if $m = 0$, and equal to:

$$(r + \delta + \eta + (\lambda_{0y} + \lambda_{1y})\ell_{it} + \nu)J_{st}(w, \alpha, x, 1) = p(\alpha, x, 1) - w + (\lambda_{0y} + \lambda_{1y})\ell_{it}J_{it}(w, \alpha, x) + \nu(1 - \beta) \max\{S_{st}(\alpha, x, 0), S_{st}(\alpha, x, 1), 0\} + \dot{J}_{st}(w, \alpha, x, 1)$$

if $m = 1$. Except for exogenous match destruction or worker retirement, the option values are as in the case of the susceptible employed.

Value of surplus. Given free entry $V_t = 0$, total surplus for a match in a contract (w, m) can be defined as follows:

$$\begin{aligned} (r + \delta + \eta + \nu + \lambda_{0y}\ell_{it}) S_{st}(\alpha, x, 0) &= p(\alpha, x, 0) - b_u \\ &\quad - \phi_t \beta \int \int \max\{S_{st}(\alpha, x, 1), S_{st}(\alpha, x, 0), 0\} d^2 F(\alpha, x) \\ &\quad + \lambda_{0y}\ell_{it} S_{it}(\alpha, x) + \nu \max\{S_{st}(\alpha, x, 0), S_{st}(\alpha, x, 1), 0\} \\ &\quad + \dot{S}_{st}(\alpha, x, 0) \end{aligned}$$

if $m = 0$, and equal to

$$\begin{aligned} (r + \delta + \eta + \nu + (\lambda_{0y} + \lambda_{1y})\ell_{it}) S_{st}(\alpha, x, 1) &= p(\alpha, x, 1) - b_u \\ &\quad - \phi_t \beta \int \int \max\{S_{st}(\alpha, x, 1), S_{st}(\alpha, x, 0), 0\} d^2 F(\alpha, x) \\ &\quad + (\lambda_{0y} + \lambda_{1y})\ell_{it} S_{it}(\alpha, x) + \lambda_{1y}\ell_{it} (U_{it} - U_{st}) \\ &\quad + \nu \max\{S_{st}(\alpha, x, 0), S_{st}(\alpha, x, 1), 0\} \\ &\quad + \dot{S}_{st}(\alpha, x, 1) \end{aligned} \tag{5}$$

if $m = 1$. Notice that for some (α, x) , it might be the case that $S_{st}(\alpha, x, 0) > S_{st}(\alpha, x, 1)$. Differently than recovered, a match with a susceptible employee might optimally set $m = 0$ and produce only through home-working.

A.2 Dynamics of Baseline Model

The evolution of the measure of unemployed workers follows dynamic system given below where the first subindex denotes the health status $H \in \{s, i, r\}$ and the second the time t .

$$\begin{aligned} \dot{u}_{st} &= \psi + \delta \int \int e_{st}(\alpha, x) d\alpha dx + \nu \int \int e_{st}(\alpha, x) \{S_{st}(\alpha, x) < 0\} d\alpha dx \\ &\quad - \phi_t \int \int \{S_{st}(\alpha, x) \geq 0\} d^2 F(\alpha, x) u_{st} - \lambda_0 \ell_{it} u_{st} - \eta u_{st} \\ \dot{u}_{it} &= \delta \int \int e_{it}(\alpha, x) d\alpha dx + \nu \int \int e_{it}(\alpha, x) \{S_{it}(\alpha, x) < 0\} d\alpha dx \\ &\quad + \lambda_0 \ell_{it} u_{st} - (\rho + \gamma(\ell_{it}) + \eta) u_{it} \\ \dot{u}_{rt} &= \delta \int \int e_{rt}(\alpha, x) d\alpha dx + \nu \int \int e_{rt}(\alpha, x) \{S_{rt}(\alpha, x) < 0\} d\alpha dx \\ &\quad + \rho u_{it} - \phi_t \int \int \{S_{rt}(\alpha, x) \geq 0\} d^2 F(\alpha, x) u_{rt} - \eta u_{rt} \end{aligned}$$

For measures of employed, we also need to keep track of their match quality (α, x) and for the susceptible whether they work at home or away from home, taking subindex zero and one, respectively. Note the total susceptible employed in match (α, x) is the sum of those employed in that match working from home and outside of the home, $e_{st}(\alpha, x) := e_{0st}(\alpha, x) + e_{1st}(\alpha, x)$.

$$\begin{aligned} \dot{e}_{0st}(\alpha, x) &= u_{st}\phi_t\{S_{st}(\alpha, x) \geq 0\}f(\alpha, x) - (\delta + \eta)e_{0st}(\alpha, x) \\ &\quad - \nu e_{0st}(\alpha, x)\{S_{st}(\alpha, x) < 0\} - \nu e_{0st}(\alpha, x)\{S_{st}(\alpha, x) \geq 0\}\{S_{st}(\alpha, x, 1) \geq S_{st}(\alpha, x, 0)\} \\ &\quad + \nu e_{1st}(\alpha, x)\{S_{st}(\alpha, x) \geq 0\}\{S_{st}(\alpha, x, 1) < S_{st}(\alpha, x, 0)\} \\ &\quad - e_{0st}(\alpha, x)\lambda_0\ell_{it} \\ \dot{e}_{1st}(\alpha, x) &= u_{st}\phi_t\{S_{st}(\alpha, x) \geq 0\}f(\alpha, x) - (\delta + \eta)e_{1st}(\alpha, x) \\ &\quad - \nu e_{1st}(\alpha, x)\{S_{st}(\alpha, x) < 0\} - \nu e_{1st}(\alpha, x)\{S_{st}(\alpha, x) \geq 0\}\{S_{st}(\alpha, x, 1) < S_{st}(\alpha, x, 0)\} \\ &\quad + \nu e_{0st}(\alpha, x)\{S_{st}(\alpha, x) \geq 0\}\{S_{st}(\alpha, x, 1) \geq S_{st}(\alpha, x, 0)\} \\ &\quad - e_{1st}(\alpha, x)(\lambda_0 + \lambda_1)\ell_{it} \\ \dot{e}_{it}(\alpha, x) &= e_{0st}(\alpha, x)\lambda_0\ell_{it} + e_{1st}(\alpha, x)(\lambda_0 + \lambda_1)\ell_{it} \\ &\quad - \nu e_{it}(\alpha, x)\{S_{it}(\alpha, x) < 0\} - (\delta + \rho + \gamma(\ell_{it}) + \eta)e_{it}(\alpha, x) \\ \dot{e}_{rt}(\alpha, x) &= u_{rt}\phi_t\{S_{rt}(\alpha, x) \geq 0\}f(\alpha, x) + \rho e_{it}(\alpha, x) \\ &\quad - (\delta + \eta)e_{rt}(\alpha, x) - \nu e_{rt}(\alpha, x)\{S_{rt}(\alpha, x) < 0\} \end{aligned}$$

The measures of retired evolve as follows:

$$\begin{aligned} \dot{o}_{st} &= \eta \left(u_{st} + \int \int (e_{0st}(\alpha, x) + e_{1st}(\alpha, x)) d\alpha dx \right) - (\lambda_0\ell_{it} + \chi) o_{st} \\ \dot{o}_{it} &= \eta \left(u_{it} + \int \int e_{it}(\alpha, x) d\alpha dx \right) + \lambda_0\ell_{it}o_{st} - (\gamma_R(\ell_{it}) + \chi + \rho) o_{it} \\ \dot{o}_{rt} &= \eta \left(u_{rt} + \int \int e_{rt}(\alpha, x) d\alpha dx \right) + \rho o_{st} - \chi o_{rt} \end{aligned}$$

Finally, the infection rate evolves as:

$$\ell_{it} = \dot{L}_{it} - \dot{L}_t$$

where

$$\dot{L}_{it} = \dot{u}_{it} + \int \int \dot{e}_{it}(\alpha, x) d\alpha dx + \dot{o}_{it} \quad \dot{L}_t = \sum_{h \in \{s, i, r\}} \left(\dot{u}_{ht} + \int \int \dot{e}_{ht}(\alpha, x) d\alpha dx + \dot{o}_{ht} \right)$$

As discussed in the main body of the text the economy is initiated from a pre-Covid steady state. That is setting the left hand side of the differential equations above and ℓ_{it} to zero.

This yields the following initial allocation. Where the superscript ss denotes steady state levels.

$$\begin{aligned}
 u_s^{ss} &= \frac{\psi(\delta + \eta)}{\delta\eta + \eta\phi^{ss} \int \int f(\alpha, x) \{S_s^{ss}(\alpha, x) \geq 0\} d\alpha dx + \eta^2} \\
 c_s^{ss}(\alpha, x) &= \frac{u_s^{ss} \phi^{ss} f(\alpha, x) \{S_s^{ss}(\alpha, x) \geq 0\}}{\delta + \eta} = e_{1s}^{ss}(\alpha, x) \\
 o_s^{ss} &= \frac{\psi}{\chi}
 \end{aligned}$$

A.3 Computational Algorithm

To solve the model we need to solve for the surplus functions denoted as $S_{st}(\alpha, x, m)$. For example, the value of a recovered individual, who will always opt to work outside of the home, yields a surplus given by

$$\begin{aligned}
 (r + \delta + \eta)S_{rt}(\alpha, x) &= p(\alpha, x, 1) - b_u - \phi_t \beta \int \int \max\{S_{rt}(\alpha, x), 0\} d^2F(\alpha, x) \\
 &\quad + \nu (\max\{S_{rt}(\alpha, x), 0\} - S_{rt}(\alpha, x)) + \dot{S}_{rt}(\alpha, x).
 \end{aligned}$$

For this surplus function and all others we approximate the state of the economy at time t by the aggregate state vector $\Omega_t := (u_{st}, u_{rt}, \ell_{it})$ such that, for an arbitrary state Ω ,

$$\begin{aligned}
 (r + \delta + \eta)S_r(\alpha, x; \Omega) &= p(\alpha, x, 1) - b_u - \phi(\Omega) \beta \int \int \max\{S_r(\alpha, x; \Omega), 0\} d^2F(\alpha, x) \\
 &\quad + \nu (\max\{S_r(\alpha, x; \Omega), 0\} - S_r(\alpha, x; \Omega)).
 \end{aligned}$$

Given the surplus functions, the transitional dynamics and the free entry condition defining $\phi(\Omega)$ can be computed exactly.¹³ The solution algorithm works as follows.

- Construct a grid for five state variables, (α, x, Ω) , where $\Omega := (u_s, u_r, L_i/L)$
- Guess $\phi^*(\Omega)$
- Solve fixed point for $S_r(\alpha, x; \Omega)$

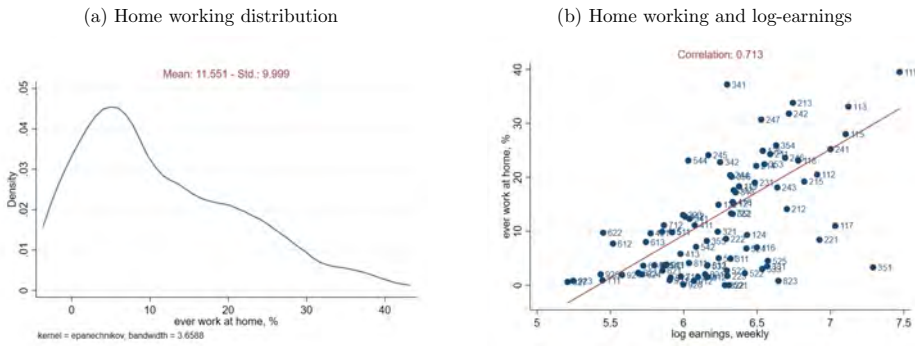
¹³The omission of the continuation value $\dot{S}_{ht}(\alpha, x, m)$ omits an equilibrium effect from the model. That is a susceptible worker would rather become infected at the start of the pandemic, as their outside option of catching it then is smaller as they are still fairly likely in becoming infected. Thus the incentive for susceptible workers to self-isolate increases as the pandemic progresses. Interestingly, this is the opposite of the *behavioral* argument put forward by British scientists that warned that starting the lockdown earlier could lead to fatigue and less compliance later on. While interesting this paper abstracts from this mechanism.

- Solve fixed point for $S_i(\alpha, x; \Omega)$
- Solve fixed point (jointly) for $S_s(\alpha, x, 0; \Omega)$ and $S_s(\alpha, x, 1; \Omega)$
- Update $\phi^*(\Omega)$ using free entry. Return to update surplus functions.

The model is solved for 50 grid points for x and α and ten for each of the aggregate states giving $(50^2 \times 10^3) = 2,500,000$ in total. After solutions are found for surpluses and job offer arrival rates the differential equations defining the aggregate states are approximated at a daily frequency.

A.4 Home working hours and earnings

Figure A.4: Home working hours and earnings



Data are taken from the Annual Population Survey (APS), a survey of a representative sample of UK residents. Selected people are asked a number of questions about their relationship with the labour market, including questions on the extent to which they work from home. In particular, the current analysis exploits the answer reported by respondents to the following question: "Have you ever worked at home for your main job?". Data are then aggregated at occupational level using 3-digit codes (94 occupations in total). Figure A.4 panel (a) displays the distribution of employed workers who reported to ever worked at home, while panel (b) scatters the average share of workers reporting to work from home in each occupation against the average wage (panel b). We exploits this data in the calibration. Specifically, we target mean and standard deviation in the distribution of home-working respondents across occupations and the correlation between home-working shares and wages.