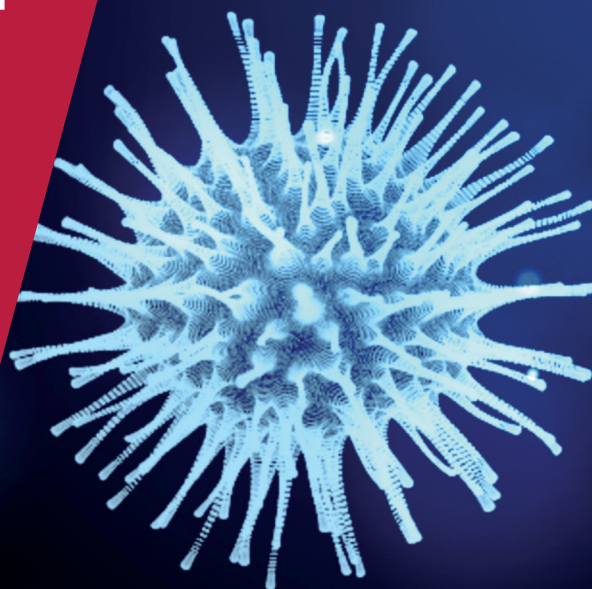


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**COVID ECONOMICS**  
VETTED AND REAL-TIME PAPERS

**ISSUE 2**  
**8 APRIL 2020**

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# Covid Economics

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*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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*Covid Economics* will publish 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 journal's articles.

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# Covid Economics

## Vetted and Real-Time Papers

Issue 2, 8 April 2020

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# Central bank swap lines during the Covid-19 pandemic

Saleem Bahaj<sup>1</sup> and Ricardo Reis<sup>2</sup>

Date submitted: 29 March 2020; Date accepted: 1 April 2020

*Facing visible strain in dollar funding markets during the Covid-19 pandemic, the Fed lowered the rate on the swap lines it had with five other central banks, and opened new ones in nine other currencies. Some of these were used, some not. We use this variation to show the impact of the swap lines on CIP deviations across currencies. The results confirm the analysis in Bahaj and Reis (2019): the swap lines put a ceiling on CIP rates only around the time of an auction.*

## 1. Introduction

Banks across the world have a total of \$12.8 trillion of US dollar-denominated borrowing used to fund international trade, financial investments, and a variety of dollar assets (Aldasoro and Ehlers, 2018). During financial crises, the money markets that lend dollars dry up, putting strains on the global banking system. The Covid-19 pandemic so far has been no exception. Given its size and global reach, this crisis has had an unusually large effect on foreign dollar funding and on the ability of private swap markets to absorb exchange-rate risk (Avdjiev et al., 2020). Preliminary data also show a sudden stop of funds to emerging economies of unprecedented size. The first, and so far largest, internationally coordinated economic policy response to the crisis was the expansion of the Federal Reserve's existing swap lines with five other central banks on 15th March, and the creation of new programmes with nine other countries on 19th March. This paper shows that these policies had a clear impact on covered interest parity (CIP) deviations with the US dollar. Since CIP deviations determine the additional

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cost of borrowing dollars for a firm with foreign-currency funding through the FX derivatives market, the swap line effectively lowers dollar funding costs. However, we also find that the effects are concentrated both in countries with active operation and on days where the swap line was actually drawn. These results are consistent with the Bagehot view of the swap lines as international lenders of last resort put forward in Bahaj and Reis (2019).

## **2. How the swap lines work and their effect**

The Fed's central bank swap lines address the role of the US dollar in international funding markets. They work as follows: the Fed lends dollars to a foreign central bank at an interest rate set as a spread to the overnight index swap (OIS) rate of the relevant maturity (usually one week). The foreign central bank then lends these dollars to their financial institutions (choosing which are eligible), collects the collateral, and bears all the credit risk, as it does all the monitoring. This way, foreign banks receive the lending of last resort in dollars that they need. Against the loan of dollars, the Fed receives a deposit of foreign currency at today's spot exchange rate. At the end of the loan, the Fed gets its currency back (with interest) and gives the foreign currency back as well, because both commit now to re-sell their currencies at the original exchange rate. The foreign currency never enters circulation; it is as if it was never printed in the first place, so it has no monetary impact on the foreign countries. On the Fed's side, being structured as a swap, this operation has minimal risk.

In Bahaj and Reis (2019), we proved the following result: the spread that the Fed charges to a foreign central bank over the OIS rate puts a ceiling on deviations from CIP between that central bank's currency and the dollar. The intuition is the following. A financial institution can always deposit domestic currency at its central bank. The presence of the swap line enables it to borrow US dollars from its central bank. Then, borrowing dollars, converting them into domestic currency via an FX swap, and depositing the proceeds at the central bank provides a (near) risk-free arbitrage opportunity if CIP deviations overly exceed the Fed's spread on borrowing from the swap line. The presence of this arbitrage trade puts a ceiling on how high CIP deviations can rise. Depending on exactly how CIP is calculated, and on differences in collateral requirements, the ceiling may have other terms, but a cut in the Fed's spread unambiguously lowers it.

In Bahaj and Reis (2019), we further show that in the over-the-counter FX derivatives market, this cut in the ceiling should reveal itself in the distribution of observed CIP deviations by both truncating the distribution to the left, and causing a fall in its mean.

A third result concerning CIP is that the swap lines do not generate a standing facility for banks. Instead, the dollars are lent out by the foreign central banks on a weekly basis through a market operation that draws on the swap line. Only on the days of the operations does the arbitrage trade that created the ceiling become available, so only in those days should the ceiling have its strong effect. In the other days of the week, there is no strict ceiling, so CIP may spike over and beyond it, although the anticipation of an operation might still have an effect.

## 2.1 The situation as of February 2020

At the start of 2020, and for the decade before, the Federal Reserve had standing swap arrangements with five other central banks – the Bank of Canada, the Bank of England, the Bank of Japan, the ECB, and the Swiss National Bank – as part of multilateral swap line network between the six central banks.

The swaps had maturities of one week and the swap line rate was 50 basis points (bps) over the one-week US dollar OIS rate. Operations had a fixed price with a full allotment, so foreign banks could borrow as much as they wanted from their central bank at the swap line rate, and there was no upper bound on the size of the drawings a central bank could make from the Fed.<sup>3</sup> The bids for these operations were typically taken on Wednesdays with the dollars reaching the recipient banks on Thursdays – the settlement day.

Each foreign central bank could choose how to run its operations, including which collateral to accept, and which haircuts to charge. There were two notable idiosyncrasies in the network. First, the Bank of Canada had not conducted a single operation, justifying it with Canadian banks having a stable US dollar deposit base and access to the Federal Reserves lending facilities through their US operations. Second, the Bank of Japan had a two-day settlement cycle due to the time difference with New York, so bids were taken on Tuesdays and settled on Thursday.

## 2.2 The March 2020 policy changes

Following the outbreak of Covid-19 and the adoption of containment measures across developed economies, interest rates in many US markets and CIP deviations involving the US dollar spiked during the week of 9th-13th March.

On 15th March, the six members of the US dollar multilateral swap line network announced that the spread on the swap line over OIS rates would be cut to 25bps and that they would start conducting new weekly 3-month dollar operations. Operations at maturities longer than one week had also been conducted during

3 Still, every individual drawing was subject to approval by the Federal Reserve.

the global financial crisis and the European sovereign debt crisis (typically at a monthly frequency), but these were discontinued in 2014. The bids on the first operations at the new rate and at the longer maturity were taken on the 18th (17th for the Bank of Japan), and settled on 19th March. The Bank of Canada announced its intention to set up a US dollar facility should the need arise, but as of 31 March 2020 has not done so, and so continues to not use the swap line.

On 20th March, the central banks in the network announced that, commencing 23rd March, their one-week dollar repo operations would be conducted daily. This closed the gap in swap line availability discussed above, bringing the operations closer to a standing facility.

On 19th March, the Fed created a new swap line arrangements with nine other countries: Australia, Brazil, Mexico, Denmark, Korea, Norway, New Zealand, Singapore, and Sweden. Amongst these, as of 31 March, the central banks of Sweden, Norway, Denmark and Singapore were the only banks to have completed a dollar swap line operation. These were first conducted on the 26th of March (Singapore: 27th) and first settled on the 30th (Singapore: 31st).<sup>4</sup> The terms of the swap line operations conducted by these four new central banks had two similar features to the ones in the original network: their maturity (three-month and weekly), and the credit risk and monitoring lying with the foreign central bank (in charge of determining eligibility and collateral criteria).

However, there are three significant differences with the four countries compared to the original network. First, the quantities that can be drawn have maxima attached. Second, and related, the operations are conducted as auctions, not full allotments. Therefore, the swap line rate forms the minimum bid rate rather than a fixed price. As an example, Singaporean banks paid on average 100bps above OIS in a 3-month operation on the 30th, rather than the fixed 25bps spread that a euro area bank would pay. Third, the frequency of the operations has yet to be determined.

### **3. The effect of the changes in the swap lines: quantities**

Table 1 shows the quantities drawn in the new facilities by the ECB, the Bank of England, and the Bank of Japan. As a reference point to these flows, note that the peak balance, that is the stock, ever drawn at any one time from the swap lines by the three central banks was on the 10th of December of 2008 at \$476.4 billion. The table also lists the peak flows both during the financial and euro crises times, and in all the years ever since.

<sup>4</sup> The Bank of Mexico and the Bank of Korea are due to conduct operations that will be settled in April.



Operation date	Settlement date	Term (days)	Amount lent (\$bn)
<b>European Central Bank</b>			
11/03/2020	16/03/2020	7	0.05
18/03/2020	19/03/2020	7	36.27
18/03/2020	19/03/2020	84	75.82
23/03/2020	24/03/2020	7	0.02
24/03/2020	25/03/2020	7	4.12
25/03/2020	26/03/2020	7	17.27
25/03/2020	26/03/2020	84	27.81
26/03/2020	27/03/2020	7	3.21
27/03/2020	30/03/2020	7	2.17
30/03/2020	31/03/2020	7	6.65
<i>Peak operation (2008-2010): \$170.9bn (15/10/2008)</i>			
<i>Peak operation (2011-2019): \$50.7bn (7/12/2011)</i>			
<b>Bank of England</b>			
11/03/2020	12/03/2020	7	0.00
18/03/2020	19/03/2020	7	8.21
18/03/2020	19/03/2020	84	7.25
23/03/2020	24/03/2020	7	0.01
24/03/2020	25/03/2020	7	3.56
25/03/2020	26/03/2020	7	7.71
25/03/2020	26/03/2020	84	6.69
26/03/2020	27/03/2020	7	9.05
27/03/2020	30/03/2020	7	0.50
30/03/2020	31/03/2020	7	5.01
<i>Peak operation (2008-2010): \$76.3bn (15/10/2008)</i>			
<i>Peak operation (2011-2019): \$0.02bn (21/08/2019)</i>			
<b>Bank of Japan</b>			
10/03/2020	12/03/2020	7	0.00
17/03/2020	19/03/2020	7	2.05
17/03/2020	19/03/2020	84	30.27
23/03/2020	25/03/2020	7	34.85
24/03/2020	26/03/2020	7	15.47
24/03/2020	26/03/2020	84	73.81
25/03/2020	27/03/2020	7	4.95
26/03/2020	30/03/2020	7	2.27
27/03/2020	31/03/2020	7	13.10
30/03/2020	01/04/2020	7	24.10
<i>Peak operation (2008-2010): \$50.2bn (21/10/2008)</i>			
<i>Peak operation (2011-2019): \$12.6bn (10/01/2012)</i>			

**Table 1** Central bank US dollar operations, 2nd half of March 2020–

The effect of the Covid-19 crisis is striking. UK banks, which had last borrowed a meaningful amount of US dollars in June 2010, borrowed positive amounts in operations in every single day since the crisis flared up and the new terms were announced. The two operations conducted by the Bank of Japan on the 24th of March lent a total of \$89 billion, almost double the previous peak of \$50 billion on 21st October 2008; the ECB's 19th March operation was the largest since 2011. The combination of a cut in the interest rate, and the funding needs associated with the crisis, have sprung the swap line back into action. Consistent with it being a lending of last resort facility, the swap lines become active during crises.

Not reported in the table are the new swap lines. By the end of March banks had borrowed \$6.9 billion from the Monetary Authority of Singapore over three operations where the maximum on offer was \$30bn. Swedish, Danish and Norwegian banks borrowed \$2.0 billion, \$2.9 billion and \$1.1 billion respectively, in operations with \$10 billion, \$20 billion and \$5 billion, respectively, on offer.

#### **4. The impact on market prices**

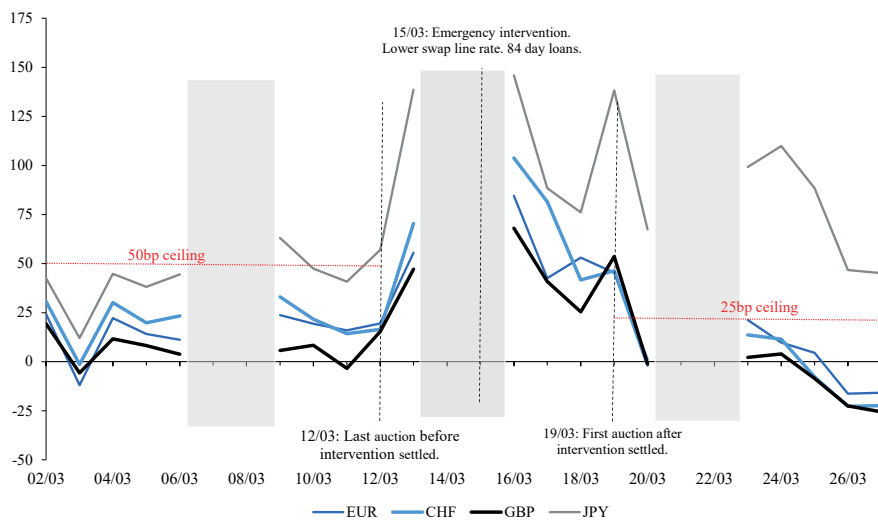
We compute CIP deviations using data on interest rates and forward markets at a daily frequency from Bloomberg (last accessed on 31st March 2020) following the standard approach in the literature (e.g., Du et al. 2018). We use 3-month tenor rates, matching the expansion of the swap line to 3-month operations on 15th March, with the exception of the Indian rupee (INR), for which Bloomberg does not report a reliable 3-month forward exchange, so we report the 1-year tenor for it instead. They are LIBOR-equivalent interest rates, because these are available across many currencies, with and without access to the swap line, including some in emerging markets. We omit the Brazilian real from the analysis, despite it receiving a swap line, because we could not find reliable data with which to compute the CIP deviations. CIP deviations are computed such that a positive figure is consistent with it being profitable to borrow in dollars and lend in the domestic currency (this is the negative of the cross-currency basis typically reported in the financial press).

Each figure that follows shows the daily CIP deviations for the four weeks starting 2nd March and ending 27th March 2020, with weekends shaded in grey. Each of them highlights three key dates: the date of the last auction before the policy changes (for the original swap line members), the date the new facilities were announced, and the date of the first operation after the change. Note that the predictions for theory are that: (i) CIP deviations should spike above the ceiling after the first date, (ii) they might fall after the announcement,

and (iii) they should fall below the ceiling after the operation. This is in cases where market equilibrium price was close to (or above) the ceiling; otherwise, the effect should be negligible as the ceiling would almost never bind.

#### 4.1 Impact on the original active network

Figure 1 shows the CIP deviations for the currencies of the four members of the original network, excluding Canada, since it did not conduct operations on its swap line. The red lines draw a hypothetical ceiling given the prevailing spread on the swap line, although note that differences between LIBOR and OIS rates as well as possibly binding collateral requirements would imply that in reality the ceiling would be higher. So, observing CIP deviations above the ceiling that is drawn in the figure only says that for that currency the equilibrium was close to the actual ceiling.



**Figure 1** CIP deviations among the original network members conducting operations

In spite of the financial crisis brewing across US financial markets, the CIP deviations stayed contained by the swap line rate as late as 12th March, when the weekly swap line operation was settled. But, the day right after, CIP deviations spiked. The ceiling is likely breached on Friday 13th March across currencies as the swap line was not open that day.

Over the weekend on the 15th, the policy of cutting the swap line rate and extending maturities was announced, but this only came into effect at the time of the next operation, which was settled on Thursday the 19th. CIP deviations rose further on the 16th, in spite of the new policy, since the swap line was closed. Only as the operation date approached did they fall. They went below the new ceiling right after the auction was settled on Friday.

From the 23rd onwards, the central banks switched to daily US dollar operations. Since then, the deviations have stayed below the hypothetical ceiling.

The Japanese yen is an exception. The higher swap line ceiling for yen CIP deviations is not specific to the Covid-19 episode; it was also a finding in Bahaj and Reis (2019). One explanation is that the two-day settlement cycle weakens the link between daily CIP deviations and the swap line rate. Regardless, once the BoJ's record operations on the 24th were settled on the 26th, yen CIP deviations fell sharply.

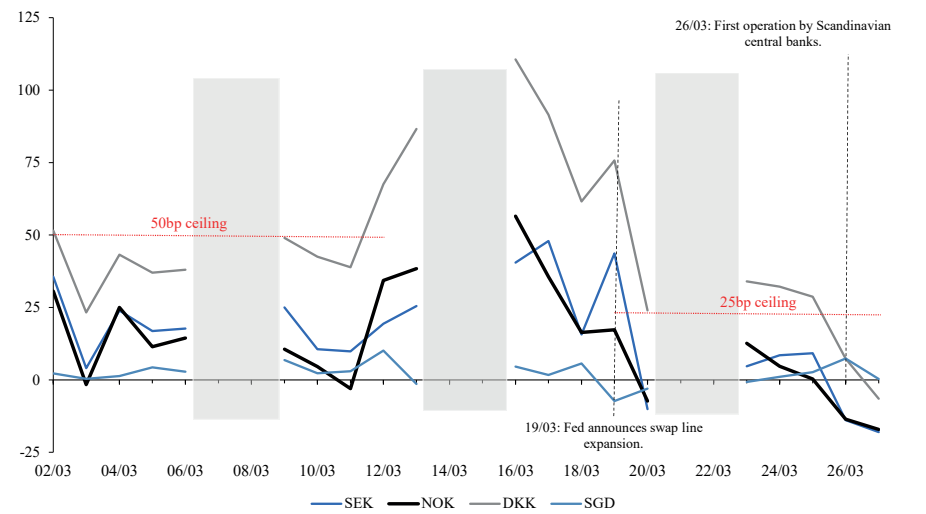
#### 4.2 Impact on the new active network

Figure 2 shows the CIP deviations in the four currencies that have joined the US dollar swap network and that have used it: the Swedish krona, the Danish krona, the Norwegian krona, and the Singaporean dollar. The CIP deviations rose during the week of 9th-14th. They fell after the announcement of the first policy change affecting the original members of the network. They fell decisively once the new swap line was announced. However, it was only when bids are taken for the first operation that the DKK CIP deviation fell below the new ceiling.

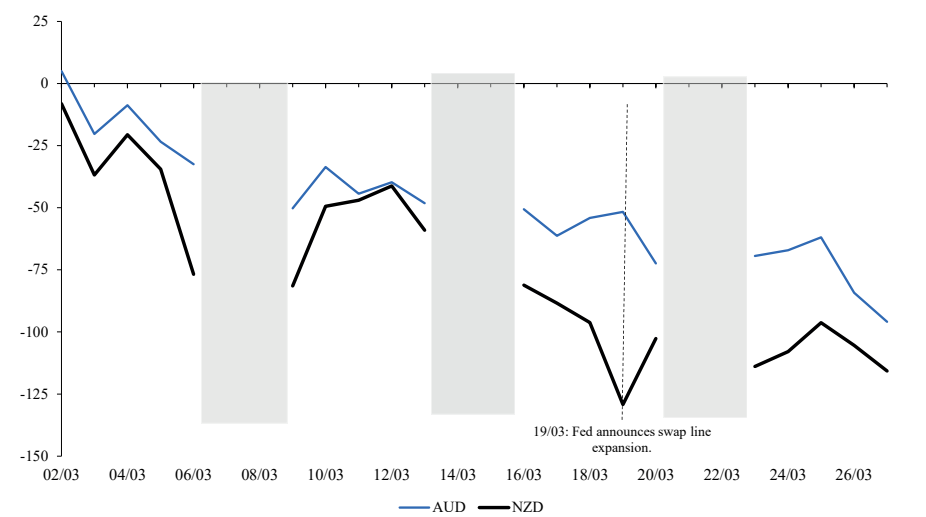
#### 4.3 Impact on the new inactive network: negative CIP deviations

Figure 3 shows the CIP deviations for the new members of the the network for which we have data, and which did not need a swap line according to the theory, namely, the Australian dollar and the New Zealand dollar. For both currencies, the CIP deviations have been negative for a long time, and they continued to be so during this month. That is, it is borrowing in these currencies and lending in dollars that creates an arbitrage opportunity for these two currencies. The swap line does not affect this.

Consistent with the swap line not being needed, these central banks have not conducted any US dollar operations. The swap line is unused. Consistent also with the theory, the policy changes in March had no appreciable effect on the market prices.



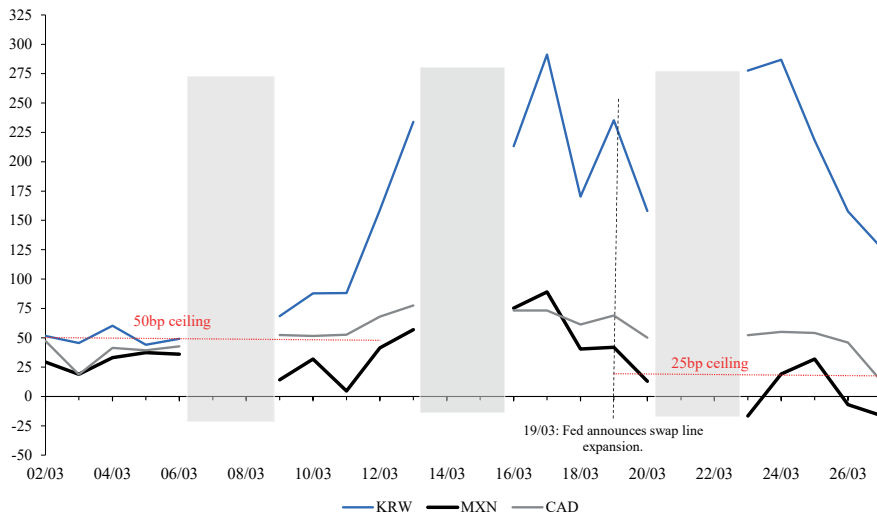
**Figure 2** CIP deviations among the new swap line currencies that conducted an operation



**Figure 3** Swap line currencies with negative CIP deviations and no operation

#### 4.4 Impact on the inactive network: positive CIP deviations

For completeness, the final group of countries in the swap line network is those who, as of the end of March 2020, had not yet completed a swap line operation to allow their banks to borrow the US dollars, even though the size of the CIP deviations could justify it. These are South Korea and Mexico among the newcomers, and Canada from the original network.<sup>5</sup> Their CIP deviations are plotted in Figure 4.



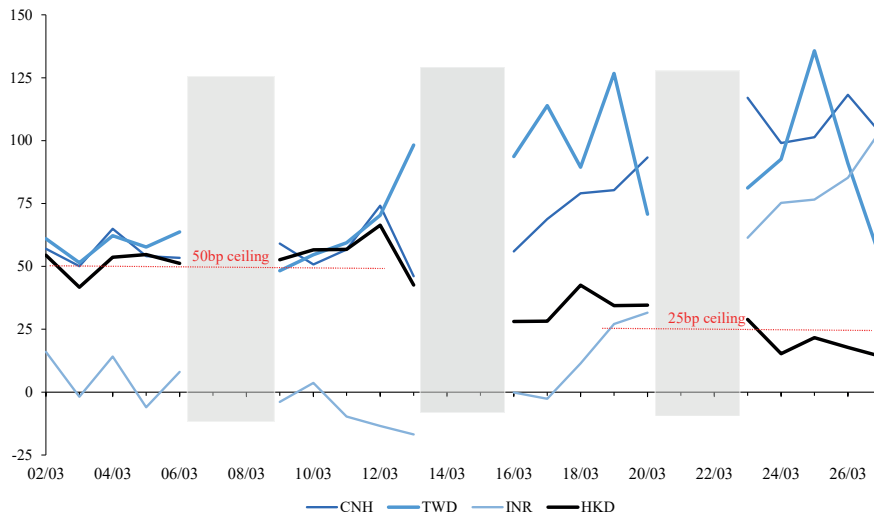
**Figure 4** Swap line currencies with positive CIP deviations and no operation

#### 4.5 Life outside of the network

Finally, Figure 5 shows the CIP deviations for four central banks that are not part of the swap line network, and which seem unlikely to join. This provides a control group for comparison with the treated groups by the policy intervention that we have discussed so far. The currencies are: the (offshore) Chinese yuan, the Taiwanese dollar, the Hong Kong dollar, and the Indian rupee.

<sup>5</sup> CAD CIP deviations measured using OIS rates rather than Libor rates are below the ceiling. This could also justify the Bank of Canada not conducting operations.

For all four of them, CIP deviation rose throughout this period, starting in the week of 9th-14th March just as it did for the treated currencies, with the exception of the rupee. However, unlike the swap-line countries, for these, the following two weeks show no significant reversal of the increase (perhaps with the exception of Taiwan in the very end of the sample, but it is hard to tell without more data).



**Figure 5** Currencies without access to a US dollar swap line

## 5. Conclusion

This paper has evaluated the behaviour of a key market price – the deviation from covered interest parity – to a major policy announcement in response to the Covid-19 crisis, namely, the extension of US dollar swap lines involving the Federal Reserve and 14 other central banks around the world. This was the first major coordinated economic policy response to the crisis. It affected different countries in different ways, depending on: (i) whether they were already in the network before or they were new, (ii) whether their deviations from CIP were positive or negative, and (iii) whether they had operations set up or not. Comparing these different cases shows signs that the swap lines are effective in providing lender of last resort to foreign financial markets, particularly when they are actually used. Since the swap line rate cut and extension lowered the cost of dollar funding in the markets that used them, they relieved some of the stress in those funding markets.

At the same time, the estimates leave a few unanswered questions: Why were some central banks able to set up dollar operations sooner than others? The criteria behind inclusion in the network have not been stated, and there is no robust correlation with need or size of private dollar funding. Will the effects persist? Theory suggests they will, since if CIP deviations rose further, an arbitrage trade would arise. At the same time, financial markets are severely disrupted right now (as is all economic activity) so that even arbitrage opportunities may be able to survive for longer than they normally would.

A bigger question is whether the swap network be further extended or complemented with other arrangement that also constrain deviations from CIP. Tooze (2020) argues that the current crisis will lead to a large collapse in emerging markets. Since these countries do not have access to the swap line, there is a case for creating some substitute access to US dollars, which perhaps could involve the IMF (Reis, 2019). At the same time, the Federal Reserve introduced on 31st March 2020 a new foreign and international monetary authorities repo facility, which lends dollars against Treasuries collateral and is open to most central banks. This is different from the swap lines, but complementary to them.

A final question is whether, while the swap lines are effective, are they welfare enhancing? Especially if they contribute the primacy of the US dollar and encourage foreign banks to ex ante accumulate large FX exposures? The narrative evidence that we showed above cannot answer this but, at the very least, it illustrates how important this topic is.

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# Business disruptions from social distancing<sup>1</sup>

Miklós Koren<sup>2</sup> and Rita Peto<sup>3</sup>

Date submitted: 28 March 2020; Date accepted: 20 March 2020

*Social distancing interventions can be effective against epidemics but are potentially detrimental for the economy. Businesses that rely heavily on face-to-face communication or close physical proximity when producing a product or providing a service are particularly vulnerable. There is, however, no systematic evidence on the role of human interactions across different lines of business and about which will be the most limited by social distancing. In this paper we provide theory-based measures of the reliance of US businesses on human interaction, detailed by industry and geographic location. We find that 49 million workers work in occupations that rely heavily on face-to-face communication or require close physical proximity to other workers. Our model suggests that when businesses are forced to reduce worker contacts by half, they need a 12% wage subsidy to compensate for the disruption in communication. Retail, hotels and restaurants, arts and entertainment and schools are the most affected sectors. Our results can help target fiscal assistance to businesses that are most disrupted by social distancing.*

## 1. Introduction

Social distancing measures are effective, non-pharmaceutical interventions against the rapid spread of epidemics (Bootsma and Ferguson 2007, Markel et al. 2007, Hatchett et al. 2007, Wilder-Smith and Freedman 2020). Many countries have implemented or are considering measures such as school

1 The authors thank Gábor Békés, Péter Harasztosi, Péter Karádi, Balázs Lengyel, Dávid Krisztián Nagy, Andrea Weber, Charles Wyplosz, and an anonymous referee for comments.

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closures, prohibition of large gatherings and restrictions imposed on non-essential stores and transportation in order to slow down the spread of the Covid-19 pandemic (Anderson et al. 2020, Cohen and Kupferschmidt 2020, Thompson and Serkez 2020, Government of New York City 2020). What are the economic effects of such social distancing interventions? Which businesses are most affected by the restrictions?

Past research has analysed the efficacy of social distancing interventions on reducing the spread of epidemics using the 1918 Spanish Flu in the US (Hatchett et al. 2007; Markel et al. 2007, Bootsma and Ferguson 2007) and seasonal viral infections in France (Adda 2016). Our knowledge of economic impacts, however, is limited (Wren-Lewis 2020). One reason for this is that past data may be less relevant to study this question, as the importance of face-to-face communication has increased steadily over the last 100 years through urbanization (Henderson 2010, Henderson 2002). Further, also specialization increased in business services (Herrendorf et al. 2014, Duarte and Restuccia 2019).

The starting point of this paper is the observation that many sectors rely heavily on face-to-face communication in the production process (Charlot and Duranton 2004, Tian 2019). We build a model of communication to understand how limiting face-to-face interaction increases production costs. Without social distancing, workers specialize in a narrow range of tasks and interact with other workers while completing other tasks. This division of labour reduces production costs but requires frequent contact between workers. In the model, the number of contacts per worker is the most frequent in high-population-density areas in businesses where the division of labour is important. When face-to-face interaction is limited, these are exactly the businesses that suffer the most.

To measure business disruptions from social distancing, we turn to recent data on the task descriptions of each occupation (National Center for O\*NET Development 2020) and the precise geographic location of non-farm businesses in the US (US Bureau of the Census 2017). We construct three groups of occupations and study their distribution in space. First, some occupations require face-to-face communication with other workers several times a week. Examples of these *teamwork-intensive* occupations include maintenance, personal care related occupations and health care professionals. Other occupations require frequent contact with customers. Counsellors, social workers and salespersons are examples of such customer-facing occupations. The third group of workers may need to be in physical proximity of one another even if they do not communicate, for example, to operate machinery or access key resources.

Examples of such occupations requiring *physical presence* are drivers and machine operators, especially in mining and water transport, where cramped working environments are common.

The spatial distribution of employment matters because face-to-face interactions are more frequent in dense cities (Charlot and Duranton 2004, Tian 2019). Hence, any social distancing intervention imposes limitations disproportionately on urban sectors. We use our theory-motivated measures to estimate which sectors and which locations will be particularly hurt by social distancing.

## 2. A model of communication

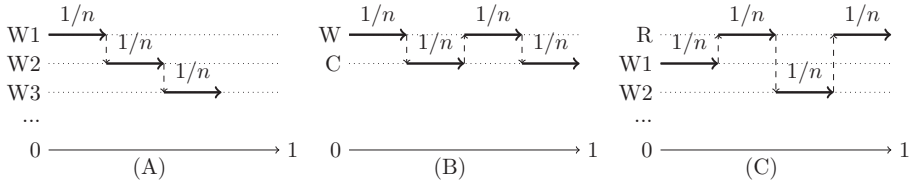
In our model, workers can divide labour more efficiently if they communicate with others. Production involves sequentially completing tasks indexed by  $z \in [0, 1]$ . A single worker can do a range of tasks, but there is a benefit to specialization and division of labour (Smith 1778, Becker and Murphy 1992). The labour cost of a worker completing  $Z < 1$  measure of tasks is  $Z^{1+\gamma}/\gamma$ , where  $\gamma > 0$  captures the benefits to the division of labour. As we show below, the higher  $\gamma$ , the more specialized each worker will be in a narrower set of tasks. Without loss of generality, we normalize the wage rate of workers to one so that all costs are expressed relative to workers' wages.

Once the range of tasks  $Z$  is completed, the worker passes the unfinished product on to another worker. This has a cost of  $\tau$ , which captures the cost of communicating and interacting across workers. The determinants of communication costs will be parametrized later. When all tasks are completed, another step of communication at cost  $\tau$  is needed to deliver the product to the customer. This cost leads to the Marshallian externality that firms want to be close to their customers and customers want to be close to their suppliers (Marshall 1920, Krugman 1991).

The firm will decide optimally how to share tasks between workers. The key trade-off is economizing on the cost of communication while exploiting the division of labour (Becker and Murphy 1992). Let  $n$  denote the number of workers involved in the production process. Because workers are symmetric, each works on  $Z = 1/n$  range of tasks before passing the product to the next worker. Production involves  $n - 1$  'contacts' (instances of communication) and there is an additional contact with the customer.

Figure 1 illustrates the division of labour between workers. Horizontal movement represents production along a range of tasks ( $Z = 1/n$ ), vertical movement represents interactions ( $\tau$ ). We note three potential interpretations of our model. First, when workers work in teams, they can divide labour efficiently

among themselves (panel A). The benefit of a larger team is more specialization. Second, communication may involve the customer (panel B). The benefit of more frequent interaction with the customer is a product or service that is better suited to their needs. Third, workers may need access to a key physical resource, such as a machine, vehicle or an oil well (panel C). In this case, even if they do not communicate, they may be influenced by social distancing measures. The key assumption behind all three interpretations is that frequent interactions increase productivity, whether happening between workers, between workers and customers, or between workers and machines.



**Figure 1** Patterns of interaction in the workplace.

*Notes:* Horizontal movement represents production, vertical movement represents interactions. (A) Each worker  $W$  works on a range  $1/n$  of tasks, passing work  $n - 1$  times. (B) Worker  $W$  and customer  $C$  engage in frequent interactions. (C) Each worker  $W$  needs physical access to a key resource  $R$ .

The firm's cost minimization problem can then be written as a function of the number of contacts alone,

$$c(\tau) = \min_n n\tau + \frac{1}{\gamma} n^{-\gamma}, \quad (1)$$

where total communication costs are  $n\tau$  and production costs are  $nZ^{1+\gamma}/\gamma$  with  $Z = 1/n$ .

Given the strict convexity of this cost function, and ignoring integer problems, the first-order condition is necessary and sufficient for the optimum,

$$n^*(\tau) = \tau^{-1/(1+\gamma)}. \quad (2)$$

The number of worker contacts is decreasing in the cost of communication, expressed relative to worker wage. When the division of labour is important,  $\gamma$  is high, and the number of contacts does not depend very strongly on communication costs.

The total cost of producing one good can be calculated by substituting in Equation 1 into Equation 2,

$$c(\tau) = \tau^\chi / \chi, \quad (3)$$

where  $\chi = \gamma/(1+\gamma) \in (0, 1)$  measures the importance of the division of labour.

This unit cost function is the same as if workers and communication were substitutable in the production function in a Cobb-Douglas fashion. Indeed,  $\chi$  captures the share of costs associated with communication and can be calibrated accordingly.

## 2.1 The cost of communication

Businesses may differ in how important communication is in their production process,  $\chi$ . Another source of heterogeneity is the cost of communication between workers, which we specify as follows.

When workers meet face-to-face, communication costs depend inversely on the population density in the neighbourhood of the firm,  $\tau = d^{-\varepsilon}$  with  $\varepsilon > 0$ . This captures the Marshallian externality of knowledge spillovers (Marshall 1920), which happen more easily in densely populated areas (Charlot and Duranton 2004, Rossi-Hansberg and Wright 2007, Ioannides et al. 2008, Tian 2019). Contacts will be more frequent in dense areas,

$$n^*(d) = d^{\varepsilon(1-\chi)}. \quad (4)$$

The unit cost of production is

$$c(d) = d^{-\varepsilon\chi}/\chi. \quad (5)$$

Firms in dense areas face lower unit costs (Ciccone and Hall 1996), but this agglomeration benefit may be offset by higher wages and land rents in places with high population density (Eberts and Gronberg 1982, Madden 1985, Combes et al. 2019). In spatial equilibrium (not modelled here), firms with high communication needs will choose to locate in high-density areas (Tian 2019).

## 2.2 Social distancing measures

We study the effect of a social distancing intervention that puts an upper limit  $N$  on the number of face-to-face contacts. Firms can mitigate the disruption from this measure by moving communication online, but this is costlier per contact than face-to-face communication.

The optimal number of contacts without social distancing is given by Equation 4. Firms with  $n^* > N$  are limited by social distancing. Without moving communication online, their unit cost will increase to  $c' = Nd^{-\varepsilon} + N^{-\gamma}/\gamma$ , which is greater than the optimal cost,

$$\frac{c'(d)}{c(d)} = \chi \frac{N}{n^*(d)} + (1-\chi) \left( \frac{N}{n^*(d)} \right)^{-\gamma} > 1. \quad (6)$$

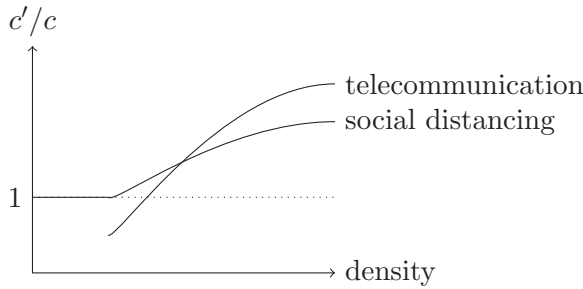
The first term of the weighted average is less than one, representing a reduction in communication costs once the number of contacts is limited. The second term is greater than one due to the fact that every worker has to complete a wider range of tasks than before, hence due to the loss of the benefit of specialization. Because  $n^*$  is the cost-minimizing communication choice of the firm, the second term dominates and production costs increase with social distancing.

If the firm chooses to use telecommunication, the cost per contact will be  $T > d^\varepsilon$  (otherwise the firm would have used telecommunication before). The proportional increase in production costs in this case is given by

$$\frac{c''(d)}{c(d)} = T^\chi d^{\varepsilon\chi} > 1. \quad (7)$$

In both cases, the cost increase is highest for communication-intensive firms (large  $\gamma$  and  $\chi$ ) and those operating in a high-density area (high  $d$  and hence high  $n^*$ ).

Figure 2 displays the ratio of production costs under social distancing to the optimal production costs as a function of density. Firms in low-density areas are unaffected by social distancing since they do not have many contacts anyway. Those in intermediate-density areas would suffer a lower increase in costs by switching to telecommunication. Firms in the highest-density areas will stick to face-to-face communication, which is still the most efficient form of communication despite restrictions. However, they will suffer the biggest cost increase.



**Figure 2** Both social distancing and telecommunication hurt firms in dense areas more

*Note:* See Equation 6 and Equation 7 for the relative production costs under the two interventions.

### 3. Data and methodology

To estimate the potential disruptions from social distancing, we need a measure of the importance of worker interactions (corresponding to  $\chi$  in the model) and their costs (captured by population density  $d$ ).

Let  $\xi_o$  be an indicator equal to one if occupation  $o$  is interaction-intensive and zero otherwise. For industry  $i$ ,  $\chi_i = \sum_o s_{io} \xi_o$  measures the fraction of workers in affected occupations, with  $s_{io}$  denoting the employment share of occupation  $o$  in industry  $i$ .

We use the Occupational Information Network (O\*NET) (National Center for O\*NET Development 2020) to measure the characteristics of a given occupation, similarly to previous studies (Firpo et al. 2011, Autor and Dorn 2013, Jin and McGill 2020, Dingel and Neiman 2020, Leibovici et al. 2020, Mongey and Weinberg 2020). The O\*NET dataset contains detailed standardized descriptions on almost 1000 occupations along eight dimensions. We focus on job characteristics that are related to recent social distancing measures, while prior work focused mainly on measuring offshorability of the given tasks (Firpo et al. 2011 Autor and Dorn 2013).

Social distancing interventions limit the interaction between people and regulate physical proximity between individuals. We thus focus on three related job characteristics based on work context and work activity described in O\*NET. The first two indicators capture how communication-intensive the job is. Communication can be of two types: internal communication with co-workers (*teamwork*) or external communication directly with customers (*customer-facing*). The third indicator takes into consideration the possibility that workers may need to be in physical proximity of one another even if they do not communicate. We create an index that shows how important *physical presence* is to perform a given job. Table 1 shows the specific O\*NET indexes that contribute to each of our three measures. As social distancing measures only limit personal communication, for communication indexes we require that the necessary face-to-face communication happens at least several times a week. In teamwork, face-to-face meetings can often be substituted by more structured communication, for which working from home is not as disruptive. To allow for this possibility, we only classify occupations as teamwork-intensive if emails, letters, and memos are less frequent forms of communication than face-to-face meetings. This excludes most managers and certain business services. Similarly, for physical presence, we require a minimal degree of proximity to other workers which corresponds to working in a shared office.

Index	Tasks	Context
Teamwork	Work with work group or team	Face-to-face discussions several times a week & more often than emails, letters, memos
	Provide consultation and advice to others	
	Coordinating the work and activities of others	
	Guiding directing and motivating subordinates	
	Developing and building teams	
Customer	Deal with external customers	Face-to-face discussions several times a week
	Performing for or working directly with the public	
	Assisting and caring for others	
	Provide consultation and advice to others	
	Establishing and maintaining interpersonal relationships	
Presence	Handling and moving objects	Density of co-workers like shared office or more
	Operating vehicles, mechanized devices or equipment	
	Repairing and maintaining electronic equipment	
	Repairing and maintaining mechanical equipment	
	Inspecting equipment, structures, or material	

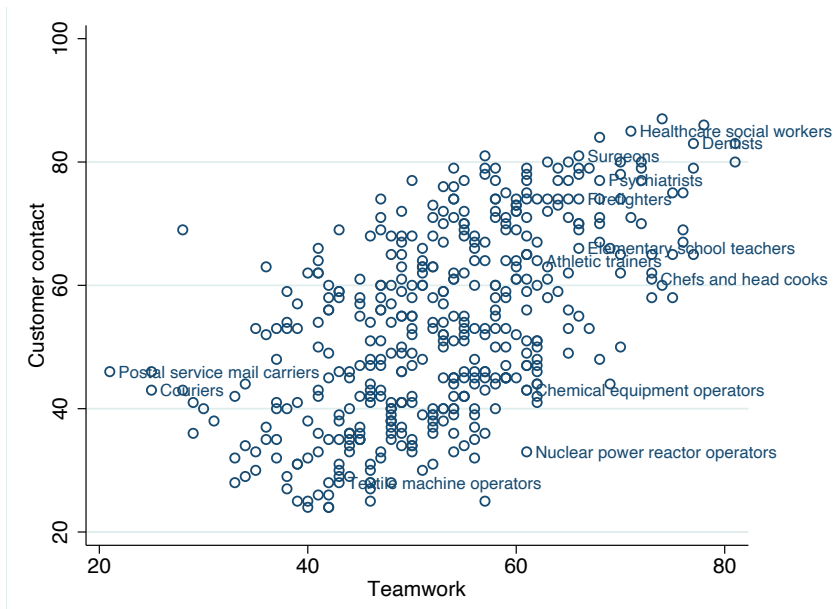
**Table 1** Definition of social distancing indexes

*Notes:* Each social distancing index (column 1) is created as an arithmetic average of the component indexes (column 2). To be classified as an affected occupation, the average has to exceed 62.5 and the work context index has to exceed the threshold in column 3.

We aggregate the measures to 6-digit occupation codes (Standard Occupational Classification, 2010-SOC). We have information on the relevance of teamwork, customer contact and physical presence for 809 occupations in SOC 2010 codes.

Teamwork and customer contacts are highly correlated (Figure 1), but they are conceptually different. While all medical occupations require teamwork and customer contact, supervisors in general are working in teams but do often not communicate directly with customers. Machine operators and production workers are in general at the bottom of both of the distributions. As managers can substitute personal communication with emails, they are not considered as teamwork-intensive occupations according to our definition. Given the high correlation between the two types of communication, we often refer to occupations that are either teamwork-intensive or customer-facing as communication-intensive occupations.





**Figure 3** Teamwork and customer contact are highly correlated

*Notes:* Each circle represents an occupation. Teamwork and customer contact indexes are constructed as explained in main text.

As a next step, we calculate for each sector the share of workers whose job requires a high level of teamwork, customer contact and physical presence. We use the same sectoral breakdown as the Current Employment Statistics (CES) (US Bureau of Labour Statistics 2020a). As all the indexes are an absolute value running from 0 to 100, we use 62.5 as a cut-off to define a job to be teamwork-intensive, customers contact-intensive or a job that require physical presence from the worker. The occupation structure of the industries is retrieved from the official industry-occupation matrix (US Bureau of Labour Statistics 2020b), where we use the employment statistics by occupation-industry for February 2020.

Based on the share of relevant occupations in industry employment, the most teamwork-intensive sectors are ‘hospitals’, ‘accommodation’ and ‘motion picture and sound recording industries’. In contrast, teamwork is not important in sectors like ‘forestry and logging’ and ‘fishing, hunting and trapping’. Customer contact is relevant in sectors like ‘hospitals’ and ‘retail’, while it is not relevant in

sectors like ‘truck transportation’ and ‘forestry and logging’. Physical presence is relevant in sectors like ‘truck transportation’, ‘repair and maintenance’, mining in general, while it is not relevant in ‘finance and information technology’ sectors.

‘Hospitals’ score high on all three measures because communication in health care teams and with patients is important, and doctors and nurses work in close physical proximity to others. We nonetheless remove this sector from the analysis because of its inevitable direct role in combating the epidemic which is not captured well in a simple model of communication.

To measure the heterogeneity in the cost of communication, we measure population density in the neighbourhood of businesses. The assumption in the model is that communication costs are lower in dense areas. This is consistent with the fact that communication-intensive sectors such as business services and advertising, together with central administrative offices of production firms tend to be concentrated in high-density areas (Aarland et al. 2007).

The location of sectors comes from the County Business Patterns (CBP) data for 2017 (US Bureau of the Census 2017). For a finer spatial resolution, we use the data tabulated by ZIP-Code Tabulation Areas. The CBP lists the number of establishments of a certain size for each ZIP-code and NAICS industry code. Because establishment sizes are given in bins (e.g. 1 - 4 employees), we take the midpoint of each bin as our estimated employment (e.g. 2.5 employees). In small industries and ZIP codes, the Census omits some size categories to protect the confidentiality of businesses. We impute employment in these plants from the national size distribution of plants in the same NAICS industry. Our estimated industry-level employment is a very good approximation to official employment statistics (US Bureau of Labor Statistics 2020a). The correlation between our estimates based on CBP and the employment reported in CES is 0.98.

To understand the heterogeneity across regions, we average the share of workers in teamwork-intensive, customer-facing and physical-presence occupations across industries for each ZIP code. For each of the three occupation groups, let  $\xi_{og}$  denote the indicator of whether occupation  $o$  belongs to group  $g$ . The industry share of workers in the occupation group is given by  $\sum_o s_{io} \xi_{og}$ . We compute the regional share of the occupation group as an employment-weighted average across industries,  $\sum_i l_{ir} \sum_o s_{io} \xi_{og} / \sum_i l_{ir}$ , where  $l_{ir}$  is the estimated employment of industry  $i$  in region (ZIP code)  $r$ . Because we only have industry but not occupation data by location, we have assumed that the occupation distribution within the sector,  $s_{io}$ , does not vary across locations. The fact that the CBP tabulates employment by establishments rather than firms makes this a good approximation. For example, a sporting good producer may also have an

administrative office and a retail store in different locations, but these will be classified under their respective NAICS sectors rather than as sporting goods manufacturing.

We use population density to measure how locations differ in the costs of communication. We also experiment with using employment densities instead of population densities. Results are very similar, as the two measures are highly correlated with the exception of very high employment-density urban centres where population is more sparse (Heblich et al. 2017).

### 3.1 Counterfactual calculations

To gauge the magnitude of the effect of social distancing, we calibrate the parameters of the model and compute the effect of a policy that limits the number of worker contacts. At the same time, we let the government introduce a proportional wage subsidy  $\lambda$  to help offset the costs from lower interaction. With this subsidy, the cost of labour will be  $(1 - \lambda)$ . We ask what level of  $\lambda$  would compensate businesses for the communication disruption caused by social distancing. Using the cost change in Equation 6, we can express

$$\lambda_{ir} = 1 - \frac{1 - \chi_i}{1 - \chi_i N / n_{ir}^*} \left( \frac{N}{n_{ir}^*} \right)^{\gamma_i} > 0. \quad (8)$$

The compensating wage subsidy increases in the importance of communication  $\chi_i$  and the optimal number of contacts  $n_{ir}^*$ , and decreases in the number of allowed contacts  $N$ . The subscripts show that the communication share is industry specific and that the optimal number of contacts is both industry and region specific.

We calibrate the upper limit on personal contacts  $N$  such that the overall number of contacts in the economy, when averaged across ZIP codes and industries, is reduced by half,  $\sum_{i,r} l_{ir} \min\{N, n_{ir}^*\} = 0.5 \sum_{i,r} l_{ir} n_{ir}^*$ . Due to the inherent nonlinearity of the model, other interventions will have different effects.

To calibrate the importance of communication  $\chi_i$ , note that it is the cost share of communication, and can therefore be calibrated to the employment share of communication-intensive occupations in industry  $i$ . Here we take all occupations that are either teamwork intensive or customer facing.

Population density in region  $r$  can be measured directly in the data, as explained above. The only remaining parameter to calibrate is the elasticity of the communication externality  $\varepsilon$ . We rely on previous estimates of agglomeration effects that capture the elasticity of total factor productivity with respect to population density (Ciccone and Hall 1996). In our model, the elasticity of unit costs (which can be construed as the inverse of productivity) with respect to

density is  $-\varepsilon\chi$  (Equation 5). We calibrate  $\varepsilon = 0.02$  so that, across all ZIP codes and industries, a regression of log model-implied productivity ( $\varepsilon\chi_i \ln d_r$ ) on log population density  $\ln d_r$  yields an elasticity of 0.04 (Ciccone and Hall 1996).

Given these parameter values, we compute the compensating wage subsidy for each industry in each ZIP code using Equation 8. We report employment-weighted averages of the compensating wage subsidy over sectors and over locations.

#### 4. Results

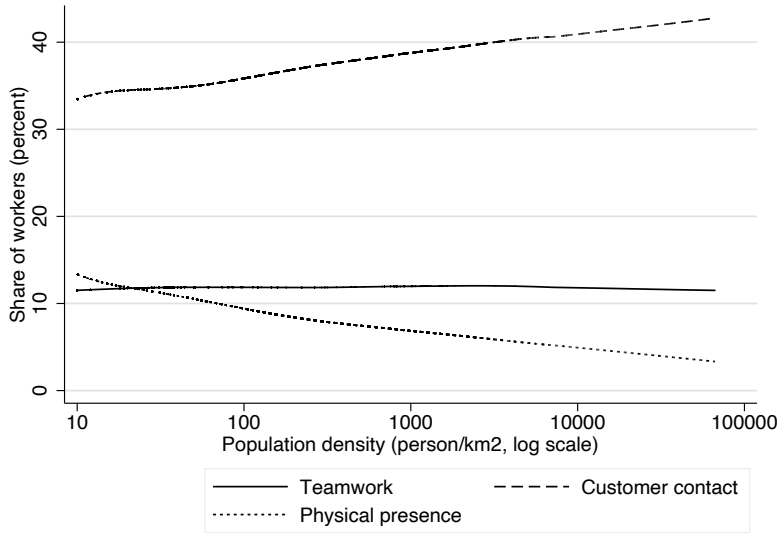
Table 2 displays the top five and the bottom five industries by 2-digit NAICS industries as sorted by the percentage of workers in communication-intensive occupations, excluding hospitals and clinics. Across industries, retail trade, accommodation and food services, arts, entertainment and recreation, other services and educational services have the highest share of communication-intensive workers, exceeding 35%. Transportation, production, construction and agricultural industries are less reliant on face-to-face communication. This heterogeneity across industries is important to understand the effect of social distancing measures.

Industry	Teamw.	Custom.	Overall	Presence
Retail trade	13	67	68	5
Accommodation & food services	8	50	51	1
Arts, entertainment, and recreation	12	40	42	2
Other services (except public admin.)	12	38	41	12
Educational services	15	35	37	1
...				
Wholesale trade	8	16	20	12
Transportation and warehousing	8	10	16	32
Manufacturing	7	6	11	10
Construction	15	5	18	28
Agri., forestry, fishing & hunting	4	4	7	23

**Table 2** Retail, professional services, finance and restaurants are the most communication intensive

*Notes:* ‘Teamw.’ and ‘Custom.’ show the percentage of workers in teamwork-intensive and customer-facing occupations, respectively. ‘Overall’ shows the percentage of workers in communication-intensive occupations that are either teamwork-intensive or customer-facing. It is less than the sum of the two indexes because some occupations rely on both types of communication. ‘Presence’ shows the percentage of workers whose jobs require physical presence in close proximity to others.

Figure 4 plots the share of workers in the three affected occupation groups across ZIP codes by population density. Customer-facing occupations are overrepresented in dense areas. In the highest population density ZIP codes, 43% of workers are employed in customer-facing occupations. Teamwork-intensive occupations are broadly distributed in space.



**Figure 4** Urban areas employ more workers in customer-facing occupations, less in occupations requiring physical presence

*Notes:* Locally weighted polynomial regression of average share of teamwork-intensive occupations, customer-facing occupations and occupations requiring physical presence across sectors within the ZIP code (bandwidth = 0.5).

In the calibrated model, a social distancing policy that puts a cap on interactions per worker such that the total number of interactions drops by half nationwide is compensated by a 12.2% wage subsidy. The distribution of the compensating wage subsidy is, however, unequal over space and across industries. New York City, with a population density of about 20 times the US average city density, would require a 13.3% wage subsidy. By contrast, the compensating wage subsidy in agriculture, transportation and manufacturing would be less than 6% (Table 3).

Industry	Wage subsidy	Employment
Retail Trade	22.1	15,659
Accommodation and food services	17.7	14,379
Arts, entertainment, and recreation	15.1	2,494
Other services (except public admin.)	14.5	5,939
Educational services	13.8	3,838
...		
Wholesale trade	7.7	5,936
Construction	6.8	7,646
Transportation and warehousing	5.9	5,523
Manufacturing	4.5	12,861
Agriculture, forestry, fishing and hunting	2.6	55
<i>Average</i>	<i>12.2</i>	<i>116,496</i>

**Table 3** The five most affected sectors require more than 20% wage subsidy

*Notes:* 'Wage subsidy' displays the percentage decrease in labour costs necessary to compensate businesses when worker contacts are reduced by half. 'Employment' is the February 2020 employment of the sector in thousands (US Bureau of Labor Statistics 2020a). The last row shows the employment-weighted average wage subsidy. The table excludes hospitals, clinics, and government establishments which are not present in CBP.

## 5. Discussion and conclusions

The main cost of social distancing in our model is insufficient division of labour. This mechanism is motivated by Smith (1778) and captures the same trade-off as Becker and Murphy (1992). Our contribution is specifying the cost function in a way that can be easily mapped to the data.

More broadly, our argument is that frequent interaction increases productivity irrespective of whether it is happening between workers, between workers and customers, or between workers and machines. In the main part of the empirical analysis, we focus only on the first two types of interactions, while we are silent on the third. But social distancing measures also affect sectors where workers need to be in physical proximity of one another even if they do not communicate, for example, to operate machinery or access key resources. This is relevant in sectors like mining, quarrying, and oil and gas extraction' and 'transportation' while it is not relevant in sectors like 'finance and insurance' and 'professional, scientific, and technical services'. As can be seen from Figure 2, occupations requiring physical presence have the highest share in low density areas where production and mining plants are located (farms are not included in the CBP). The share of these occupations in the most dense areas is only 3%.

To a greater or lesser extent, all sectors will be affected by social distancing. Some sectors are hit by the intervention due to restricted face-to-face communication, others are hit because physical proximity of people is restricted. Some sectors are less affected across all dimensions. Examples include ‘fishing, hunting and trapping’, ‘printing and related support activities’, and manufacturing in general.

Our results are consistent with parallel research on the overall economic effects of the Covid-19 pandemic using O\*NET data. Recent research found that about 34% of US jobs can be performed from home (Dingel and Neiman 2020). However, as our analysis points out, even among jobs that do not fall into this category, some are more likely to be negatively affected by social distancing than others. The share of workers working in close physical proximity to other people is similar to other recent estimates (Leibovici et al. 2020). Workers in this group are found to be the most vulnerable across a wide range of socio-economic measures (Jin and McGill 2020, Mongey and Weinberg 2020). We contribute to this work by (i) building a model to understand how social distancing measures affect production, (ii) identifying three groups of occupations affected by social distancing and (iii) taking into account the disproportionate costs borne by urban sectors.

We see four avenues for further research. The first concerns the demand side of the economy, which we have mostly neglected by focusing only on the production function. The employment response to a production disruption greatly depends on the elasticity of demand. We hypothesize that sectors like schooling and health care have inelastic demand and will continue to employ many workers despite significant disruptions. However, personal services, small grocery stores and restaurants may face more elastic demand and respond to large production cost increases by laying off a significant fraction of their work force.

The second direction concerns the interaction between sectors and regions. Whenever productivity in any business drops, this shock can propagate to its buyers and suppliers. The aggregate consequences of the epidemic will hence be modulated by input-output linkages between sectors, regions and countries (Caliendo et al. 2014, Caselli et al. 2020, Baldwin and Tomiura 2020).

The third and fourth directions concern the long-run response of businesses as they try to become more resilient to such shocks in the future. Whether the share of telecommunication remains large in the long run depends crucially on how easily it substitutes for face-to-face interaction. In our model, the two are perfect substitutes with the only distinction that the efficiency of face-to-face meetings improves with population density, whereas telecommunication does not depend on agglomeration (Rossi-Hansberg and Wright 2007, Ioannides et al. 2008, Tian 2019). Previous work has found face-to-face communication to be more effective

in high-intensity communication which is particularly helpful to overcome incentive problems in joint production (Gaspar and Glaeser 1998, Storper and Venables 2004). Data on internet flows suggests that telecommunication is not a good substitute for face-to-face meetings (Cuberes 2013). However, none of these papers discuss disruptions from social distancing measures. Further studies on the modes of communication in the O\*NET occupation survey can shed light on whether telecommunication can act as a low-cost substitute for face-to-face meetings.

Fourth, businesses may change their location in response to perceived threats and disruptions. As we discussed, epidemics have a disproportionate effect on cities. Hence, it is conceivable that in a post-pandemic spatial equilibrium (not modelled here, but see Tian (2019)), the agglomeration premium falls and firms find it less attractive to locate in cities. A poignant point of comparison is the increased threat of terrorism in major cities following devastating attacks on New York, Washington, London, Paris, Madrid, Moscow and Mumbai. The general conclusion about terror threat is that cities have remained resilient and a robust attractor of businesses (Glaeser and Shapiro 2002, Harrigan and Martin 2002). We speculate that epidemics and social distancing can be more detrimental to cities than terror threats, because they tear apart the very fabric of urban life. However, we have too limited data to make further predictions.

### Supporting information

**S1 Full table of sectors. Social distancing exposure by sector.** The percentage share of workers in teamwork-intensive, customer-facing, and physical-proximity occupations within the industry. ‘Communication share’ refers to the share of workers who are either teamwork-intensive or customer-facing. ‘Affected share’ refers to the share of workers in any of the three occupation groups. Available at <https://github.com/ceumicrodata/social-distancing/blob/v1.3/data/derived/industry-index.csv>

**S2 Full table of ZIP-codes. Social distancing exposure by location.** The percentage share of workers in teamwork-intensive, customer-facing, and physical-proximity occupations within the ZIP code. ‘Communication share’ refers to the share of workers who are either teamwork-intensive or customer-facing. ‘Affected share’ refers to the share of workers in any of the three occupation groups. Available at <https://github.com/ceumicrodata/social-distancing/blob/v1.3/data/derived/location-index.csv>



**S3 Data repository. Replication code and data.** Replication code and data are available at <https://github.com/ceumicrodata/social-distancing/tree/v1.3>

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# Group testing against Covid-19<sup>1</sup>

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*It is well-known that group testing is an efficient strategy to screen for the presence of a virus. It consists of pooling  $n$  individual samples with a single test using RT-PCR. If no individual in the group is infected, the group test is negative. Thus, a single test may reveal this crucial information. We show how group testing can be optimised in three applications to multiply the power of tests against Covid-19: Estimating virus prevalence to measure the evolution of the pandemic, bringing negative groups back to work to exit the current lockdown, and testing for individual infectious status to treat sick people. For an infection level around 2%, group testing could multiply the power of testing by a factor of 20. The implementation of this strategy in the short run requires limited investments and could bypass the current immense shortage of testing capacity.*

## 1. Introduction

As the coronavirus pandemic develops, governments around the world have now reacted and imposed lockdowns in many countries. Since India imposed strict lockdown restrictions on more than 1.3 billion residents, the total world population under lockdown is now around three billion. By stopping many production processes, the economic cost of the lockdown is very large. For example, Thunstrom et al. (2020) estimate the cost of the lockdown in the US at \$7.2 trillion. Finding a way forward is a critical issue. No doubt that the decision to unlock people in the next few weeks or months will be a complex political,

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health, social, and economic issue. A major risk exists that once the pandemic slows down or appears to be under control and lockdown measures are lifted, new waves of Covid-19 reappear. The 20th century has known three influenza pandemics: the 1918 'Spanish flu', the 1957 'Asian flu', and the 1968 H3N2 'Hong Kong flu'. The 21st century has already witnessed the 2009 'Swine Flu'. These four pandemics came in waves, with subsequent waves being more deadly than the first (Miller et al. 2009).

Therefore, a key element to reduce the economic consequences of Covid-19 is the ability to test individuals, given the large prevalence of asymptomatic but highly contagious people in the population. Massive testing is necessary to monitor the prevalence of the virus in the population in different times and geographical areas. It is also a necessary component to detect infected individuals, quarantine them, and provide medical treatment whenever necessary. Moreover, mass reliable testing would bring back people who have tested negative to work in strategic sectors of the economy, without risking a second wave of contagion. As shown by the experience of South Korea, mass testing is crucial to control the pandemic. As stated by Dewatripont et al. (2020), "restarting production in the economy requires the reliable identification of individuals who will not contract the virus or transmit it to others, whether they have previously displayed the associated symptoms or not."

The standard method for testing for the presence of Covid-19 in a sample is called Real-Time Polymerase Chain Reaction (RT-PCR), which involves a chemical reaction that produces fluorescent light if viral DNA is present. Testing involves two steps - first taking samples from individuals, then amplifying parts of the virus DNA known as markers through a PCR machine. The first step is relatively cheap, but the second one is the bottleneck that limits our testing capacities. Scaling up the capacity of RT-PCR testing for the SARS-COV-2 virus responsible for Covid-19 will take time. It reduces our expectation of a rapid exit from the current lockdown strategy. The US is currently scaling up production up to 1.2 million per week (for a population of 330 million), Germany is producing 500,000 tests per week (population 84 million) and France is producing a mere 84,000 tests per week, scaling up to 210,000 per week in April (population 65 million). Current test production levels are insufficient for mass testing in these countries, not to mention the huge need for tests in developing countries. Each Covid-19 test has to be viewed as a precious resource, to be utilised as efficiently as possible.

In this paper, we exploit a standard testing methodology in which individual samples are pooled.<sup>4</sup> This pooled sample is then tested with a single test. If the test of the combined sample is negative, then all individuals in the group are known to be virus-free, a highly valuable information if the size of the group is large. The implementation of this methodology at the Technion University for Covid-19 suggests that the dilution effect of pooling individual samples is very limited.<sup>5</sup> While individual testing determines whether a given person is a carrier of the virus, group testing will determine whether the virus is present in the group sample or not. Therefore, group testing will be able to reach one of two conclusions: a negative outcome will indicate that none of the individuals of the group is a carrier of the virus, while a positive outcome will indicate that at least one individual in the group is a virus carrier, without any further information on the identity of this person. The optimisation of the group testing strategy depends upon the objective pursued by the test. In this paper, we examine three highly relevant objectives in the context of the Covid-19 pandemic, and we characterise efficient detection strategies to attain them.

## 2. Applications of group testing

Group testing is not a new idea. It originated in Dorfman (1943) in the context of syphilis detection, but it has also been applied in the case of hepatitis B, avian pneumovirus, and HIV (see for example May et al. 2010). A more advanced mathematical theory of group testing can be found for instance in Mézard et al. (2007) and Mézard et al. (2011). A recent survey is Aldridge et al. (2019). Our paper illustrates three applications of this theory to the problem of fighting Covid-19 in the coming weeks. Group testing can be used for the same purposes as individual testing. However, the protocol needs to be adapted to the situation. We detail below practical applications of group testing and discuss its efficiency in comparison with individual testing.

As we write this article, group testing for Covid-19 has already been implemented in Nebraska<sup>6</sup> and in Israel.

4 See also Jain and Jain (2020).

5 PCR was able to detect the presence of the virus in a pooled sample from 64 individuals with a single infected person. See <https://www.technion.ac.il/en/2020/03/pooling-method-for-accelerated-testing-of-Covid-19/>. A team at the University of Frankfurt came to a similar conclusion: <https://aktuelles.uni-frankfurt.de/englisch/pool-testing-of-sars-cov-2-samples-increases-worldwide-test-capacities-many-times-over/>.

6 <https://www.3newsnow.com/news/coronavirus/live-gov-ricketts-provides-coronavirus-briefing-3-24-20>

### 3. Prevalence estimation

There is widespread discussion about the prevalence of the virus in different populations. This information is of crucial importance and will impact policy in many cases. In particular, it allows close monitoring of the spread of the disease. It becomes possible to estimate the ratio of critical cases over total number of cases, as well as the fatality rate, and it allows identification of geographical zones with high infection levels.

The main reason why the information is not well known is the limited availability of tests. Typically, a testing method would involve randomly sampling and testing a group in the population. Relying on hospital admissions is not satisfactory as many cases are either asymptomatic or symptoms are mild enough to recommend prolonged confinement without testing. Here we show how group testing leads to more accurate results with a fewer number of tests (see also Pritchard and Tebbs 2011).

We compare two methods for estimating the prevalence of the virus in the population: (i) individual testing, in which a sample of 12,000 people are tested for the virus, and a standard binomial test is applied to derive a 95% confidence interval, and (ii) group testing, in which 500 groups of 35 people are tested (total population involved 17,500).

#### 3.1 Individual testing

Assume that 2% of people in the sample are infected, returning 240 positive tests.<sup>7</sup> A standard binomial test returns the following 95% confidence interval on the infected population:

$$CI_{IT} = [1.76\%, 2.27\%].$$

#### 3.2 Group testing

Assume again that 2% of individuals in the sampled population are infected, and that individuals are allocated to groups randomly for testing. For each group of 35, there is a probability of  $1 - (1 - 0.02)^{35} \sim 50.7\%$  that it contains at least one infected person, meaning the test returns positive. This corresponds to 253 group tests returning positive, and 247 returning negative. With such data, the 95% confidence interval on the proportion of groups of 35 in the population

<sup>7</sup> For simplification, the tests are assumed in these applications to return no false positives or negatives.

containing at least one infected person is: [46.1%, 55.1%]. The corresponding confidence interval on the underlying proportion of infected people in the population is:<sup>8</sup>

$$CI_{GT} = [1.75\%, 2.26\%].$$

### 3.3 Comparison of results

Both group testing and individual testing return the same point estimate on the proportion of infected individuals (2%). They return slightly different confidence intervals due to a non-linearity in the formulas involved. Both confidence intervals have the same size of 0.5%, which is a reasonable size on which policy making decisions can be based. However, the cost in terms of number of tests is drastically lower for group testing (500) compared to individual testing (12,000). In this application, group testing allows to economise on tests by a factor of 24.

Note that group size 35 is optimised so that each group test positive with probability circa 0.5 for 2% prevalence. In principle, prevalence is not known, so group size may not be chosen optimally. This will lead to a slightly degraded performance of group testing. In this application, group testing allows to economise on tests by a factor 24 while keeping groups of reasonable size.

### 3.4 Optimal group size

Given a prevalence level  $p$  and a number of groups, the variance estimator is minimized for a group size such that the probability  $q$  that a group of size  $n$  is tested positive satisfies  $q \sim -\ln(1 - q)/2$ , which gives  $q \sim 0.80$ , and  $n \sim \frac{\ln 2}{\ln(1-p)}$ .<sup>9</sup> For a prevalence of 2%, groups of size 80 are optimal from the statistical point of view. In practice, technical limitations as well as the cost of collection of individual samples put a downwards pressure on group size.

## 4. A plan to exit the lockdown

Building testing capacity will take time, even with a wartime mobilisation of means. We therefore propose to complement this investment plan with an immediate expansion of the testing capacity by using group testing. Contrary to Dorfman (1943), we don't attempt in this section to identify infected individuals. We rather determine the size of group testing that maximises the number of individuals whose testing demonstrates they are not infected. The scarcity of tests obviously means that it is better to use a test to detect the virus in another

<sup>8</sup> The confidence interval on proportion of infected people is given by  $[1 - (1 - .455)^{\frac{1}{35}}, 1 - (1 - .455)^{\frac{1}{35}}]$ .

<sup>9</sup> The authors are grateful to Xavier d'Hautfeuille for this insight.



untested group than to try to discover who is infected in a positive group. This is because the value of information from the test does not come from the treatment of infected people in the absence of an efficient drug to do that. In the context of Covid-19, the value of the test rather comes from sending healthy people back to work as soon as possible, without risking infection.

Suppose that the prevalence rate of the virus in the target population is  $p$ . The testing capacity is assumed to be very limited in the sense that even group testing will not allow for testing the entire population. We assume that when a group is detected with the virus, their members remain confined. Let  $n$  denote the size of the groups to be tested. If  $n$  is too large, too many groups will be detected with the virus, and that will reduce the expected number of people who will be allowed to get back to work. Technically, the frequency of groups tested negative is equal to  $(1 - p)^n$ , so that the expected number of people freed from confinement with a single test is equal to  $n(1 - p)^n$ . The optimal size of group testing maximises this function of  $n$ . It satisfies the following first-order condition:

$$n = \frac{-1}{\log(1 - p)} \approx \frac{1}{p}. \quad (1)$$

The optimal size of the group is decreasing with the prevalence ratio. It is optimal that the group size be approximately equal to the inverse of the prevalence ratio. The above equation gives us the following expected number  $N$  of people back to work with a single test:

$$N = \frac{(1 - p)^{\frac{-1}{\log(1 - p)}}}{-\log(1 - p)}. \quad (2)$$

The expected number of people freed from confinement with a single test is decreasing in the prevalence ratio. The individual testing strategy with one test allows for freeing an expected number of people equalling  $1 - p$ . We obtain that the power of the group testing strategy over the individual testing strategy is equal to

$$P = \frac{(1 - p)^{\frac{-1}{\log(1 - p)} - 1}}{-\log(1 - p)}. \quad (3)$$

This means that the optimal group testing strategy frees in expectation  $P$  times more people from the lockdown than when using the individual testing strategy.

We can also value the benefit of increasing the testing capacity. To do this, we need to measure the social cost  $q$  of individual confinement. Suppose that the optimal confinement strategy in the absence of testing is to remain idle for two months. Therefore, we can assume that this social cost equals two months of

GDP per capita. For the EU whose GDP per capita is approximately €31,000 per annum, this corresponds to  $q = €5,167$ . The social value of each test is thus equal  $qN$ .

#### 4.1 Individual testing

Suppose for example that the prevalence ratio is 2%. Each individual has 98% chances of not being infected and released after testing. Each test allows the release of 0.98 people on average. The value of a single test is thus equal to €5,063.

#### 4.2 Group testing

Consider testing groups of  $n = 50$  people. Each test returns negative if everyone in the group is healthy, which has probability  $0.98^{50} \sim 36\%$ . The average number of people each test allows to release is then  $N = .36 \times 50 \sim 18.2$ . The value of a single test is thus equal to €94,077. Although fewer tests are negative with group testing, each of them allows to release 50 people back to work. Group testing is more efficient than individual testing by a factor  $P = 18.6$ .

In Table 1, we describe the characteristics of the optimal strategy for different values of the prevalence ratio, taking account of the integer nature of  $n$ . We assumed that the health status is i.i.d. in the target population. In practice, group size must be tailored according to available information on risk prevalence. Also, groups of people may be correlated in their risks of being infected.

Prevalence ratio ( $p$ )	Optimal size ( $n$ )	Expected number deconfined ( $N$ )	Power of group testing ( $P$ )	Expected benefit ( $qN$ , in euros)
0.01	99	36.60	36.97	189 129
0.02	49	18.21	18.58	94 083
0.05	19	7.17	7.55	37 046
0.1	9	3.49	3.87	18 016
0.2	4	1.64	2.05	8 466
0.3	3	1.03	1.47	5 317
0.4	2	0.72	1.20	3 720

**Table 1** Optimal group testing strategy

*Notes:* Optimal group testing strategy as a function of the prevalence rate in the target population. We assume that  $q = €5167$ .

Testing positively correlated groups and adjusting group size adequately would increase performance of the system. People working in the same production units, such as production lines or offices, have a high degree of correlation in their infectious statuses. Individual workers also have a high degree of complementarity. In such situations, it is efficient to test a whole production unit as a group and close it when the test returns positive.

## 5. Testing individuals with group testing

One of the most important applications of testing is to know whether an individual is infected. Group testing can allow for a much more efficient way of testing each individual in a population than individual testing.

Here we present a protocol for testing whether individuals in a population carry the virus, based on sequential group tests. Each individual in the population will be marked as positive ('+'), negative ('-'), or unknown ('?'). Initially everyone is marked as '?'.

### **Box 1**      Testing protocol

**T32** Test a group of 32 individuals.

1. If the test is negative, mark all 32 individuals as '-' and the protocol stops
2. If the test is positive, form two subgroups of 16, tagged 16A and 16B

**Test the group 16A**

1. If 16A is positive, mark everyone in 16B as '?', from 16A create two subgroups of 8 individuals, tagged 8A and 8B
2. If 16A is negative, mark everyone in 16A as '-', from 16B create two subgroups of 8 individuals, tagged 8A and 8B

**T8** Test the group 8A

1. If 8A is positive, mark everyone in 8B as '?', from 8A create two subgroups of 4 individuals, tagged 4A and 4B
2. If 8A is negative, mark everyone in 8A as '-', from 8B create two subgroups of 4 individuals tagged 4A and 4B

Proceed until a group of 2 individuals is known to hold at least one virus holder.

**T1** Test one of the two individuals

1. If the test returns positive, mark this individual '+', the other as '?'
2. If the test returns negative, mark this individual '-', the other as '+'

The protocol returns the infectious status of individuals marked '+' or '-'. No information is known about those marked '?' and these individuals re-enter the protocol in newly formed groups of 32.

### *Estimation of the protocol efficiency*

We estimate the average number of tests for each run of the protocol, as well as the average number of individuals for whom the infection status returns as known. For simplification we make the approximation that a group of 32 individuals has probability 50% to contain at least one infected person.

In case the first group is negative, the protocol ends. In case it is positive, it runs tests T32, T16, T8, T4, T2, and T1, hence 6 tests. So on average the protocol runs  $7/2$  tests.

If the first test is negative, all 32 people's status is returned as known. If the first test is positive, each test TX ( $X = 16, 8, 4, 2, 1$ ) returns either positive or negative with probabilities approximately  $1/2$ . If it returns positive,  $X$  people exit the protocol with unknown status at this stage; if it returns negative none exit with unknown status at this stage. Therefore, the average number of people who exit with unknown status is:

$$\frac{1}{2} \left( \frac{1}{2} 16 + \frac{1}{2} 8 + \frac{1}{2} 4 + \frac{1}{2} 2 + \frac{1}{2} 1 \right) = \frac{31}{4},$$

So the number of people returning with known status is on average  $32 - 31/4 = 97/4$ .

Each test therefore returns the status of on average  $\frac{97}{4} / \frac{7}{2} \sim 6.9$ .

Applying the protocol is tantamount to an increase of test production by a factor of almost seven. Even a factor of three would mean a huge scaling up in world testing capabilities.

## 5.1 Two-stage protocols

Note that the sequential protocol may require several swabs for a given individual. Given the cost of collecting a swab, including its labour cost, is much smaller than the cost of testing a sample, we find this point essentially non-problematic. In practice, one should probably amend the protocol in order to have a reasonable upper bound on the number of swabs each individual is required to provide.

With only two swabs, both Technion Institute of Technology and Nebraska hospitals have started implementing the original algorithm of Dorfman (1943), which goes as follows:

- Test a group of  $n$  individuals
  - If the test is negative, all  $n$  individuals are negative
  - If the test is positive, test each individual separately

With a probability  $p$  of each individual of being infected, the average number of tests per individual is

$$T_p(n) = \frac{1 + (1 - (1 - p)^n)n}{n}$$

Given  $p$ , we must adjust group size to minimize  $T_p(n)$ . For  $p = 2\%$ , we find that  $n = 8$  is optimal, using 0.27 tests per individual, thus allowing to find out about 3.65 individual conditions per test used. For  $p = 1\%$ ,  $n = 11$  is optimal, allowing to find out about 5.11 individual conditions per test.

In practice, such a simple algorithm is not optimal, but already allows for very significant savings in the number of tests used.

## 6. Errors and information theory

Abstracting from virus detection, sequential group testing can be viewed as a coding problem. The list of infectious status of all individuals in the population consists of a message, and a sequence of test results read should be enough to recover this message. Information Theory (Shannon 1948, Cover and Thomas 2006) tells us that a lower bound on the number of tests required per individual in the population is:

$$h/C$$

where

- $C$  is known as the capacity of the channel and depends on the test accuracy. A perfect test returning the infectious status of the patient (positive or negative) with no errors has a capacity of 1. Tests with lower accuracy also have lower capacities, and
- $h$  is the entropy per individual in the population. In the case of an i.i.d. population with prevalence  $p$ ,  $h = H(p) = -p \log_2(p) - (1 - p) \log_2(1 - p)$ . When  $p = 2\%$ ,  $h \sim 0.112$ . Assuming a test with no errors, the theoretical bound on the number of tests per individual is then  $1/0.112 \sim 7.1$ , showing that the protocol suggested above achieves near-optimality.

## 7. Conclusion

Testing for Covid-19 is a bottleneck that we face in front of the pandemic. Test production is currently much below what is necessary for mass testing strategies which are required in order to control the pandemic while letting people go back to work. Adequate use of group testing can save many tests, between 85% and 95% depending on the applications. Although this work is of theoretical nature and does not account for many technical details of group testing such as maximal group sizes and error types, a very conservative assessment of the tests that can be saved in this application is about two-thirds, which means that use of group testing is equivalent to a scaling up of test production by a factor of three or more.

In this paper, we focused our attention to RT-PCR tests that are able to detect infection. Alternatively, serological tests are used to detect the presence of antibodies, thus the immunity of the individual. In the absence of a vaccine, it is an urgent strategic issue to detect immunity in the most essential professions, and group testing should also be used for this purpose.

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# The propagation of the economic impact through supply chains: The case of a mega-city lockdown to contain the spread of Covid-19<sup>1</sup>

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*This study quantifies the economic effect of a possible lockdown of Tokyo to prevent the spread of Covid-19. The negative effect of the lockdown may propagate to other regions through supply chains because of a shortage of supply and demand. Applying an agent-based model to the actual supply chains of nearly 1.6 million firms in Japan, we simulate what would happen to production activities outside Tokyo when production activities that are not essential to citizens' survival in Tokyo were shut down for a certain period. We find that when Tokyo is locked down for a month, the indirect effect on other regions would be twice as large as the direct effect on Tokyo, leading to a total production loss of 27 trillion yen in Japan, or 5.3% of its annual GDP. Although the shut down in Tokyo accounts for 21% of the total production in Japan, the lockdown would result in a reduction in the daily production in Japan of 86% in a month.*

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## 1. Introduction

Covid-19, the novel coronavirus disease, has been spreading all over the world. As of 31 March 2020, the total number of confirmed cases of Covid-19 reached 775,306 and the total number of deaths was 37,083.<sup>4</sup> To prevent the spread of Covid-19, most countries have implemented unprecedented restrictions, such as shutdowns of national borders, limits on public gatherings, and closures of schools, shops, and restaurants.

In some cases, cities and regions are locked down. For example, Wuhan, the epicentre of the virus, was locked down from 23 January to 27 March 2020, shutting down all public transports and all companies not essential to citizens' survival including manufacturing plants during most of the period (Reuters, 11 March 2020). Apparently, the lockdown heavily affected the economy of Wuhan, a city with a population of 11 million. Moreover, because Wuhan, known as one of China's 'Detroits', is a centre of the automobile industry and supplies automobile parts and components to both domestic and foreign plants, the effect of the lockdown propagated to other regions of China and other countries through supply chains. For example, Honda, a Japanese automobile manufacturer that operates plants in Wuhan, reduced production of automobiles in Japan due to lack of supplies of parts from China in early March 2020 (Nikkei Newspaper, 2 March 2020).

Recently, many studies have confirmed empirically that economic shocks propagate across regions and countries through supply chains (Barrot and Sauvagnat, 2016; Carvalho et al., 2016; Kashiwagi et al., 2018; Inoue and Todo, 2019; Boehm et al., 2019), mostly using natural disasters as sources of shocks. For example, Inoue and Todo (2019) employ the actual supply chains of approximately one million firms in Japan and the production trajectory after the Great East Japan Earthquake in 2011 to calibrate an agent-based model with firm-to-firm supply chains. They find that while the production loss due to the direct effect of the earthquake and subsequent tsunamis was approximately 100 billion yen, or 0.02% of GDP, the production loss due to supply chain disruptions in areas that were not directly hit by the earthquake or by tsunamis was 11 trillion yen, or 2.3% of GDP. Their result indicates that the propagation effect of an economic shock through supply chains can be substantially larger than its direct effect.

The authors also show that complex network characteristics of supply chains, such as scale-free properties and complex loops, aggravate the propagation effect. Without any network complexity – i.e., if they assume no firm-level inter-linkages but only inter-industry linkages, or assume a randomly determined



network with no complexity – they find the propagation effect is quite small. These results are consistent with recent findings in the network science literature that the structure of networks significantly influences diffusion (Watts and Strogatz, 1998; Watts, 2002; Burt, 2004; Centola, 2010; Newman, 2010; Barabasi, 2016).

Therefore, when a large industrial city connected with other regions and countries through supply chains in a complex manner is locked down to prevent the spread of Covid-19, the economic effect is most likely to propagate across regions and countries. To confirm this conjecture, we utilise the framework of Inoue and Todo (2019) and quantify the economic effect of a lockdown of Tokyo on other regions. Tokyo is an appropriate case for the purpose of this study, because it is one of the largest cities in the world and a hub in global supply chains, and because recently policymakers, including the governor of the Tokyo, have mentioned the possibility of a lockdown of the city. Specifically, applying the agent-based model developed by Inoue and Todo to actual supply chains in Japan, we simulate what would happen to production activities outside Tokyo if the city were locked down, or non-essential production activities were shut down for a certain period.

Several studies have estimated economic impacts of the spread of Covid-19. For example, the OECD (2020) predicted in early March 2020 that if outbreaks of Covid-19 were to spread widely in Asia and advanced countries in the northern hemisphere, the growth rate of real GDP in the world in 2020 would be 1.4%, which is 1.5 percentage points lower than its estimate before the spread of Covid-19. McKibbin and Fernando (2020) suggest that in their worst scenario where all countries are hit, the spread of Covid-19 would reduce the GDP of China, Japan, the United Kingdom, and the United States by 6.2%, 9.9%, 6.0%, and 8.4%, respectively. However, these studies rely on either a macroeconomic econometric model at the country level (OECD, 2020) or a general equilibrium model assuming international and inter-sectoral input-output linkages (McKibbin and Fernando 2020) and thus do not incorporate complex inter-firm linkages. As a result, the estimates of the previous studies may be largely undervalued, as suggested by the finding of Inoue and Todo (2019). Therefore, in this study we attempt to quantify the economic effect of Covid-19 that takes into account propagation of the effect across regions through inter-firm supply chains for the first time in the literature.

## 2. Data

The data used in this study are taken from the Company Information Database and Company Linkage Database collected by Tokyo Shoko Research (TSR), one of the largest credit research companies in Japan. Because of data availability, we utilise data for firm attributes and supply chains in 2016 and the input-output (IO) table in 2015. The former includes information about attributes of each firm, including the location, the industry, sales, and the number of employees; the latter includes major customers and suppliers of each firm. The number of firms in the data is 1,668,567, and the number of supply-chain links is 5,943,073. That is, our data identify major supply chains of most firms in Japan, although they lack information about supply-chain links with foreign entities. Because the transaction value of each supply-chain tie is not available in the data, we estimate sales from a particular supplier to each of its customers and consumers using the total sales of the supplier and its customers and the IO table for Japan in 2015. In this estimation process, we have to drop firms for which we have no sales information. Accordingly, the number of firms in our further analysis is 966,627, and the number of links is 3,544,343. Although firms in the TSR data are classified into 1,460 industries according to the Japan Standard Industrial Classification, we simplify them into 187 industries classified in the IO table. Appendix B provides details of the data construction process.

In the supply-chain data described above, the degree, or the number, of links of firms follows a power-law distribution (Figure A.1), as often found in the literature (Barabasi, 2016). The average of the path length between firms, or the number of steps between them through supply chains, is 4.8. This small average path length indicates that the supply chains have a small-world property – in other words, firms are indirectly connected closely through supply chains. Therefore, we would predict that economic shocks propagate quickly through the supply chains. Using the same data set, previous studies (Fujiwara and Aoyama, 2010; Inoue and Todo, 2019) find that 46–48% of firms are included in the ‘giant strongly connected component’ (GSCC), in which all firms are indirectly connected to each other through supply chains. The large size of the GSCC shows prominently that the network has numerous cycles and a complex nature, which is unlike the common image of a layered supply-chain structure.

### 3. Method

#### 3.1 Model

Our simulation employs the dynamic agent-based model of Inoue and Todo (2019), an extension of the model of Hallegatte (2008), which assumes supply chains at the firm level. In the model, each firm utilises inputs purchased from other firms to produce an output and sells it to other firms and consumers. Supply chains are pre-determined and do not change over time in the following two respects. First, each firm utilises a firm-specific set of input varieties and does not change the input set over time. The variety of input is determined by the industry of the producer, and hence firms in a particular industry are assumed to produce the same output. Second, each firm is linked with fixed suppliers and customers and cannot be linked with any new one over time. Further, we assume that each firm keeps inventories of each input at a level randomly determined from the Poisson distribution. Following Inoue and Todo (2019), where parameter values are calibrated from the case of the Great East Japan Earthquake, we assume that firms target maintaining inventories for nine days of production on average.

When a lockdown directly or indirectly causes a reduction in production of particular firms, the supply of products of these firms to their customer firms declines. One way to keep the current level of production of the customers is to use their inventories of inputs. Alternatively, the customers can procure the input from their other suppliers in the same industry already connected prior to the lockdown, if these suppliers have additional production capacity. If the inventories and inputs from substitute suppliers are insufficient, the customers have to shrink their production because of shortage of inputs. In addition, suppliers of the firms directly affected by the lockdown may have to reduce production because of the reduction of demand from the affected customers. Accordingly, the economic shock propagates both downstream and upstream through supply chains. Appendix C provides details of the model.

#### 3.2 Simulation procedure

In the simulation, we assume that all production activities not essential to citizens' survival (hereafter, referred to as non-essential production activities) in the central part of Tokyo (23 wards, hereafter simply referred to as Tokyo) are shut down for either one day, one week, two weeks, one month, or two months. Essential production activities are defined as those in the wholesale, retail,

utility, transport, storage, communication, healthcare, and welfare sectors.<sup>5</sup> After the lockdown period, all sectors immediately resume production at the same level as in the pre-lockdown period. Because the inventory target of each firm is randomly sampled from the Poisson distribution (Section 3.1), we run five simulations with different sets of the inventory targets of firms for each lockdown duration and average over the five sets of results.

## 4. Result

### 4.1 Benchmark result

When Tokyo is locked down, the value added production of Tokyo immediately becomes almost zero. Because the daily production of non-essential sectors in Tokyo is estimated to be 309 billion yen (approximately \$2.9 billion), the total direct loss of production in Tokyo due to the lockdown is 309 billion yen multiplied by the number of days during the lockdown period. Table 1 shows the direct production loss in Tokyo for each case (second column) and the production loss outside Tokyo due to the propagation effect through supply chains (third column). These results are the averages of the simulations.

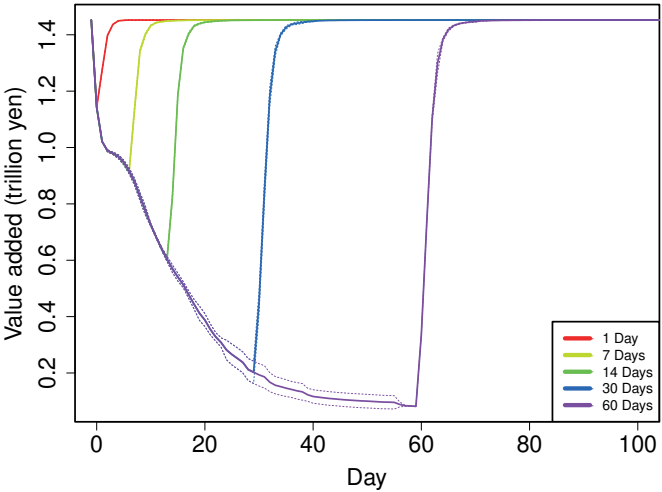
The results indicate that when Tokyo is locked down for only one day, the production loss outside Tokyo, though not locked down, is already 252 billion yen (i.e., 82% of the production loss in Tokyo). When the lockdown continues for a month, the indirect effect on other regions is twice as large as the direct effect on Tokyo, with an estimated total production loss of 27.8 trillion yen, or 5.25% of the annual GDP. In Figure 1, each line shows the dynamics of total daily value added in Japan in each case assuming different lockdown duration. When the lockdown continues for a month, Japan's daily value-added production becomes only approximately one-seventh of that before the lockdown. This implies that even when the initial production loss in Tokyo is small, its propagation effect on other regions can become large as the lockdown is prolonged.

Figure 2 shows temporal and geographical visualisations of the lockdown simulations. The red dots indicate firms whose production is less than or equal to 20% of their capacity, while the light red and orange dots show firms with a more moderate decline in production. The left-hand panel illustrates that a non-negligible number of firms distant from Tokyo are already affected on the first day of the lockdown. Two weeks later, affected firms are spread all over the country, as shown in the right-hand panel. These visualisations support the indirect effect propagating geographically as the lockdown is prolonged.

	Direct effect on Tokyo	Indirect effect on other regions in Japan	Total effect (% of GDP)
1 day	0.309	0.252	0.561 (0.106)
1 week	2.17	1.56	3.72 (0.720)
2 weeks	4.33	5.01	9.34 (1.76)
1 month	9.28	18.5	27.8 (5.25)
2 months	18.6	50.0	68.2 (12.9)

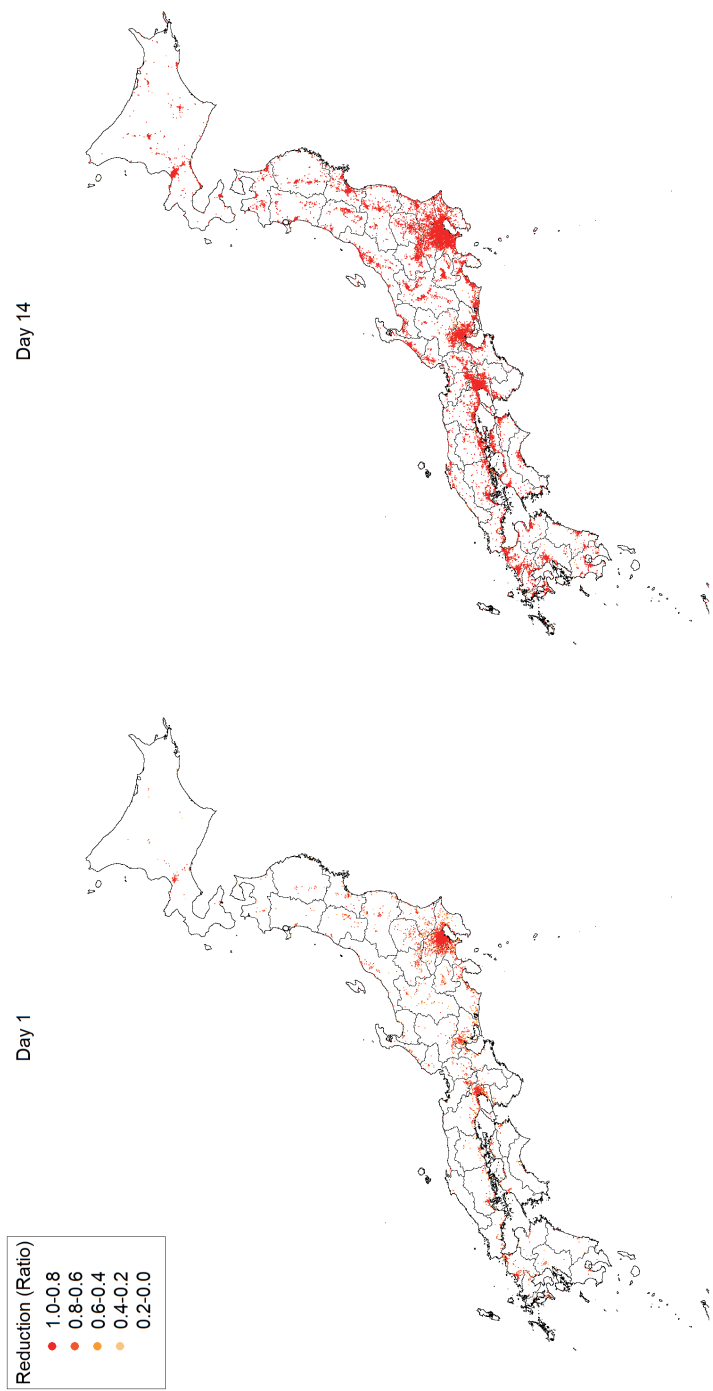
**Table 1**     The loss of value added because of a Tokyo lockdown (trillion yen)

*Notes:* This table shows the results from the simulations assuming shutdown of all non-essential production activities. These results are based on the average of the simulations.



**Figure 1**     The dynamics of daily value added in Japan after the lockdowns of Tokyo

*Notes:* Each line shows the average of five simulations assuming different inventory sizes. The dotted lines show the standard deviations. This figure shows simulation results assuming shutdown of all non-essential production activities.



**Figure 2** Temporal and geographical visualisations of the reduction of the production

*Notes:* The left and right panels show the first day and the 2 weeks after the lockdown respectively. The red and orange dots indicate firms whose actual production is substantially and moderately, respectively, smaller than their capacity before a lockdown. Since there are more than 1 million dots in the original data, we randomly choose 100,000 firms to draw.

## 4.2 Alternative specifications

In addition to the benchmark simulations above, we experiment with two alternative sets of simulations. First, we assume that all production activities, including essential activities, are shut down. Then, the daily production loss in Tokyo is 471 billion yen, 52% larger than that in the benchmark simulations (309 billion yen). However, we find that the total production loss in Japan from a lockdown of Tokyo for a month is 32.0 trillion yen, only 15% larger than that in the benchmark (27.8 trillion yen) (see Appendix D for detail).

Second, we assume that industrial demand is prioritised over consumer demand so that production activities outside Tokyo is less affected. For example, computers can be used both by customer firms for production and citizens for consumption. In the benchmark simulation, when the output of a product is not sufficient because of a lockdown, we assume that the limited output is rationed to customer firms and consumers based on their relative demand prior to the lockdown. However, in this alternative simulation, customer firms are prioritised to maximise production in downstream firms (see Appendix C for detail). Then, we find that a one-month lockdown results in a production loss in Japan of 27.0 trillion yen. Because the production loss does not substantially change from the benchmark result (27.8 trillion yen), we conclude that industry prioritisation is not very effective in alleviating the propagation effect of a lockdown.

## 5. Discussion and conclusion

The simulation results clearly show that the effect of a lockdown of Tokyo quickly propagates to other regions outside Tokyo, leading to a substantial effect on the entire Japanese economy. Although the production of non-essential sectors in Tokyo accounts for 21.3% of the total production in Japan, a lockdown of Tokyo for a month would result in a reduction of the daily production in Japan by 86.1%, or 1.25 trillion yen.

In addition, the effect on other regions becomes progressively larger as the duration of the lockdown becomes longer. When the duration doubles, the production loss more than doubles. In the case of a lockdown for one day, the total loss of value added outside Tokyo is 82% of the loss in Tokyo. However, when the lockdown continues for a month, the loss outside Tokyo is twice as large as the loss in Tokyo. This implies that the effect of a longer lockdown can reach firms that are 'further' from Tokyo along supply chains.

To alleviate the propagation effect through supply chains, one could limit production activities that are shut down or prioritise producers' use of goods and services over consumers' use. However, our results indicate that these measures would not work well, particularly when the duration of the lockdown is long.

Our analysis provides several policy implications. First, because the overall effect of a lockdown of a major city on the entire economy is extremely large when we take into account its propagation effects through supply chains, we should consider lockdowns as the last resort. Instead, we should prevent the spread of Covid-19 earlier using other means and avoid any lockdown of a mega-city. Second, because the total effect of a lockdown progressively increases with its duration, a mega-city lockdown, if it cannot be avoided, should be as short as possible. Policymakers should be aware that policies to alleviate the propagation effect may not work when the lockdown duration is long.

Several caveats of this study should be mentioned. First, we assume that firms cannot find any new supplier when supplies from their suppliers in Tokyo are disrupted, although they can request their existing suppliers outside Tokyo to supply more. This assumption may be too strong in practice, leading to an overestimation of the propagation effect. However, because we particularly examine a short-term lockdown for at most two months, the possible overestimation can be minimal as finding new suppliers in the short period of time is not easy.

Second, the TSR data reports only the location of the headquarter of each firm, not the location of its branches. Because headquarters of firms concentrate in Tokyo, production activities in Tokyo are most likely to be overvalued in our analysis. Therefore, the direct effect of a lockdown of Tokyo may be overestimated while its propagation effect on other regions may be underestimated. Because we still found a large propagation effect despite of this possible underestimation, our key conclusion should remain the same.

Third, because of data limitations, we cannot estimate the propagation effect of a lockdown of Tokyo on economies outside of Japan. Kashiwagi et al. (2018) find no international propagation effect in the case of Hurricane Sandy in the United States, suggesting that substitution for damaged suppliers can alleviate propagation. However, in the case of the spread of Covid-19, because all industrial countries are affected, input substitution across countries is quite difficult. Therefore, we would expect international propagation of the economic effect of a lockdown of a city amid the spread of Covid-19, but quantifying this propagation is beyond the scope of this study.



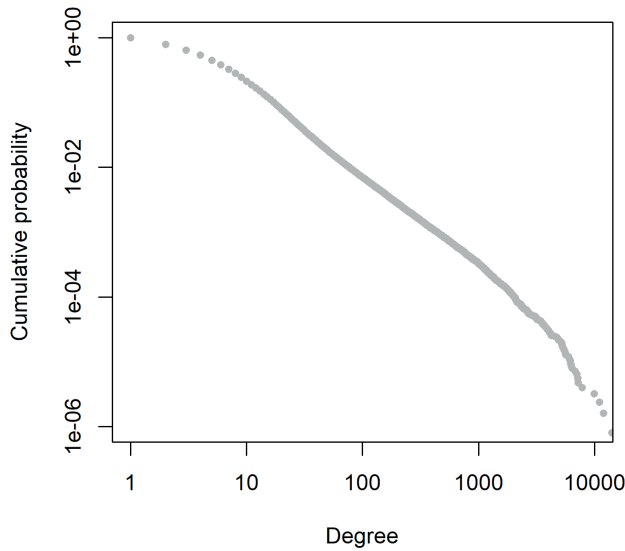
Finally, we should emphasise that this study focuses on the economic effect of a lockdown of a major industrial city, rather than the overall economic effect of Covid-19. In practice, Covid-19 affects economies outside of a mega-city not only through propagation of the effect of the lockdown of that city, but also directly through other restrictions in the region and indirectly through propagation of the effect of lockdowns of foreign cities. Because these effects are not included in our simulation, the total economic effect of Covid-19 can be considerably larger than estimated here.

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### Appendix A: Degree distribution of supply-chain networks



**Figure A.1** Degree distribution of supply chains in Japan

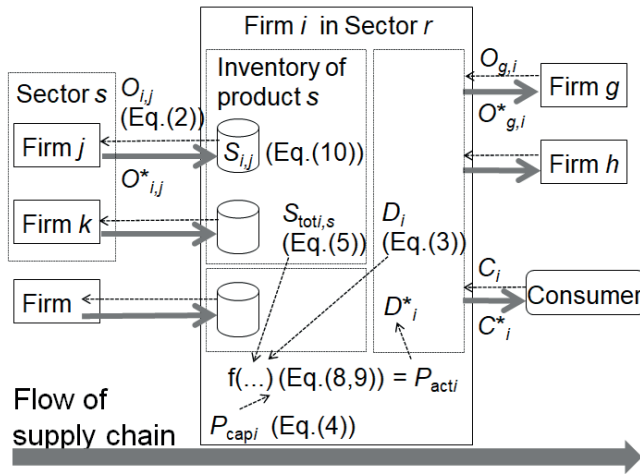
### Appendix B: Data

In the TSR data, the maximum number of suppliers and customers reported by each firm is 24. However, we can capture more than 24 by looking at the supplier–customer relations from the opposite direction. Because the TSR data include the address of the headquarters of each firm, we can identify the longitude and latitude of each headquarters by using the geocoding service provided by the Center for Spatial Information Science at the University of Tokyo.

We estimate the value of each transaction between two firms in two steps. First, we divide each supplier's sales into its customers in proportion to the sales of customers, defining a tentative sales value. Second, we employ the IO table for Japan in 2015<sup>6</sup> to transform these tentative values into more realistic ones. Specifically, we aggregate the tentative values at the firm–pair level to obtain the total sales for each pair of sectors. We then divide the total sales for each sector pair by the transaction values for the corresponding pair in the IO tables. The ratio is then used to estimate the transaction values between firms. The final consumption of each sector is allocated to all firms in the sector, using their sales as weights.

### Appendix C: Model

We rely on the model of Inoue and Todo (2019), an extension of existing agent-based models used to examine the propagation of shocks by natural disasters through supply chains of Hallegatte (2008). Each firm uses a variety of intermediates as inputs and delivers a sector-specific product to other firms and the final consumers. Firms have an inventory of intermediates to deal with possible supply shortages. Figure C.1 provides an overview of the model, showing the flows of products to and from firm  $i$  in sector  $r$ .



**Figure C.1** Overview of the agent-based model

Notes: Products flow from left to right, whereas orders flow in the opposite direction. The equation numbers correspond to those in Appendix 3.1.

In the initial stage before an economic shock, the daily trade volume from supplier  $j$  to customer  $i$  is denoted by  $A_{i,j}$ , whereas the daily trade volume from firm  $i$  to the final consumers is denoted as  $C_i$ . Then, the initial production of firm  $i$  in a day is given by

$$P_{\text{ini}i} = \sum_j A_{j,i} + C_i. \quad (1)$$

On day  $t$  after the initial stage, the previous day's demand for firm  $i$ 's product is  $D_i^*(t-1)$ . The firm thus make orders to each supplier  $j$  so that the amount of its product of supplier  $j$  can meet this demand,  $A_{i,j}D_i^*(t-1)/P_{\text{ini}i}$ . We assume that firm  $i$  has an inventory of the intermediate goods produced by firm  $j$  on day  $t$ ,  $S_{i,j}(t)$ , and aims to restore this inventory to a level equal to a given number of days  $n_i$  of the utilisation of product of supplier  $j$ . The constant  $n_i$  is assumed to be Poisson distributed, where its mean is  $n$ , which is a parameter. That is, when the actual inventory is smaller than its target, firm  $i$  increases its inventory gradually by  $1/\tau$  of the gap, so that it reaches the target in  $\tau$  days, where  $\tau$  is assumed to be six to follow the original model (Hallegatte, 2008). Therefore, the order from firm  $i$  to its supplier  $j$  on day  $t$ , denoted as  $O_{i,j}(t)$ , is given by

$$O_{i,j}(t) = A_{i,j} \frac{D_i^*(t-1)}{P_{\text{ini}i}} + \frac{1}{\tau} [n_i A_{i,j} - S_{i,j}(t)], \quad (2)$$

where the inventory gap is in brackets. Accordingly, total demand for the product of supplier  $i$  on day  $t$ ,  $D_i(t)$ , is given by the sum of final demand from final consumers and total orders from customers:

$$D_i(t) = \sum_j O_{j,i}(t) + C_i, \quad (3)$$

Now, suppose that an economic shock hits the economy on day 0 and that firm  $i$  is directly damaged. Subsequently, the proportion  $\delta_i(t)$  of the production capital of firm  $i$  is malfunctioning, although  $\delta_i(t)$  decreases over time because of the recovery effort, as we explain in the following paragraph. Hence, the production capacity of firm  $i$ , defined as its maximum production assuming no supply shortages,  $P_{\text{cap}i}(t)$ , is given by

$$P_{\text{cap}i}(t) = P_{\text{ini}i}(1 - \delta_i(t)). \quad (4)$$

The production of firm  $i$  might also be limited by the shortage of supplies on day 0. Because we assume that firms in the same sector produce the same product, shortage of supplies suffered by firm  $j$  in sector  $s$  can be compensated for by supplies from firm  $k$  in the same sector. Firms cannot substitute new suppliers for damaged ones after the disaster, as we assume fixed supply chains.

Thus, the total inventory of the products delivered by firms in sector  $s$  in firm  $i$  on day  $t$  is

$$S_{\text{tot}i,s}(t) = \sum_{j \in s} S_{i,j}(t). \quad (5)$$

The initial consumption of products in sector  $s$  at firm  $i$  before the disaster is also defined for convenience:

$$A_{\text{tot}i,s} = \sum_{j \in s} A_{i,j}. \quad (6)$$

The maximum possible production of firm  $i$  limited by the inventory of product of sector  $s$  on day  $t$ ,  $P_{\text{pro}i,s}(t)$ , is given by

$$P_{\text{pro}i,s}(t) = \frac{S_{\text{tot}i,s}(t)}{A_{\text{tot}i,s}} P_{\text{ini}i}. \quad (7)$$

Then, we can determine the maximum production of firm  $i$  on day  $t$ , considering its production capacity,  $P_{\text{capi}}(t)$ , and its production constraints due to the shortage of supplies,  $P_{\text{pro}i,s}(t)$ :

$$P_{\text{max}i}(t) = \text{Min} (P_{\text{capi}}(t), \text{Min}_s(P_{\text{pro}i,s}(t))). \quad (8)$$

Therefore, the actual production of firm  $i$  on day  $t$  is given by

$$P_{\text{act}i}(t) = \text{Min} (P_{\text{max}i}(t), D_i(t)). \quad (9)$$

When demand for a firm is greater than its production capacity, the firm cannot completely satisfy its demand, as is denoted by Equation (9). In this case, firms should ration their production to their customers. We propose a rationing policy in which customers and final consumers are prioritized according to their amount of order after the economic shock to their initial order, rather than they are treated equally as in the previous work (Hallegatte, 2008). Suppose that firm  $i$  has customers  $j$  and a final consumer. Then the ratio of the order from customers  $j$  and the final consumer after the shock to the one before the shock denoted as  $O_{j,i}^{\text{rel}}$  and  $O_c^{\text{rel}}$ , respectively, are determined by the following steps, where  $O_{j,i}^{\text{sub}}$  and  $O_c^{\text{sub}}$  are temporal variables to calculate the realized order and set to be zero initially.

1. Get the remaining production  $r$  of firm  $i$
2. Calculate  $O_{\text{min}}^{\text{rel}} = \text{Min}(O_{j,i}^{\text{rel}}, O_c^{\text{rel}})$
3. If  $r \leq (\sum_j O_{\text{min}}^{\text{rel}} O_{j,i} + O_{\text{min}}^{\text{rel}} C_i)$  then proceed to 8
4. Add  $O_{\text{min}}^{\text{rel}}$  to  $O_{j,i}^{\text{sub}}$  and  $O_c^{\text{sub}}$

5. Subtract  $(\sum_j O_{\min}^{rel} O_{j,i} + O_{\min}^{rel} C_i)$  from  $r$
6. Remove the customer or the final consumer that indicated  $O_{\min}^{rel}$  from the calculation
7. Return to 2
8. Calculate  $O^{rea}$  that satisfies  $r = (\sum_j O^{rea} O_{j,i} + O^{rea} C_i)$
9. Get  $O_{j,i}^* = O^{rea} O_{j,i} + O_{j,i}^{sub} O_{j,i}$  and  $C_i^* = O^{rea} C_i + O_c^{sub} C_i$ , where the realized order from firm  $j$  to supplier  $i$  is denoted as  $O_{j,i}^*(t)$ , and the realized order from a final consumer is  $C_i^*$
10. Finalize the calculation

The above rationing is used for the benchmark simulations. In the alternative specification with priority of industry, we use the same algorithm but final consumers are excluded from the calculation. Instead, only when all demand of the customer firms are fulfilled, the remaining production after rationing customer firms is assigned to the final consumer.

Under this rationing policy, total realized demand for firm  $i$ ,  $D_i^*(t)$ , is given by

$$D_i^*(t) = \sum_j O_{i,j}^*(t) + C_i^*, \quad (10)$$

where the realized order from firm  $i$  to supplier  $j$  is denoted as  $O_{i,j}^*(t)$  and that from the final consumers is  $C_i^*$ . According to firms' production and procurement activities on day  $t$ , the inventory of firm  $j$ 's product in firm  $i$  on day  $t + 1$  is updated to

$$S_{i,j}(t + 1) = S_{i,j}(t) + O_{i,j}^*(t) - A_{i,j} \frac{P_{acti}(t - 1)}{P_{ini}}. \quad (11)$$

**Appendix D Results from alternative specifications**

<b>Direct effect on Tokyo</b>		<b>Indirect effect on other regions in Japan</b>	<b>Total effect (% of GDP)</b>	<b>Total effect difference with benchmark</b>
<b>A. All production activities are shut down</b>				
1 day	0.471	0.349	0.820 (0.155)	0.259
1 week	3.30	1.58	4.88 (0.922)	1.16
2 weeks	6.60	4.88	11.47 (2.17)	2.13
1 month	14.1	17.8	31.96 (6.04)	4.16
2 months	28.3	44.5	72.74 (13.7)	4.54
<b>B. Producers' use is prioritised over final consumers' use</b>				
1 day	0.309	0.252	0.561 (0.106)	-9.06×10 <sup>-4</sup>
1 week	2.17	1.53	3.69 (0.700)	-3.09×10 <sup>-3</sup>
2 weeks	4.33	4.87	9.20 (1.74)	-2.27
1 month	9.28	17.7	27.0 (5.09)	-4.96
2 months	18.6	47.9	66.4 (12.5)	-6.34

**Table D.1** The loss of value added because of a Tokyo lockdown on alternative specifications (trillion yen)

# Mitigating the work-safety trade-off<sup>1</sup>

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*How many jobs can be carried out without putting workers at risk of contracting Covid-19? And how many of these jobs can be activated as soon as the most severe restrictions to mobility will be lifted? To which extent do these jobs belong to the chain involved in the war against Covid-19? In this paper, we aim to provide preliminary answers to these questions drawing on the case of Italy, the first Western country to be hit by the pandemic.*

In this war, timing is essential. Italy was the first Western country to be hit by the pandemic, and will likely be the first that is able to lift its most restrictive confinement measures. Four weeks down the road in the lockdown, with a health system almost at the limits of its capacity and some evidence that we are beyond the peak in the contagion, it is necessary to think of ways to mitigate the work-safety trade-off and mobilise labour for the war against Covid-19.

Three issues are particularly relevant in this context:

1. How many jobs can be carried out while guaranteeing safety at work under the threat of coronavirus?
2. How many of these jobs can be activated as soon as the most severe restrictions to mobility are lifted?
3. How many of these 'safe' jobs are essential in fighting the war against Covid-19?

<sup>1</sup> We would like to thank an anonymous referee for comments that greatly improved our initial draft.

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In this paper, we offer some preliminary answers and hints to how this analysis can be extended to other countries. In the absence of real-time data on how firms and workers are adjusting to the crisis, our estimates are necessarily based on data collected in ‘normal times’. Evidence on behaviours adopted by firms and industries, such as the provision of protective gear, may affect our conclusions, which must therefore be interpreted as a lower-bound on the number of jobs that can *potentially* be carried out under the current circumstances.

## 1. How many jobs are safe under the epidemic?

Working from home is obviously the safest way to perform your job without incurring the risk of becoming infected. Although this risk is never zero, precautionary measures that do not interfere with the work itself can be envisaged (e.g., living separately from family members who work outside and can thus be a vehicle of contagion).

But how many jobs can be carried out remotely? In most countries, the share of workers covered by teleworking or smart working arrangements (including fully working from home) in normal times is below 10% (Eurofound and ILO, 2017). The confinement has induced the spread of these arrangements among persons that so far were only mildly involved in this organisation of work. For instance, in Italy, 7 out of 10 managers interviewed in a survey carried out at the beginning of March 2020 by a managerial association (Manageritalia) declared having adopted smart working practices for their employees; this was the first experience of this kind for about 40% of the workers involved. Taking the survey data at face value, we may expect that the number of workers involved has increased to reach about 15% of employment in the average EU country.

The crucial issue is, however, how many jobs can *potentially* be carried out remotely. In order to answer this question, we use the O-Net (Occupational Information Network) classification, listing 968 occupations and describing to what extent they require personal contact. Unfortunately, O-Net does not specify whether face-to-face contact is required or whether it can also be done online or at least at a distance, preventing Covid-19 contagion. We therefore had to complement the O-Net classification with information from a survey of the Italian Statistical Office and INAPP (<http://fabbisogni.isfol.it/>) and our own personal assessment. In particular, we classified every occupation listed in O-Net according to whether or not it could be carried out remotely. As the EU Labor Force Survey uses the ISCO classification, we mapped the O-Net coding onto ISCO, passing through the SOC classification for which we had conversion tables available. Whenever there was no one-to-one correspondence, we weighted averages using the US employment shares for each O-Net occupation between

2012 and 2014. This procedure should be able to deliver estimates that take into account the current level of technology and ICT present in occupations, without being based on US technology levels or on any specific dataset.

The results of this exercise are displayed in Table 1, which reports the share of jobs that can be carried out from home (online or through other means). We label these jobs as type 1 jobs. These jobs are mainly concentrated in services. Professors, engineers, lawyers, architects are just some examples of the occupations included in this category.<sup>5</sup> Within manufacturing, type 1 jobs concern mainly administrative and marketing activities. In Italy, manufacturing jobs account for around 20% of all jobs, whereas they account for only 11% of our type 1 jobs. Indeed, only 14% of all manufacturing jobs in Italy belong to type 1. A similar pattern is detected for the construction industry, with only 7% of all construction jobs included this category.

Country	Share of type 1 jobs (work from home)
Italy	23.95%
France	28.22%
Germany	28.70%
Spain	25.44%
Sweden	30.74%
UK	31.38%

**Table 1** Share of type-1 jobs in selected countries

## **2. How many more jobs are there with limited mobility and safe personal face-to-face contact?**

As soon as the most restrictive confinement measures are lifted, it will be possible to carry out a wider range of occupations. In particular, this will include jobs involving (i) limited mobility away from home and no personal contact (veterinarians, animal caretakers, foresters and conservation workers, archivists, jewellers, chemists, etc.); and (ii) limited mobility and infrequent and

<sup>5</sup> Indeed, professional and scientific activities are overrepresented in this category: workers in these occupations account for 17% of type 1 jobs, whereas they represent a share of around 6% of all Italian occupations. Sixty-four percent of professional and scientific occupations belong to type 1, almost twice the average across all industries reported in Table 2.

safe face-to-face contact (mechanics, plumbers, electricians, drivers, etc.). Table 2 offers our estimates (obtained with the same methodology adopted in the measurement of the potential for smart working) for two categories of jobs: type 2 jobs can be carried out by relaxing the mobility constraint but not the personal face-to-face contact, while type 3 relaxes both the mobility and the face-to-face constraint (assuming that these contacts are infrequent and interactions can happen at a safe distance).

Country	Share of type 2 jobs (relaxing the mobility constraint)	Share of type 3 jobs (relaxing the no-contact constraint)
Italy	31.27%	46.23%
France	32.80%	47.87%
Germany	32.93%	48.93%
Spain	29.05%	42.93%
Sweden	34.33%	49.17%
UK	34.63%	47.71%

**Table 1** Share of type-2 and type-3 jobs in selected countries

Overall, even after allowing for limited face-to-face contact, the share of ‘safe’ jobs remains below 50% in all countries for which we carried out this exercise.

### **3. To what extent would these jobs contribute to fighting the war against Covid-19?**

Unfortunately, the fraction of safe jobs is particularly low in most of the strategic industries involved in the war against coronavirus, notably those that could help enhance capacity in the health sector, such as the manufacturing of basic pharmaceutical products, pharmaceutical preparations, electromedical and measuring equipment and medical instruments and supplies. These industries amount to around 1% of all jobs in Italy (0.86% to be precise) and are slightly underrepresented among type 1 jobs, but not among type 2 or type 3 jobs.

The higher prevalence among type 2 and 3 jobs is probably due to the fact that some activities in these industries need to be carried out in laboratories or other controlled environments where contact among workers is very limited, but cannot be performed from home. The downside is that, while the aim is for production to increase in order to supply sufficient equipment to face this

emergency, the increase is likely to be limited given the context in which workers in these industries operate. Land availability is a major factor preventing more dispersed assembly lines, and even more so in this specific case. Expanding production will require some reconversion of assembly lines that currently produce other goods<sup>6</sup> and further investment in automation. Ironically, the robots and machines that are creating a lot of anxiety among workers over the future of their jobs are becoming, under Covid-19, a way to preserve labour, by allowing workers to operate assembly lines from a distance and by creating more jobs in maintenance and supervisory roles.

As we stressed at the start of this paper, evaluating the speed at which investments in automation or other forms of reorganisation of assembly and production lines are occurring is impossible with the currently available data. Scaling up real-time data collection is therefore essential, not only to better evaluate how the epidemic is spreading – as rightly pointed out by Bloom and Canning (2020) and Dewatripont et al. (2020) – but also for evaluating the possibility of lifting the current restrictions on economic activity.

But how advanced is automation in manufacturing? Clearly the answer varies from country to country. In Italy, a survey carried out by the statistical office together with the employers' association suggested that 19.3% of firms in manufacturing with 10 or more employees use robotics in their activities. The broad sector including the industry producing equipment for the health sector (manufacturing of computer, clocks, optical products, electromedical and measuring equipment) displays an incidence of robotics in line with the average (19.0%).

Another option to sustain the necessary levels of production is to allow younger workers to go back to work, as they appear to have a much lower risk of contracting severe forms of Covid-19-related diseases. There are, however, a few problems with this strategy.

First, we estimate that only one out of four 'unsafe' jobs (the complement to the three categories described above) are currently held by workers aged under 35, which limits the scope for sustaining production via this channel. Moreover, many young people – in Italy even more than in other countries – live with their parents, and could therefore contaminate more vulnerable people if they resumed work. As almost 60% of young workers in 'unsafe' occupations still live with their parents or older relatives, only about 10% of the unsafe jobs can be reactivated by young workers without running a substantial risk of increasing

6 Anecdotal evidence tells us that this is already happening, with some textile companies starting to produce masks rather than clothes, for instance.

even further the death toll of Covid-19. Indeed, as suggested by Anelli et al. (2020), in principle one should separate the young workers who go back to work from the elderly and the immunocompromised.

Second, young people are over-represented in occupations that can more easily be carried out under teleworking or smart-working arrangements, i.e. the only jobs that can be carried out even under full confinement. This is not surprising, as young workers are more familiar with the ICT devices that are often a prerequisite for smart-working. There would therefore be a potential production loss in other sectors if we were to reallocate young people from their current jobs to 'unsafe' jobs in strategic industries.

This is essentially a mismatch problem: we would like the elderly to have jobs that can be carried out from home, rather than the young. One possibility for solving this problem could be to mobilise workers who have been put in short-time work or on temporary unemployment benefit. The former could be allowed to take up temporarily jobs in the strategic sector without losing the option to go back to their original occupation when the emergency is over (Giupponi and Landais, 2020). This reallocation can be encouraged by integrating even further the income of the short-time workers, which means that we would combine income support provision with a wage subsidy for strategic industries.

#### **4. Final remarks**

Summarising, the share of jobs that can be performed without putting workers at risk of contracting Covid-19 is limited, and probably does not reach 50%. Importantly, the share is no higher in strategic industries that supply the health sector. There seems, therefore, to be scope for automation in many industries, especially in those that need to scale up capacity. Young workers could be mobilised in these industries as they are at less risk from Covid-19, but they are under-represented in 'unsafe' jobs and are over-represented in jobs that can be carried out via smart-working. A possible solution to this mismatch would be to re-sort young workers in short-time work or on temporary unemployment benefit. They could also be usefully employed in cases of labour shortages in firms that have shifted their production lines towards strategic equipment requested by the health sector.

What do these employment numbers mean in terms of value added? Being mainly service jobs and involving more skilled labour, they may account for more in value than is proportionate to their employment share. However some productivity losses are to be expected in the transition, as putting people back to work in a world in which Covid-19 has not yet been eradicated will likely require profound changes in the organisation of work. Remote working is one extreme

example, and one which has already been investigated in normal times (e.g., Blinder and Krueger, 2013; Bloom et al., 2015; Angelici and Profeta 2020), but jobs that we have categorised as type 2 or type 3 will also probably need to be carried out differently than before. The impacts on productivity, at least in the short-medium term, are likely to be negative, as workers will have to adapt to different ways of working.

Finally, we would like once more to emphasise that our exercise returns lower-bound estimates. Indeed, the news are full of anecdotal evidence on firms and sectors already providing their workers with equipments, protection gear and working barriers in order to continue the production reducing the risk of contagion. To our knowledge, no representative data that would allow us to take this important aspect into consideration more formally are presently available. Ad hoc surveys of households and, most importantly, on establishments would be required, but they cannot be conducted under the current circumstances.

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# Fiscal policy during a pandemic

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*I use a dynamic stochastic general equilibrium model to study the effects of the 2019-20 coronavirus pandemic in the US. The pandemic is modelled as a large negative shock to the utility of consumption of contact-intensive services. General equilibrium forces propagate this negative shock to the non-services and financial sectors, triggering a deep recession. I use a calibrated version of the model to analyse different types of fiscal policies: (i) government purchases, (ii) income tax cuts, (iii) unemployment insurance benefits, (iv) unconditional transfers, and (v) liquidity assistance to service firms. I find that UI benefits are the most effective tool to stabilize income for borrowers, who are hit the hardest, while savers favour unconditional transfers. Liquidity assistance programs are effective if the policy objective is to stabilize employment in the affected sector.*

## 1. Introduction

The ongoing COVID-19 outbreak is causing widespread disruption in the world's advanced economies. Monetary authorities were quick to react, with the Federal Reserve and other major central banks returning to their 2008-09 Financial Crisis toolkits. Following these steps, fiscal authorities around the globe are in the process of designing and approving stabilization packages to help sustain household and firm balance sheets.

<sup>1</sup> Economist, Federal Reserve Bank of St. Louis. I thank, without implicating, Bill Dupor for a conversation that inspired this paper. Thanks to Michael Boutros for helpful suggestions. The views expressed here are those of the author and do not necessarily reflect the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System. First version: March 18, 2020. Contact: miguel.fariaecastro@stls.frb.org.

In this paper, I adapt a macroeconomic model in order to simulate the macroeconomic effects of a pandemic and to study the effects of different types of fiscal policy instruments. The pandemic is modelled as a sudden stop of the contact-intensive service sector. The shutdown of this sector propagates to the non-service sector through aggregate demand externalities, and to the financial sector through balance sheet linkages. The rise in unemployment leads to a wave of defaults, disrupting financial intermediation and amplifying the recession. The pandemic scenario is pessimistic: the shock lasts for three quarters (through the end of 2020) and results in an unemployment rate of about 20%. Borrower households, who derive most of their income from employment and rely on bank credit to fund consumption, are the most affected group.

I use a calibrated version of the model to study the effects of different types of discretionary fiscal policy: (i) an increase in non-service government purchases, (ii) a decrease in the income tax, (iii) an expansion of unemployment insurance (UI), (iv) an unconditional transfer, (v) payment of wages by the government to service firms.

In terms of measuring the effectiveness of different policies the traditional concept of the GDP multiplier might not be appropriate in this context. The shut-down of economic activity is largely intentional as it is part of pandemic suppression measures, and focusing on GDP stabilization could be detrimental in fighting the pandemic. For that reason, I evaluate different policies based on consumption and household income multipliers, which measure the dollar impact of fiscal spending on consumption of either type of household, and on labour income net of government transfers. I find that there is considerable variation in the distribution effects of different types of policies. Borrowers, who are most affected by the crisis, receive a larger consumption boost from policies that resemble cash transfers, such as an increase in UI benefits. I find that unconditional transfers of the type that are currently being proposed generate similar distributional effects, with the added benefit of a potentially less costly implementation. Finally, I show that liquidity assistance to firms yields weaker effects on household income and consumption per dollar spent, but can be very effective if maintaining employment levels in the affected sector is a policy objective.

Finally, it is worth noting that the pandemic scenario is assumed to be a completely exogenous shock to the economy. In practice, it is likely that the most effective type of fiscal policy would be one that targets the underlying source of the shock, i.e. investment in public health measures related to prevention, suppression, mitigation, and/or cure.



## 1.1 Literature

The exercise in this paper is very similar to the analysis conducted by Drautzburg and Uhlig (2015) and Taylor (2018) for the American Recovery and Reinvestment Act of 2009, where the authors use a dynamic stochastic general equilibrium (DSGE) model to simulate a recession scenario and then consider the effects of a policy package. Faria-e-Castro (2018) conducts a similar analysis, while also taking into account financial sector interventions that involved asset purchases such as in the Trouble Asset Relief Program (TARP). I mostly abstract from issues related to financial sector interventions in this paper.

This paper also contributes to the literature on modelling a pandemic in a macroeconomic model. Fornaro and Wolf (2020) study how monetary and fiscal policy can be used to respond to the current pandemic by preventing the economy from falling into stagnation traps following persistent negative shocks to productivity growth. Eichenbaum et al. (2020) embed a canonical epidemiology model (the SIR model) in a real business cycle model. Since they endogenize the dynamics of the epidemic, their model allows them to study optimal health policy responses. They find that a severe recession, generated by agents' optimal decision to cut back on consumption and hours worked, helps reduce the severity of the epidemic. My analysis is complementary to theirs: I take the epidemic as exogenous and given, and study how a fiscal authority can help stabilize income and consumption during the epidemic.

Section 2 presents the model, section 3 explains the calibration and describes the modelling of a pandemic, section 4 discusses fiscal policy, and section 5 concludes with an extensive discussion of the caveats of the present analysis.

## 2. Model

Time is discrete and infinite. There are two types of households: borrowers and savers. Financial intermediaries use deposits raised from savers as well as their own retained earnings to finance loans to borrowers. There are two sectors in this economy: a non-service sector (sector  $n$ ), and a service sector (sector  $a$ ). Labour markets are frictional in reduced form, and employment is demand-determined in both sectors. A central bank sets the interest rate, and a fiscal authority collects taxes and has the possibility to undertake different types of discretionary interventions.

The model is adapted from Faria-e-Castro (2018) and many of its elements are standard in tractable heterogeneous agent (TANK) models. For this reason, I mostly focus on what is different.

## 2.1 Households

There are two types of households in fixed types: borrowers in mass  $\chi$  and savers in mass  $1 - \chi$ .

### 2.1.1 Borrowers, debt, and default

There is a representative borrower family that consists of a continuum of agents  $i \in [0, 1]$ . Each of these agents can be employed in the  $n$ -sector, employed in the  $a$ -sector, or unemployed. Let  $N_t^{n,b}, N_t^{a,b}$  denote the mass of agents working in the  $n$ - and  $a$ -sectors, respectively, and let  $1 - N_t^{a,b} - N_t^{n,b}$  denote the mass of unemployed agents.

To generate realistic default rates in the context of a representative agent model, I assume that the members of the borrower household are subject to a cash-in-advance constraint and liquidity shocks. The borrower family enters the period with a stock of debt to be repaid equal to  $B_{t-1}^b$ . Each member of the household is responsible for repaying an equal amount  $B_{t-1}^b$  at the beginning of the period. At this point, the only available resources are labour income, net government transfers, and a liquidity shock  $\varepsilon_t(i) \sim F^e, F^u$ , where  $F^e, F^u$  are distributions with support on the real line.<sup>2</sup> Total cash in hand is therefore given by

$$\mathbb{1}[i \in N_t^{n,b}]w_t^n(1 - \tau_t^l) + \mathbb{1}[i \in N_t^{a,b}]w_t^a(1 - \tau_t^l) + \mathbb{1}[i \notin N_t^{n,b}, N_t^{a,b}]ui_t + T_t^b + \varepsilon_t(i)$$

where  $T_t^b$  is an unconditional transfer from the government, and  $ui_t$  is unemployment insurance. Default is liquidity-based: agent  $i$  compares cash-in-hand to the required repayment  $B_{t-1}^b$  and defaults if she does not have enough resources to repay. This allows me to define three thresholds that determine default rates for each of the possible employment states,

$$\begin{aligned}\varepsilon_t^a &= \frac{B_{t-1}^b}{\Pi_t} - w_t^a(1 - \tau_t^l) - T_t^b \\ \varepsilon_t^n &= \frac{B_{t-1}^b}{\Pi_t} - w_t^n(1 - \tau_t^l) - T_t^b \\ \varepsilon_t^u &= \frac{B_{t-1}^b}{\Pi_t} - ui_t - T_t^b\end{aligned}$$

The total default rate is then given by

$$F_t^b = N_t^{a,b}F^e(\varepsilon_t^a) + N_t^{n,b}F^e(\varepsilon_t^n) + (1 - N_t^{a,b} - N_t^{n,b})F^u(\varepsilon_t^u)$$

After default decisions are made, the borrower household jointly takes all other relevant decisions at the household level. The borrower solves the following program,

$$V_t^b(B_{t-1}^b) = \max_{C_t^b, B_t^b} u(C_t^b) + \beta^b \mathbb{E}_t V_{t+1}^b(B_t^b)$$

s.t.

$$C_t^b + \frac{B_{t-1}^b}{\Pi_t}(1 - F_t^b) = N_t^{a,b} w_t^a(1 - \tau_t^l) + N_t^{n,b} w_t^n(1 - \tau_t^l) + (1 - N_t^{a,b} - N_t^{n,b}) \text{ui}_t + T_t^b + Q_t^b B_t^b$$

$$B_t^b \leq \Gamma$$

where  $C_t^b$  is non-service consumption, the first constraint is the budget constraint, and the second constraint is a borrowing constraint expressed in terms of a limit to total repayment.

### 2.2.2 Savers

Savers also supply labour to both sectors. They save in government bonds and bank deposits, and own all firms and banks in this economy. Additionally, they derive utility from consumption in the service sector,  $C_t^a$ . They solve the following problem,

$$V_t^s(D_{t-1}, B_{t-1}^g) = \max_{C_t^s, C_t^a, B_t^g, D_t} u(C_t^s) + \alpha_t \frac{(C_t^a)^{1-\sigma_a}}{1-\sigma_a} + \beta^s \mathbb{E}_t V_{t+1}^s(D_t, B_t^g)$$

s.t.

$$C_t^s + p_t^a C_t^a + Q_t(D_t + B_t^g) = N_t^{a,s} w_t^a(1 - \tau_t^l) + N_t^{n,s} w_t^n(1 - \tau_t^l)$$

$$+ (1 - N_t^{a,s} - N_t^{n,s}) \text{ui}_t + \frac{B_{t-1}^g + D_{t-1}}{\Pi_t} + (1 - \tau^k) \mathcal{P}_t - T_t + T_t^b$$

where  $p_t^a$  is the price of  $a$ -sector goods in terms of the numeraire (final  $n$ -goods),  $D_t$  is bank deposits,  $B_t^g$  is government debt, and  $\Pi_t$  is the inflation rate in terms of non-service goods.  $P_t$  are total profits from firms and banks, which are taxed at some flat rate  $\tau^k$ . I assume that deposits are safe, hence they pay the same return as government bonds.  $T_t$  is a lump-sum tax paid to the government. It is useful to define the stochastic discount factor (SDF) of savers as

$$\Lambda_{t+1}^s = \beta^s \frac{u'(C_{t+1}^s)}{u'(C_t^s)}$$

Finally,  $\alpha_t$  is a shock to the utility derived from the consumption of services. This shock plays an important role in what follows. Demand for services is given by

$$C_t^a = \left[ \alpha_t \frac{1}{p_t^a u'(C_t^s)} \right]^{1/\sigma_a}$$

## 2.2 Financial intermediaries

Financial intermediaries are modelled following Gertler and Karadi (2011). There is a continuum of intermediaries indexed by  $j$  that take deposits from savers and issue loans to borrowers. Intermediation is subject to two important frictions: first, there is a market leverage constraint which imposes that the value of the intermediary's assets does not exceed a multiple of its market value. Second, the intermediary must pay a fraction  $1 - \theta$  of its earnings as dividends every period. The problem of an intermediary is

$$\begin{aligned} V_t^k(D_{t-1}(j), B_{t-1}^b(j)) &= \max_{B_t(j), D_t(j)} (1 - \theta)\pi_t(j) + \mathbb{E}_t \Lambda_{t+1}^s V_{t+1}^k(D_t(j), B_t^b(j)) \\ \text{s.t.} \\ Q_t^b B_t^b(j) &= \theta \pi_t(j) + Q_t D_t(j) \\ \kappa Q_t^b B_t^b(j) &\leq \mathbb{E}_t \Lambda_{t+1}^s V_{t+1}^k(D_t(j), B_t^b(j)) \\ \pi_t(j) &= (1 - F_t^b) \frac{B_{t-1}^b(j)}{\Pi_t} - \frac{D_{t-1}(j)}{\Pi_t} \end{aligned}$$

The value of the intermediary is equal to dividends paid today, a fraction  $1 - \theta$  of its earnings, plus the continuation value. The first constraint is a balance sheet constraint: assets must be financed with either retained earnings or deposits. The second constraint is a market leverage constraint: bank assets cannot exceed a multiple  $1/\kappa$  of ex-dividend bank value. Finally, the third constraint is the law of motion for earnings: the bank earns revenues for non-defaulted loans and must pay out previously borrowed deposits.

It is possible to show that the value function is homogeneous of degree one in earnings, and hence allows for aggregation. That is, letting  $\pi_t$  be the relevant state variable, I can show that  $V_t^k(\pi_t(j)) = \Phi_t \theta \pi_t(j)$ , and that  $\Phi_t$  is the same for all banks. Define aggregate retained earnings as

$$E_t = \theta \left[ (1 - F_t^b) \frac{B_{t-1}^b(j)}{\Pi_t} - \frac{D_{t-1}(j)}{\Pi_t} \right] + \varpi$$

where  $\varpi$  is a small (gross) equity injection from savers. Then, I can work with a representative bank that has retained earnings equal to  $E_t$ .

The first-order condition for lending takes the form

$$\mathbb{E}_t \frac{\Lambda_{t+1}^s}{\Pi_{t+1}} (1 - \theta + \theta \Phi_{t+1}) \left[ \frac{1 - F_{t+1}^b}{Q_t^b} - \frac{1}{Q_t} \right] = \mu_t \kappa$$

where  $\mu_t$  is the Lagrange multiplier on the leverage constraint, and

$$\frac{\Lambda_{t+1}^s}{\Pi_{t+1}}(1 - \theta + \theta\Phi_{t+1}) \equiv \Omega_{t+1}$$

is the bank's SDF. When the constraint binds  $\mu_t > 0$ , this generates excess returns on lending over and above what would be warranted by pure credit risk. The constraint will typically bind when the bank is undercapitalized, i.e. when its value is low. Binding constraints allow the bank to recapitalize itself by generating a positive wedge between the cost of borrowing  $1/Q_t$  and the return on lending  $(1 - F_{t+1}^b)/Q_t^b$ . This means that banks tend to lend less and at higher interest rates when they are in bad shape.

### 2.3 Production

There are two sectors in this economy: non-service and service sector.

#### 2.1.1 Non-service sector

The  $n$ -sector is the largest sector in this economy, and  $n$ -sector final goods work as the numeraire. This sector operates like the single sector in a standard New Keynesian model. Goods in the  $n$ -sector are produced by a continuum of producers that operate under monopolistic competition and are subject to costs when adjusting their prices. The final-goods aggregator for  $n$ -sector intermediates is

$$Y_t = \left[ \int_0^1 Y_t(l)^{\frac{\epsilon-1}{\epsilon}} dl \right]^{\frac{\epsilon}{\epsilon-1}}$$

Firms in the  $n$ -sector operate a linear technology that produces variety  $l$  using labour,

$$Y_t(l) = A_t N_t^n(l)$$

where  $A_t$  is an aggregate total factor productivity (TFP) shock. They sell their good at price  $P_t(l)$  and face adjustment costs a la Rotemberg (1982),

$$d[P_t(l), P_{t-1}(l)] = Y_t \frac{\eta}{2} \left[ \frac{P_t(l)}{P_{t-1}(l)\Pi} - 1 \right]^2$$

where  $\eta$  measures the degree of nominal rigidity and  $\Pi$  is steady state inflation (indexing). From the aggregator, each producer faces a demand curve given by  $Y_t(l) = [P_t(l)/P_t]^{-\epsilon} Y_t$ , where  $P_t$  is the price level for  $n$ -sector goods. Standard derivations together with imposing a symmetric equilibrium in price-setting yield a New-Keynesian Phillips Curve

$$\eta \mathbb{E}_t \left\{ \Lambda_{t+1}^s \frac{Y_{t+1}}{Y_t} \frac{\Pi_{t+1}}{\Pi} \left( \frac{\Pi_{t+1}}{\Pi} - 1 \right) \right\} - \epsilon \left( \frac{\epsilon - 1}{\epsilon} - \frac{w_t^n}{A_t} \right) = \eta \frac{\Pi_t}{\Pi} \left( \frac{\Pi_t}{\Pi} - 1 \right)$$

where  $\frac{w_t^n}{A_t}$  is the real marginal cost. Aggregate production in this sector is

$$Y_t^n = A_t N_t^n [1 - d(\Pi_t)]$$

where  $d(\Pi_t)$  are resource costs from price adjustment.

### 2.2.2 Service sector

The service sector is smaller and operates differently. There is a continuum of firms indexed by  $k$ . At the beginning of the period, each firm observes the aggregate state and draws an idiosyncratic cost shock  $c \sim H \in [0, \infty)$ . It may choose to exit or operate and produce. If it exits, it receives a payoff of zero. If it operates, it hires one unit of labour and produces one unit of service output. Its value is

$$V_t^a(A_t) = p_t^a A_t - w_t^a + T_t^a w_t^a + \mathbb{E}_t \Lambda_{t+1}^s \int_c \max\{0, V_{t+1}^a(A_{t+1}) - c\} dH(c)$$

It is possible to show that there exists a threshold  $\bar{c}_t(A_t)$  such that a firm decides to operate if its costs are below this threshold, and exit otherwise. This threshold is  $\bar{c}_t(A_t) = V_t^a(A_t)$ . Every period, firms that exit are replaced by an equal mass of entrants so that the total number of firms is constant and equal to 1. Entrants cannot produce in the first period, and do not draw a shock either. The mass of active firms is therefore given by

$$H_t^a = H[\bar{c}_t(A_t)]$$

Since each firm hires one worker, this will also be the total demand for labour in this sector. Total output from this sector is therefore given by

$$Y_t^a = A_t H_t^a$$

### 2.3.3 Labour markets

Since there is no disutility of work, I assume that both savers and borrowers supply as much labour as firms demand. I assume reduced-form rules for wages in each sector,

$$w_t^n = \xi^n A_t (N_t^n)^\zeta$$

$$w_t^a = \xi^a A_t (N_t^a)^\zeta$$

where  $\xi^n$ ,  $\xi^a$  are sector-specific constants. Wages co-move with labour productivity  $A_t$ , and respond to a measure of market tightness in each sector. Similar wage rules could be derived from more complicated models that make labour market frictions explicit (Christiano et al. 2016, McKay and Reis 2016). I assume that labour is rationed in equal proportion among savers and borrowers such that

$$\begin{aligned} N_t^{b,a} &= N_t^{s,a} = N_t^a \\ N_t^{b,n} &= N_t^{s,n} = N_t^n \end{aligned}$$

## 2.4 Fiscal and monetary policy

### 2.1.1 Central bank

The central bank follows a standard Taylor rule subject to an explicit zero lower bound,

$$\frac{1}{Q_t} = \max \left\{ 1, \left( \frac{\Pi_t}{\bar{\Pi}} \right)^{\phi_\Pi} \left( \frac{p_t^a}{p_{t-1}^a} \right)^{\phi_a} \left( \frac{GDP_t}{\bar{GDP}} \right)^{\phi_{GDP}} \right\}$$

I allow the central bank to respond to fluctuations in inflation in the n (numeraire) sector and in the services sector. GDP is defined as

$$GDP_t = Y_t^n + p_t^a Y_t^a$$

### 2.2.2 Fiscal authority

The fiscal authority has outflows related to non-service consumption  $G_t$ , unemployment insurance  $ui_t$ , and debt repayments  $B_{t-1}^g/\Pi_t$ . Its inflows are labour income/payroll taxes  $\tau_t^l(w_t^a N_t^a + w_t^n N_t^n)$ , capital income/profit taxes  $\tau_t^k P_t$ , debt issuance  $B_t^g$ , and lump-sum taxes  $T_t$ . Additionally, the fiscal authority can engage in a variety of other types of spending. Net spending of other types is denoted  $N_t$ . The government budget constraint is

$$G_t + \frac{B_{t-1}^g}{\Pi_t} + ui_t(1 - N_t^a - N_t^n) + N_t = \tau_t^l(w_t^a N_t^a + w_t^n N_t^n) + \tau_t^k P_t + B_t^g + T_t$$

Lump-sum taxes adjust to ensure government solvency in the long-run. The adjustment rule is standard (Leeper et al., 2010),

$$T_t = \left[ \frac{B_{t-1}^g}{\bar{B}^g} \right]^{\phi_\tau} - 1$$

and  $\phi_\tau$  controls the speed of adjustment. A low value means that current spending is mostly deficit-financed.

**Discretionary fiscal policy.** I assume that the fiscal authority has access to an additional set of instruments. Given their extraordinary nature, these interventions will be treated as one-time shocks that are completely unexpected, but once deployed, their paths are perfectly anticipated. These components of  $N_t$  are: (i) unconditional transfers to all agents in the economy,  $T_t^b$ , and (ii) transfers to service-sector firms that are proportional to their wages,  $T_t^a w_t^a$ . Thus,

$$\mathcal{N}_t = T_t^b + T_t^a w_t^a H_t^a$$

Additionally, I assume that the government can implement one-time changes to existing fiscal instruments: (i) an increase in non-service consumption  $G_t$ , (ii) an increase in unemployment insurance transfers  $uit$ , and (iii) a reduction in the income tax  $\tau_t^l$ .

## 2.5 Resource constraints

The resource constraint for non-service goods is

$$\chi C_t^b + (1 - \chi)C_t^s + G_t + \Psi[\bar{c}_t(A_t)] = A_t N_t^n [1 - d(\Pi_t)]$$

where  $\Psi[\bar{c}_t(A_t)] \equiv \int_0^{\bar{c}(A_t)} c dH(c)$  is total operating costs paid by non-exiting service sector firms, expressed in terms of non-service goods. The resource constraint for service goods is

$$(1 - \chi)C_t^a = A_t H_t^a$$

A full list of equilibrium conditions is shown in Appendix A.

## 3. Numerical experiment

### 3.1 Model calibration

The model steady state is calibrated to the US economy on the eve of the coronavirus pandemic. The model calibration is very preliminary at this stage and is still very much work in progress. The calibration is summarized in Table 1. In terms of functional forms, the utility of non-service consumption is isoelastic,

$$u(C) = \frac{C^{1-\sigma}}{1-\sigma}.$$

The distributions of liquidity shocks  $F^e$ ,  $F^u$  are Gaussian with mean zero and variances  $\sigma^e$ ,  $\sigma^u$ , which are calibrated to match total average charge-off rates and default rates for unemployed households. The distribution of cost shocks for service sector firms is assumed to be log-normal with mean 1 and variance  $\sigma_k$ .



Parameter	Description	Value	Target
<i>Saver Parameters</i>			
$\beta^s$	Discount factor saver	0.9951	Annualized real interest rate of 2%
$\sigma$	Elasticity of intertemporal substitution	1	Standard/log utility
$\alpha$	Utility of services	3.234	Implied by other parameters
$\sigma_a$	EIS for services	1	
<i>Borrower Parameters</i>			
$\beta^b$	Borrower discount factor	0.9453	Constrained at steady state
$\Gamma$	Borrowing constraint	0.1769	Payment to income ratio of 30%
$\chi$	Fraction of borrowers	0.50	
$\sigma^e$	SD of liquidity shock, employed	0.2083	Default rate of 8%, yearly
$\sigma^u$	SD of liquidity shock, unemployed	0.1546	Default rate of 40%, yearly
<i>Production/Labor Market Parameters</i>			
$\epsilon$	Elasticity of subst. sector $n$	4	25% markup in SS
$\eta$	Rotemberg menu cost	35.47	$\simeq$ Calvo parameter of 0.75
$\phi$	Labor in $a$ -sector	0.45	BLS: % of employment in contact-intensive industries
$N$	Employment at SS	0.925	SS unemployment rate of 7.5%
$\zeta$	Sector elasticity of wage to employment	0.05	
$p^a/w^a$	$a$ -sector markup at SS	1.01	
$\sigma_k$	Variance of $a$ -sector shock	4.2153	Employment in the $a$ -sector
<i>Banking Parameters</i>			
$\theta$	Retained earnings	0.90	Net payouts of 3.5% (Baron, <a href="#">Forthcoming</a> )
$\kappa$	Leverage constraint	0.10	Leverage of money center banks
$\varpi$	Transfer to new banks	0.0004	Annual lending spread of 1%
<i>Policy Parameters</i>			
$\Pi$	Trend inflation	1.02 <sup>0.25</sup>	2% for the U.S.
$\phi_\Pi$	Taylor rule: Inflation sector $n$	1.5	Standard
$\phi_a$	Taylor rule: Inflation sector $a$	0.0	
$\phi_Y$	Taylor rule: Output	0.5/4	Standard
$\bar{G}$	Govt Consumption of $n$ -goods	$0.2 \times Y^n$	Standard
$\bar{B}^g$	Govt debt at SS	$0.9 \times Y^n$	US, 2019
$\phi_\tau$	Fiscal rule parameter	0.25	
$\bar{u}$	Unemployment insurance	$0.5 \times w$	
$\tau^l$	Labor income tax rate	15%	Avg for the US
$\tau^k$	Tax rate on profits	27%	Implied by other parameters

**Table 1** Summary of the calibration

### 3.2 What is a pandemic in a DSGE model?

The main purpose of this paper is to study the dynamic response of the economy to different types of fiscal policy instruments during a pandemic event. It is not obvious, in principle, how to model a pandemic in an otherwise standard DSGE model. It seems to be widely accepted that a highly contagious pandemic results in a reduction in economic activity as households start isolating themselves from others. This leads to a sharp reduction in activity in sectors of the economy that are contact-intensive, such as hospitality and leisure, as well as certain types of retail (brick and mortar) and transportation (air travel).

Arguments can be made for a negative shock to the marginal utility of consumption or the discount factor, or a positive shock to the disutility of labour (Baas and Shamsfakhr 2017). For different reasons neither of these is ideal in isolation. A shock to the marginal utility of consumption leads to a fall in aggregate demand that results in unemployment in this model. However,

this could easily be countered with an increase in non-service government consumption, for example. In practice, it is very unlikely that any type of stimulus based on government consumption can restore activity in, say, leisure. A shock to the marginal disutility of labour, on the other hand, generates counterfactual implications in terms of wages and potentially welfare. A more sophisticated approach is taken by Eichenbaum et al. (2020), who embed an epidemiology model in a real business cycle framework. In their model, agents may become infected by ‘meeting’ other infected agents while purchasing consumption goods or working. For this reason, the outbreak of an epidemic results in a contraction of consumption and hours worked.

Since I want to be able to preserve some tractability in order to be able to talk about different types of stabilization policies, I decide to model a pandemic as a shock to the marginal utility of one particular sector in the economy. For technical reasons, I assume that only savers are subject to this type of shock. A sufficiently large shock to  $\alpha_t$  leads to a large drop in employment in this sector. This affects mostly borrowers, who are constrained and have a very high marginal propensity to consume. As their income falls due to a loss of employment, default rates rise. This constrains banks, which in turn demand higher interest rates on their loans. These two effects contribute to a decline in non-service consumption, which in turn triggers a fall in inflation and a drop in the demand for non-service labour. The central bank responds to these shocks by lowering interest rates. This helps banks by lowering their cost of funding, but eventually interest rates are limited by the zero lower bound. If the shock is sufficiently severe, the economy hits the zero lower bound and a large recession ensues.

### 3.3 Size and duration of the pandemic

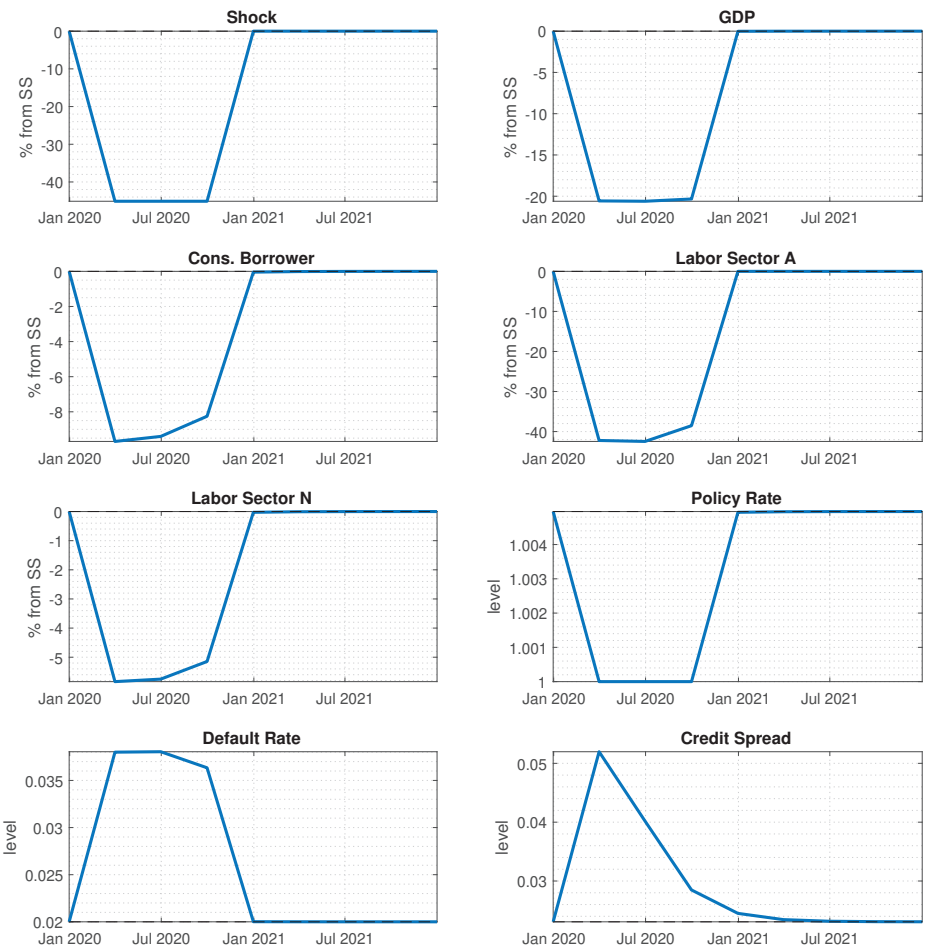
To calibrate the intensity and duration of the shock, I adopt a pessimistic approach. The size of the shock is chosen so that the unemployment rate rises to 20%, following the worst-case scenario put forward by Treasury Secretary Mnuchin to Members of Congress on 17 March 2020.<sup>3</sup> This can be achieved with a drop in  $\alpha_t$  of 60%. I assume that the shock lasts for three quarters: from 2020Q2 through 2020Q4. Finally, I assume that there is an equal shock in each quarter, as it is highly unlikely that people will start using services again as long as the pandemic is active, but that the shock has no persistence. Once the pandemic is gone, saver utility from consuming services returns to normal.

3 Source: <https://blogs.wsj.com/economics/2020/03/18/newsletter-the-layoffs-are-starting/>

Throughout, I take the intensity and duration of the pandemic as given; I do not explicitly model government investment in healthcare and mitigation or how it could potentially reduce both of these characteristics. That is outside the scope of this exercise.

3.4 Pandemic experiment

Figure 1 plots the response of selected variables to the  $\alpha_t$  shock.



**Figure 1** Response to a 60% negative shock to  $\alpha_t$  that lasts for 3 quarters and has zero persistence

The path of the shock is plotted in the first panel. The shock causes a 40% drop in employment in the service sector (4th panel). The loss of these jobs affects borrowers, whose consumption falls by almost 10%. This drop in non-service consumption also leads to a fall of about 6% in employment in the other sector. Combined, these reductions in employment lead to a 20% contraction in GDP that lasts for the full three quarters. The 6th panel shows that this recession pushes the economy to the zero lower bound for the entire period. The bottom two panels show that the fall in employment leads to a doubling of (quarterly) default rates. This in turn affects the financial sector, and lending spreads rise. This further amplifies the drop in borrower consumption and the rise in defaults. One thing to note is that while deep, the crisis is not very persistent. This is to be expected for several reasons. First and foremost, the shock is assumed not to be persistent. Second, for simplicity, there are no slow-moving state variables on the production side of the economy (such as physical capital). The recession could be made more persistent by either adding capital (an additional state variable), or by imposing frictions/barriers to entry in the service sector.<sup>4</sup>

#### 4. Fiscal policy response to the pandemic

I consider the effects of deploying the following instruments one by one:

1. Increase in government consumption in sector  $n$ ,  $G_t$
2. Labour income tax cut,  $\tau_t^l$
3. Increase in unemployment insurance,  $u_t^i$
4. Unconditional transfers to all agents,  $T_t^b$
5. Transfers to service sector firms,  $T_t^a$

In all cases, I consider a one-time impulse with zero persistence. The impulse arrives at the beginning of 2020Q2, as the pandemic starts. This is a very rough and simplistic exercise, but the point is to try to isolate the different effects of these policies. A richer analysis would consider policy packages consisting of multiple instruments, as well as more persistent policies. That is work in progress.

The model responses are nonlinear and computed with perfect foresight. This means that shocks are completely unanticipated, but once they hit, their path is perfectly anticipated.

<sup>4</sup> A version of the model with limited entry is presented in Appendix B. While the dynamics are different, the main results are unchanged.

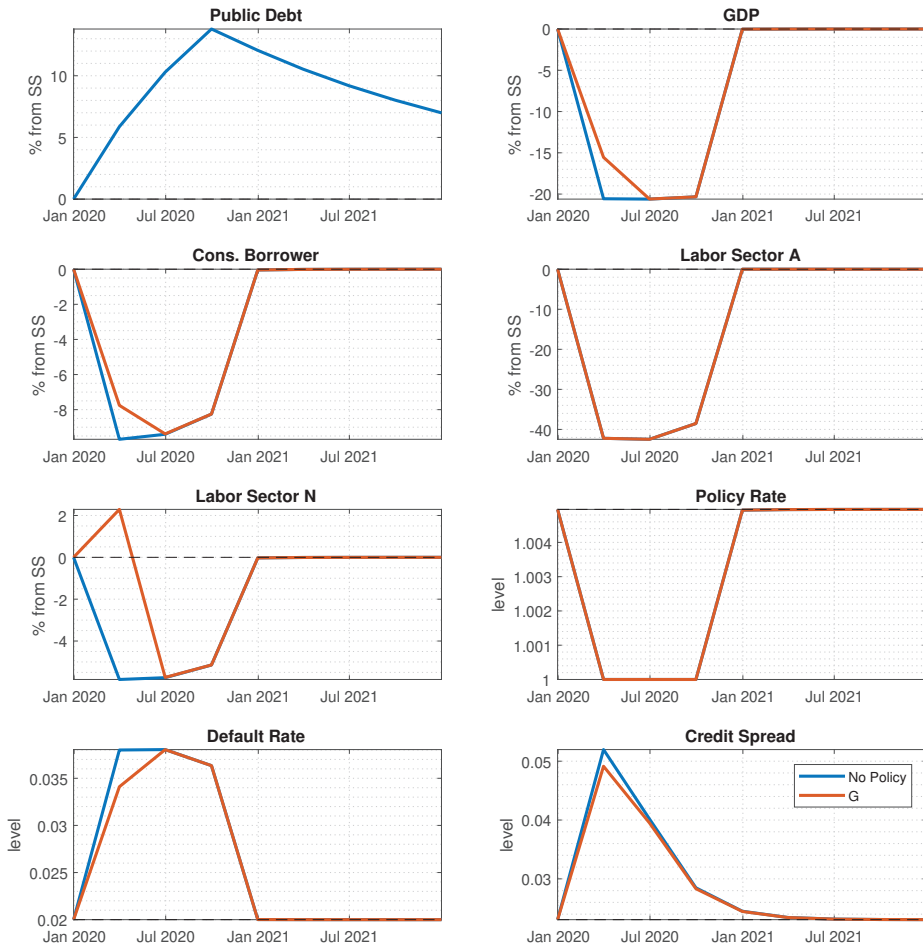
I choose the impulses such that the resulting deficits are somewhat comparable and of similar magnitudes. I focus on packages that involve a quarterly increase in the deficit on impact of \$200 billion, or roughly 3.7% of quarterly GDP. The size and intensity of the interventions certainly matter since the model features nonlinearities such as the zero lower bound. A deeper exploration into the ideal size of each impulse is left for further research. At the end of this section, I present tables with present-value fiscal multipliers, which partly account for differing sizes of the interventions.

Next, I describe the effects of these policies in more detail. Many of the policies generate similar effects from a qualitative perspective. The quantitative effects are different, however. For a summary of the quantitative effects, feel free to skip to the next section where I compare measures of fiscal multipliers.

#### 4.1 The effects of different policies

**Government consumption of non-service goods.** This is comparable to the traditional increase in  $G_t$  in one-sector New Keynesian models. I assume that it is not feasible for the government to purchase services directly as this would be roughly equivalent to a transfer to those firms, which is a policy considered separately.

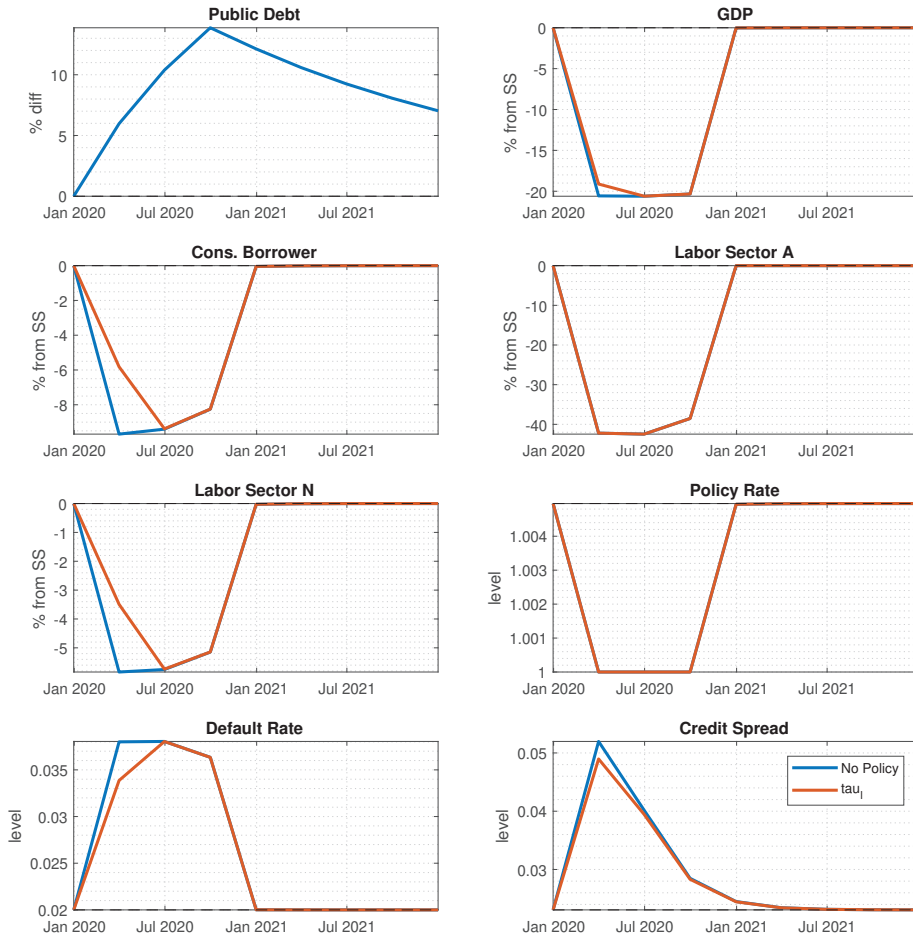
Figure 2 plots the effects of this policy on selected variables. The blue line corresponds to the crisis absent any interventions (as in Figure 1), while the orange line includes the considered intervention. The key effect of the policy is seen in the 5th panel: a large increase in government consumption helps sustain employment in the non-service sector. This, in turn, somewhat moderates the drop in borrower consumption and in GDP. Finally, the fact that employment does not fall by as much further helps to contain default rates and, via the banking system, credit spreads.



**Figure 2** Response to a ~\$200 billion increase in  $G_t$ , government consumption of non-service goods

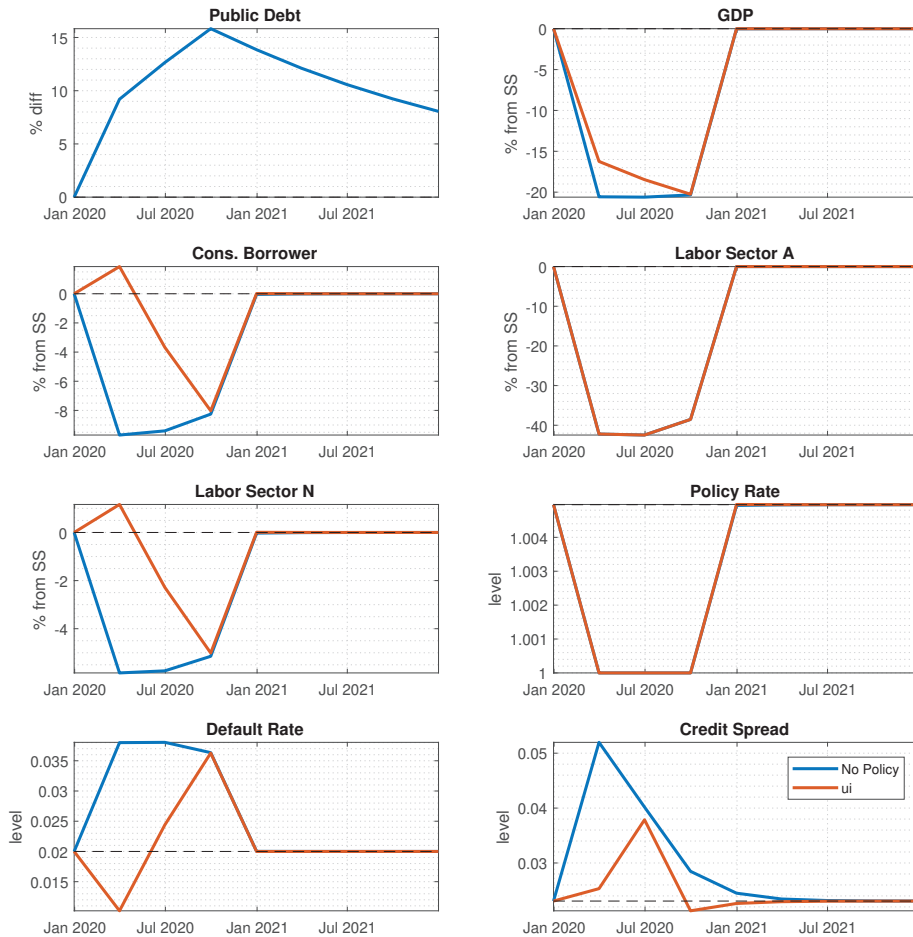
**Labour Income Tax Cuts.** To achieve a total deficit of the same size as the above policy, the intervention consists of a one-time tax cut of 50%, i.e. the tax rate is cut by half. The effects of the income tax cut in Figure 3 look relatively similar, with one main exception: tax cuts do not stimulate labour in the non-service sector as much as the more targeted policy of government consumption. They still help sustain borrower income, which in turn leads to a slightly lower drop in GDP and a decrease in default rates. However, it is important to note that this

model may underestimate the effectiveness of tax cuts due to the assumption of labour market rationing, there are no direct benefits from removing labour market distortions.



**Figure 3** Response to a ~\$200 billion income tax cut

**Unemployment insurance.** Next, I consider a one-time increase in unemployment insurance payments. To achieve a \$200 bn intervention, the unemployment insurance transfer per agent is raised by 75%. The effects on borrower consumption are noticeably larger, and borrower consumption is now sustained on impact, as seen in Figure 4.

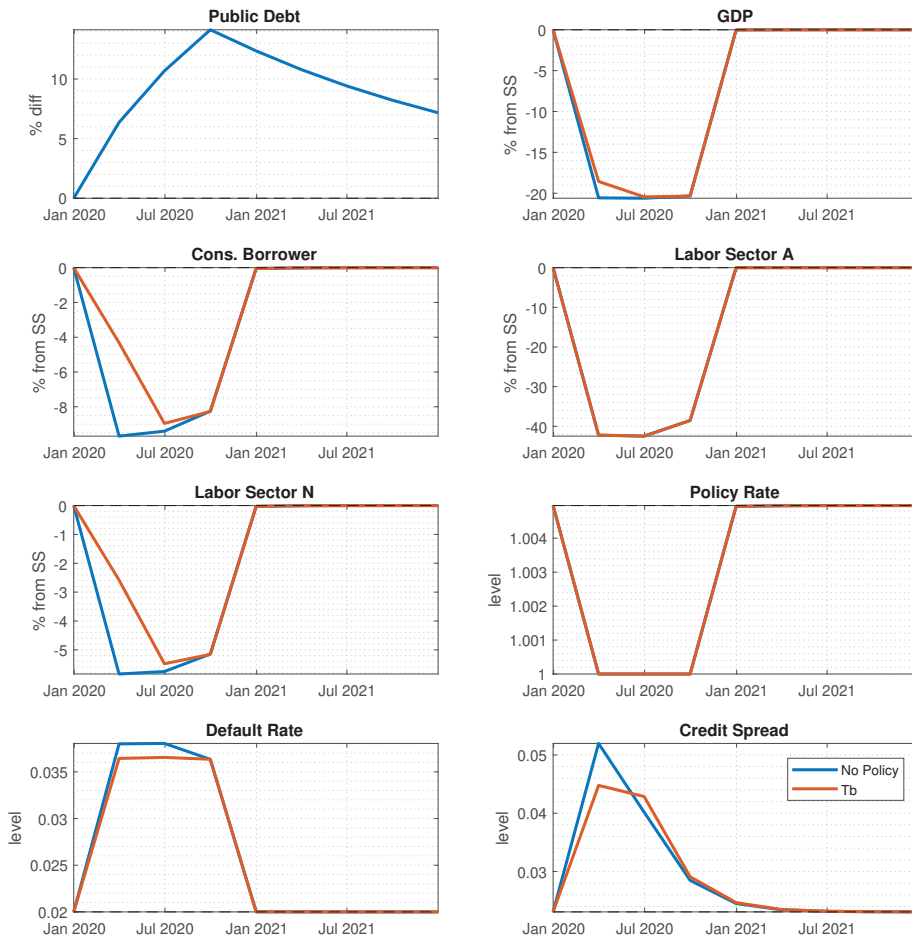


**Figure 4** Response to a ~\$200 billion increase in UI

This is somewhat predictable: income tax cuts benefit agents who remain employed, at a time when a large fraction of agents becomes unemployed. With unemployment insurance, it's the opposite: it helps unemployed agents at a time when a large fraction of agents becomes unemployed. The rise in borrower consumption further helps sustain demand in the non-service sector, which results in a 2.5% gain in GDP. Also note that while the intervention happens only in one quarter, the effects are relatively persistent. This is due to borrowing costs remaining low, which results in an implicit recapitalization of the banking system. Borrowing costs stay relatively low as the increase in unemployment insurance lowers default rates considerably because unemployed agents tend to have higher default rates than employed ones.



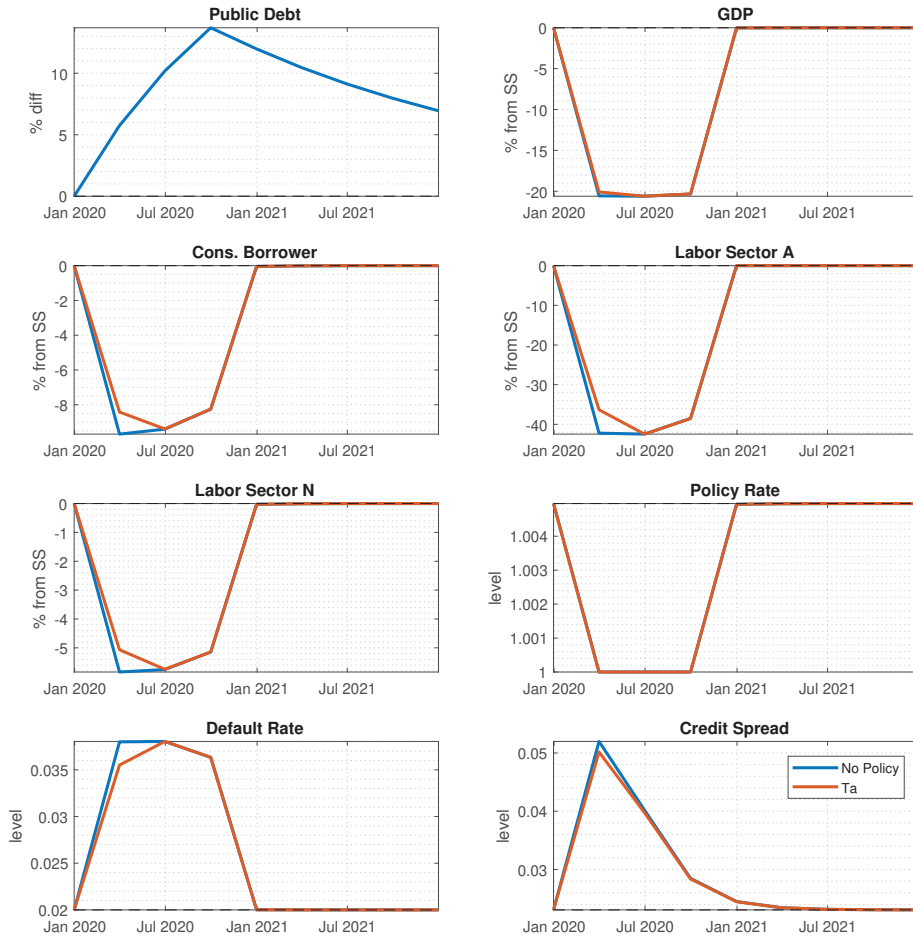
**Unconditional transfers.** Figure 5 plots the effect of a transfer given to everyone in this economy, including savers. The effects are similar to those of the payroll tax cut, which is not surprising as the incidence is effectively the same.



**Figure 5** Response to a ~\$200 billion unconditional transfer

Liquidity assistance to service firms. Figure 6 shows the effects of a per-wage subsidy to firms in the service sector. Unlike other interventions, this one is able to reduce the decline in service employment for one period. The general equilibrium effects are reflected in borrower consumption and labour in the non-service sector. This experiment is not totally fair to this policy however, as this is the only policy that explicitly targets the a-sector but does so for only one period, while agents expect the negative demand shock to last for an extra two

periods. The remaining two periods without assistance affect the value of service firms,  $V_t(A_t)$ , which does not rise by as much as it would should the assistance last for the duration of the pandemic.



**Figure 6** Response to a ~\$200 billion transfer to service firms

#### 4.2 Fiscal multipliers

While the cost of all interventions are calibrated to be around \$200 bn, or 3.7% of quarterly GDP, there are dynamic and general equilibrium effects that influence the path of government expenditure and revenue differently across instruments. One common way to control for these effects together with the

size of the intervention, is to compute present-value discounted multipliers as in Mountford and Uhlig (2009) or Ramey (2011). For a given outcome variable of interest  $x$ , the multiplier is computed as

$$\mathcal{M}_T(\omega) = \frac{\sum_{t=1}^T \prod_{j=1}^t R_j^{-1} (x_t^{\text{Stimulus}} - x_t^{\text{No Stimulus}})}{\sum_{t=1}^T \prod_{j=1}^t R_j^{-1} (\text{Spending}_t^{\text{Stimulus}} - \text{Spending}_t^{\text{No Stimulus}})}$$

The multiplier is computed for a given instrument  $\omega \in \{G, \tau_t^l, \text{ui}, T_t^b, T_t^a\}$  and at a given horizon  $T$ . Since the effects of shocks are not very persistent in this model, I set  $T$  equal to 20 quarters. Further, as the discount rate  $R_j$  differs across the economies with policy and without policy, it is not obvious which one to use. I use the interest rate in the no-policy economy so as to keep the comparison between different tools as fair as possible.

Instrument	Description	$\mathcal{M}_{20}(\omega), \text{Income}$	$\mathcal{M}_{20}(\omega), C_t^b$	$\mathcal{M}_{20}(\omega), C_t^s$	$\mathcal{M}_{20}(\omega), \text{GDP}$
$G$	Govt. Consumption	0.3439	0.3413	-0.0000	1.1705
$\tau_t^l$	Income Tax	1.2570	1.2520	-0.0000	0.6259
$\varsigma$	UI	1.4953	1.4821	0.0001	0.7410
$T_t^b$	Uncond. Transfer	1.1720	1.1741	0.0002	0.5872
$T_t^a$	Liquidity Assist.	0.4223	0.4193	-0.0000	0.2099

**Table 2** Fiscal multipliers

Table 2 compares multipliers for income net of government transfers, borrower consumption, saver consumption of non-service goods, and GDP. Income net of transfers is defined as

$$\text{Income}_t = (1 - \tau_t^l)(w_t^a N_t^a + w_t^n N_t^n) + (1 - N_t^n - N_t^a)\text{ui}_t + T_t^b$$

The largest income multipliers are generated by UI. Income tax cuts and unconditional transfers are also effective, but generate lower multipliers as they are less well-targeted to agents with lower incomes. UI is, furthermore, very well targeted in terms of timing, as this transfer arrives precisely at a time when unemployment surges. Multipliers on borrower consumption are very similar to those of income, which is to be expected since borrowers are constrained and therefore have a high marginal propensity to consume out of their current income. Any differences reflect changes in the cost of credit from banks.

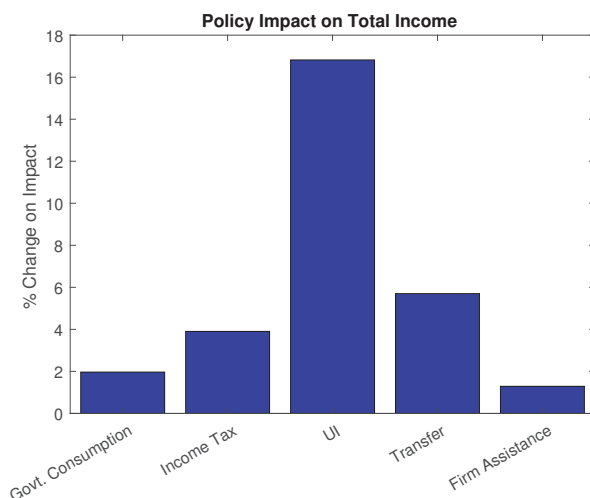
Multipliers on saver consumption are very low. Savers react relatively little to fiscal policy as they are unconstrained. Savers are ‘Ricardian’ in the sense that they purchase public debt and pay lump-sum taxes and, therefore, react to changes in the present value of government liabilities. Note however that the general equilibrium effects are strong enough to offset the usual fall in consumption for

savers. Naturally, they react more positively to the unconditional transfer and more negatively to the increase in unemployment insurance, which is the closest instrument to a targeted transfer to borrowers in this environment.

GDP multipliers are reported in the last column. As argued before, it is not clear that adopting measures that stabilize GDP is appropriate in this situation. Still, I report the multipliers for completeness. The policy that yields the largest GDP multiplier is government consumption. It is well known that it is ‘hard to beat’ government consumption in this class of models (Oh and Reis 2012), especially in the absence of very strong links between the balance sheets of households and the financial system. Income tax cuts, increases in unemployment insurance and unconditional transfers all deliver somewhat similar results. UI performs the best as it is the most well-targeted, while unconditional transfers perform the worst as it is the least well-targeted. Liquidity assistance to firms seems to be the policy performing the worst but this is subject to the caveats pointed out in the next subsection.

#### 4.3 Dissecting the effect on borrower income

The change on borrower income on impact is shown in Figure 7.

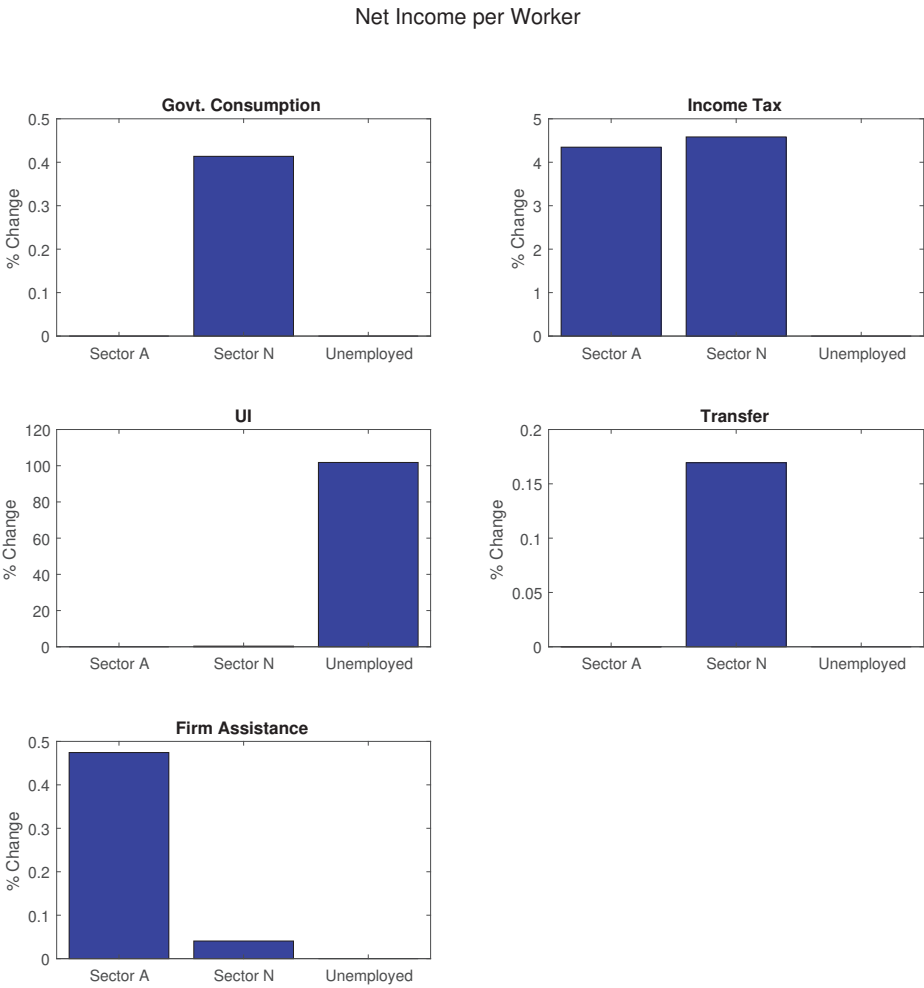


**Figure 7** Percentage change on income due to policy, on impact

This figure confirms that UI increases have the largest effect. Note that in this picture (and in subsequent pictures), I am comparing percentage changes for a given impulse, and not adjusting for dollars spent as in the previous paragraphs. Transfers generate better results than income tax cuts. It all boils down to how well targeted a policy is.

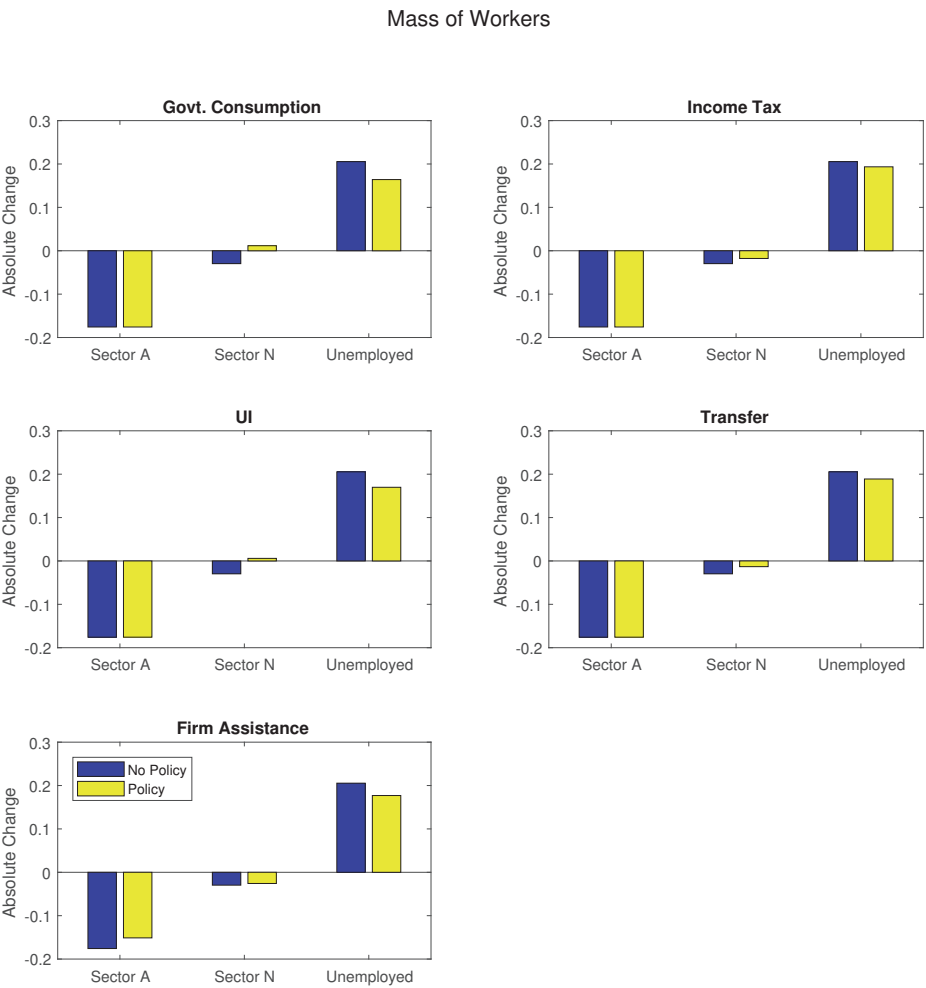
Figures 8 and 9 help us understand how well/poorly targeted each type of policy is by decomposing the effect of each policy on prices and quantities (on impact). Figure 8 plots net income per worker in each sector ( $n$ ,  $a$ , or unemployed), across policies. It shows, for example, that income tax cuts raise incomes for employed workers exclusively, while UI raises incomes for unemployed workers almost exclusively. Transfers and government consumption of non-service goods operate via traditional aggregate demand effects, thus raising demand for  $n$ -sector goods and therefore earnings in this sector, but having no effect on other types of workers. Finally, liquidity assistance to  $a$ -sector firms helps sustain wages in this sector. Figure 9 plots absolute changes in the number of workers in each sector, in the baseline economy with no policy (blue bar) and in the economy with the policy impulse (yellow bar).<sup>5</sup> While there are minor variations across policies, the overall pattern is the same: the shock leads to a large reduction in sector  $a$  employment, a moderate reduction in sector  $n$  employment and a large increase in unemployment. These two figures combined show why UI is the best policy to stabilize household income, as it targets the category of households that increases the most due to the shock.

5 Absolute changes are easier to compare since the steady state/initial distribution across sectors is very uneven, with relatively few unemployed agents.



**Figure 8** Percentage change in net income per worker due to policy, across sectors

*Note:* Each panel has a different scale.



**Figure 9** Total change in workers, across sectors

#### 4.4 Liquidity assistance programs

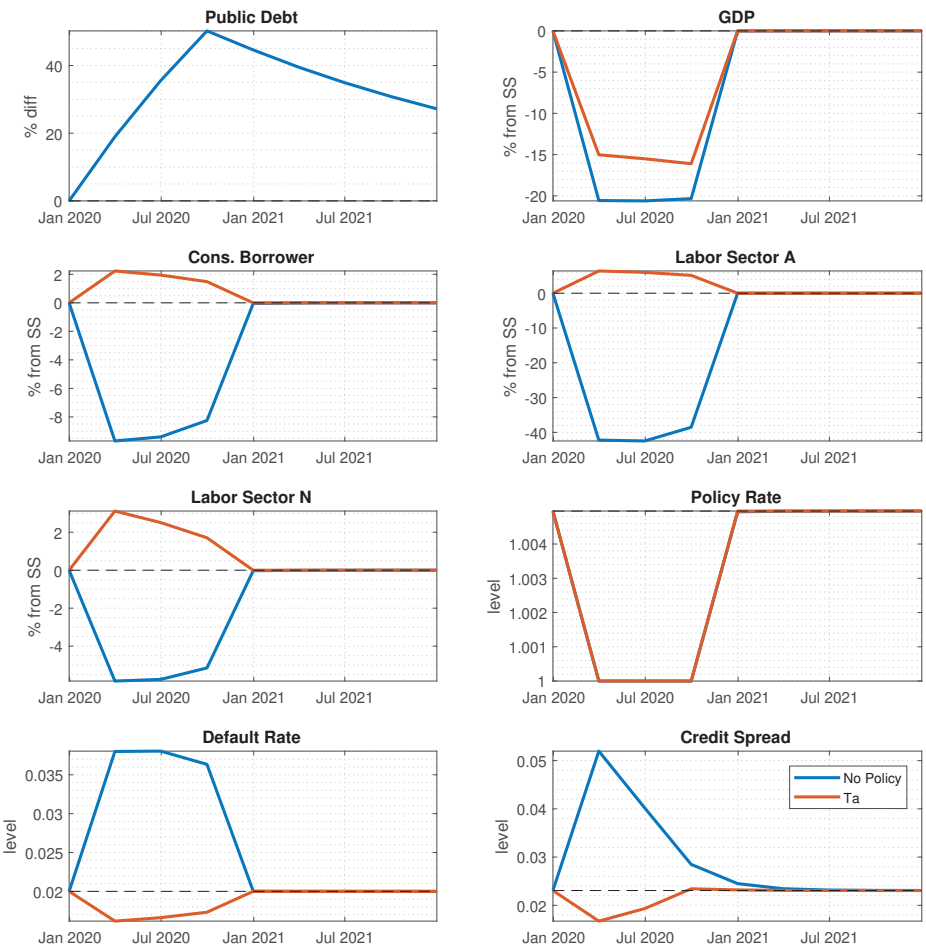
Liquidity assistance policies to the service sector yield relatively low multipliers compared to transfer-based programs. There are two reasons for this. First, it may be that a \$200 billion program is simply not generous enough, and that the wage subsidy is not large enough to keep a sufficient number of firms alive and workers hired. To investigate whether this is the case, I consider a larger and longer program where the government fully subsidizes wages in the service sector for the full duration of the pandemic shock (3 quarters). That is, the government sets  $T_t^a = 1$  regardless of the total cost of the program. The effects of this policy are shown in Figure 10. Under this policy, the government is able to completely offset any changes in service employment as well as in borrower consumption, even generating a small boom in the non-service sector. This small boom is not sufficient to offset the drop in the relative price of services however, which in turn causes a large drop in GDP.

Such a policy is extremely expensive. Contrary to the baseline case, where public debt would increase by 15% at its peak, this new intervention involves an increase in public debt of almost 50%. In fact, the multipliers are even smaller: 0.2056 for income, and 0.2051 for borrower consumption.<sup>6</sup> This brings us to the second reason why the multipliers are low: this policy is treated as a pure cash grant to service firms. While this type of policy is currently discussed by the US Congress, many other countries have opted for opening credit lines that allow these firms to borrow from the government instead. The fact that the fiscal authority could recoup (at least part) of its cost with the policy is likely to raise the value of the multipliers. On the other hand, this could also reduce the stimulating effects of the policy, as firms internalize the fact that the government intervention comes in the form of a liability. For this reason, it is not clear whether considering credit lines would raise or lower the multipliers for this policy.<sup>7</sup> Nevertheless, if the objective is to preserve service-sector employment, a large liquidity assistance program is a very effective policy.

6 The multiplier on saver consumption is 0.0002, the multiplier on GDP is 0.1235.

7 See Faria-e-Castro (2018) for a discussion on how to compute fiscal multipliers for government credit facilities.





**Figure 10** Response to a full wage subsidy for services firms,  $T_t^a = 1$

## 5. The Effects of the CARES Act of 2020

I use the model to quantify the effects of the Coronavirus Aid, Relief, and Economic Security (CARES) Act of 2020 – the \$2 trillion package that is to be considered by the House on 27 March 2020. As of the time of this writing, the main components of the bill are:

1. \$423 billion (2% of GDP) in small business loans, payroll subsidies, and relief for affected industries ( $T_t^a$ )
2. \$250 billion (1.2% of GDP) in payments to individuals in the form of rebates to taxpayers ( $T_t^b$ )
3. \$250 billion (1.2% of GDP) in expanded unemployment insurance ( $ui_t$ )
4. \$490 billion (2.3% of GDP) in state fiscal aid and federal spending across departments and programs ( $G_t$ )

The bill does not explicitly include direct tax cuts, even though it does include tax relief measures such as the delaying of filing dates. For that reason, I do not explicitly model any  $\tau_t^l$  intervention as part of this package. Excluded from the analysis are \$454 billion that are allocated as a backstop to Federal Reserve credit facilities. I jointly simulate interventions of these sizes in the model. For liquidity assistance, unemployment insurance, and government purchases, I assume that the spending is spread across four quarters (i.e., a fiscal year) starting on the quarter of the shock (which has a duration of three quarters). For transfer payments, I assume that they are a one-time shock happening on the first quarter of the shock (2020Q2).

The result for the aggregate multipliers are show in Table 3. The fiscal package has an income multiplier of 1.16. The following rows decompose the multiplier across different policies. These numbers are obtained by considering one policy at a time, similar to the exercise in previous sections. Even though the interventions have different sizes and lengths, the results from the baseline exercise are virtually unchanged, with UI and transfer payments providing most of the income and consumption stabilization.

Instrument	Description	$\mathcal{M}_{20}(\omega)$ , Income	$\mathcal{M}_{20}(\omega)$ , $C_t^b$	$\mathcal{M}_{20}(\omega)$ , $C_t^s$	$\mathcal{M}_{20}(\omega)$ , GDP
All Policies		1.1648	1.1574	-0.0161	1.0094
$G$	Govt. Consumption	0.3248	0.3187	-0.0303	1.1105
$\varsigma$	UI	1.4874	1.4782	-0.0053	0.7303
$T_t^b$	Uncond. Transfer	1.1726	1.1772	0.0003	0.5890
$T_t^a$	Liquidity Assist.	0.3962	0.3949	-0.0028	0.2018

**Table 3** Aggregate multipliers for the CARES Act of 2020 and decomposition

## 6. Caveats and discussion

In the context of a simple DSGE model, the most effective tool to stabilize household income and borrower consumption when facing an exogenous shock that leads to the shut-down of the service sector seems to be an increase in unemployment insurance benefits. Overall, programs that involve transfers to households of some kind seem to be effective, with UI being the best targeted policy. Unconditional transfers are likely to be less costly in terms of implementation, may be favoured by savers, and deliver somewhat similar (but weaker) results. Firm liquidity assistance programs are effective at maintaining employment in the quarantined sector.

The analysis in this paper is very simple, takes many shortcuts, and abstracts from many important things. Many of these caveats were already mentioned in the main analysis but are worth repeating. First, for the sake of comparison, I only consider one-time ‘fiscal impulses’. In practice, fiscal policy packages are likely to be persistent and implemented over a certain horizon. As discussed, this is especially important in the case of liquidity assistance to service sector firms, and potentially for unemployment insurance. Second, these impulses are of a fixed size. In practice, size does matter and multipliers can be nonlinear (Brinca et al. 2019). Third, I consider each policy separately, in single-instrument packages. There can be strong complementarities and substitutabilities between policies. In a previous paper (Faria-e-Castro 2018), I argue that there were strong complementarities between financial sector bailouts and transfers to households during the 2008-09 Global Crisis and subsequent recession. None of that is considered here. Fourth, the absence of an endogenous labour supply decision tends to underestimate the effects of an income tax cut and overestimate the effects of UI, as it does not consider the efficiency gains/losses from these policies. Fifth, the macroeconomic scenario caused by the pandemic is possibly too extreme, with a complete shutdown of the service sector for three full quarters and a GDP contraction of 15% per quarter. I completely abstract from the possibility that fiscal policy can be deployed to reduce the duration and intensity of the shock caused by the pandemic. Finally, I also abstract from the fact that stimulating economic activity may actually be *detrimental* in fighting the pandemic.

There are other important caveats that were not discussed previously. Implementation lags can be aggravated by attempts to target policies better. Better targeted policies may additionally entail extra costs associated with bureaucracy. It may sometimes be better to undertake a slightly worse policy whose implementation requires less information and time, i.e. unconditional

transfers versus expansion of unemployment insurance eligibility. Furthermore, I completely abstract from other potential policies that have been part of the debate such as the role of state fiscal policy, health insurance, debt forgiveness and restructuring, moratoria on debt (and bill) repayments, etc. For a detailed discussion of some of these policies see Dupor (2020).

Household-banking interactions are extremely simplified and abstract from many important feedback effects. In particular, I abstract from endogenous collateral, which can have a large effect on the consumption response to shocks and stimuli. As I show in previous research, many interventions that look like transfers to borrowers serve as implicit recapitalizations of the banking system and can have very strong spillovers to other sectors. For this reason, I am likely understating the effects of this type of interventions. Finally, I abstract from any direct intervention to the financial system. Due to this, I abstract from unconventional monetary policy as well as the extraordinary measures taken by the Federal Reserve to restore confidence in financial markets. I also abstract from linkages between the financial system and the corporate sector. These are likely to be very important, especially at a time when corporate debt is at unprecedented levels in the US. This would be a natural first direction to extend the model.

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## Appendix A: Full list of equilibrium conditions

Borrowers ( $\lambda_t$  is the Lagrange multiplier on the borrowing constraint),

$$\begin{aligned}
 \varepsilon_t^a &= \frac{B_{t-1}^b}{\chi \Pi_t} - w_t^a(1 - \tau_t^l) \\
 \varepsilon_t^n &= \frac{B_{t-1}^b}{\chi \Pi_t} - w_t^n(1 - \tau_t^l) \\
 \varepsilon_t^u &= \frac{B_{t-1}^b}{\chi \Pi_t} - w_t^u \\
 F_t^b &= N_t^a F^e(\varepsilon_t^a) + N_t^n F^e(\varepsilon_t^n) + (1 - N_t^a - N_t^n) F^u(\varepsilon_t^u) \\
 m_{t+1}^b &\equiv \beta^b \frac{u'(C_{t+1}^b)}{u'(C_t^b)} \\
 Q_t^b - \lambda_t &= \mathbb{E}_t \frac{m_{t+1}^b}{\Pi_{t+1}} (1 - F_{t+1}^b) \\
 C_t^b + \frac{B_{t-1}^b}{\chi \Pi_t} (1 - F_t^b) &\leq (w_t^a N_t^a + w_t^n N_t^n) (1 - \tau_t) + (1 - N_t^a - N_t^n) w_t^u + Q_t^b B_t^b / \chi + T_t^b \\
 Q_t^b B_t^b \chi &\leq \Gamma \perp \lambda_t \geq 0
 \end{aligned}$$

Banks ( $\mu_t$  is the Lagrange multiplier on the leverage constraint),

$$\begin{aligned}
 \mathbb{E}_t \frac{m_{t+1}^s}{\Pi_{t+1}} (1 - \theta + \theta \Phi_{t+1}) \left[ \frac{1 - F_{t+1}^b}{Q_t^b} - \frac{1}{Q_t} \right] &= \mu_t \kappa \\
 \mathbb{E}_t \frac{m_{t+1}^s}{\Pi_{t+1}} (1 - \theta + \theta \Phi_{t+1}) &= \Phi_t (1 - \mu_t) Q_t \\
 Q_t^b B_t^b &= E_t + Q_t^d D_t \\
 \kappa Q_t^b B_t^b &\leq \Phi_t E_t \perp \mu_t \geq 0 \\
 E_t &= \Pi_t^{-1} \theta ((1 - F_t^b) B_{t-1}^b - D_{t-1}) + \varpi
 \end{aligned}$$

Savers,

$$\begin{aligned}
 m_{t+1}^s &\equiv \beta^s \frac{u'(C_{t+1}^s)}{u'(C_t^s)} \\
 Q_t &= \mathbb{E}_t \frac{m_{t+1}^s}{\Pi_{t+1}} \\
 C_t^a &= \left[ \alpha_t \frac{1}{p_t^a u'(C_t^s)} \right]^{1/\sigma_a}
 \end{aligned}$$

**Non-services sector,**

$$\eta \frac{\Pi_t}{\Pi} \left( \frac{\Pi_t}{\Pi} - 1 \right) + \epsilon \left[ \frac{\epsilon - 1}{\epsilon} - \frac{w_t^n}{A_t} \right] = \eta \mathbb{E}_t m_{t+1}^s \frac{Y_{t+1}^n}{Y_t^n} \frac{\Pi_{t+1}}{\Pi} \left( \frac{\Pi_{t+1}}{\Pi} - 1 \right)$$

$$Y_t^n = A_t N_t^n \left[ 1 - 0.5 \eta \left( \frac{\Pi_t}{\Pi} - 1 \right)^2 \right]$$

$$C_t = C_t^s + C_t^b$$

$$C_t + G_t + \Psi(\bar{c}_t) = Y_t^n$$

$$w_t^n = \xi^n A_t (N_t^n)^\zeta$$

**Services sector,**

$$\bar{c}_t = A_t p_t^a - w_t^a + w_t^a T_t^a + \mathbb{E}_t m_{t+1}^s [G_{t+1}^a \bar{c}_{t+1} - \Psi[\bar{c}_{t+1}]]$$

$$N_t^a = H_t^a$$

$$H_t^a = \int_0^{\bar{c}_t} dH(c)$$

$$\Psi[\bar{c}_t] = \int_0^{\bar{c}_t} c dH(c)$$

$$w_t^a = \xi^a A_t (N_t^a)^\zeta$$

$$(1 - \chi) C_t^a = A_t N_t^a$$

**Government and central bank,**

$$G_t + \frac{B_{t-1}^g}{\Pi_t} + (1$$

$$= (w_t^n N_t^n + w_t^a N_t^a$$

$$T_t = \left( \frac{B_{t-1}^g}{B^g} \right)^{\phi_\tau}$$

## Appendix B: Model with limited entry

Instead of assuming that  $1 - H_t^a$  service firms enter the economy every period to replace firms that exit, the mass of entrants is limited by some parameter  $\varsigma$ . This means that the mass of service-sector firms in the economy is now a state variable, given by  $f_t$ . The law of motion for this state variable is

$$f_t = f_{t-1}H_t^a + \varsigma$$

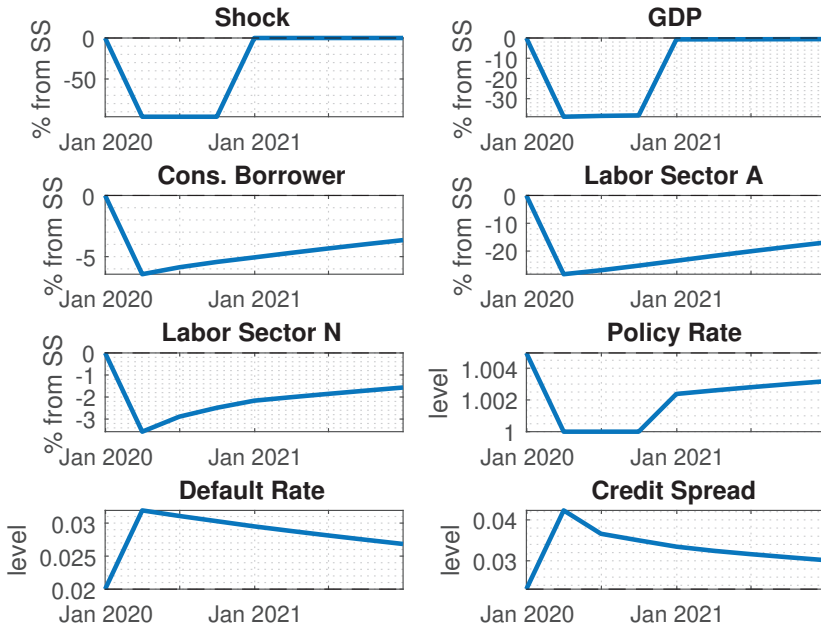
and the labour market clearing condition for this sector is now given by

$$N_t^a = f_t$$

Finally, the resource constraint for the n-good is now given by

$$C_t + G_t + f_{t-1}\Psi[\bar{c}_t] = Y_t^n$$

Other than this, nothing else changes in the model. Figure 11 plots the crisis path in this alternative version of the model. Qualitatively, the main results hold, but the crisis is now more persistent due to the presence of this new slow-moving state variable. I set  $\varsigma = 2\%$  to match a business entry rate of 8% yearly. Table 4 presents the result for the fiscal multipliers of different instruments. While the numbers are different, the same qualitative analysis holds.



**Figure 11** Pandemic crisis in the model with limited entry



Instrument	Description	$\mathcal{M}_{20}(\omega), \text{Income}$	$\mathcal{M}_{20}(\omega), C_t^b$	$\mathcal{M}_{20}(\omega), C_t^s$	$\mathcal{M}_{20}(\omega), \text{GDP}$
$G$	Govt. Consumption	0.3442	0.3416	-0.0000	1.1706
$\tau_t^l$	Income Tax	1.2576	1.2523	-0.0000	0.6260
$\varsigma$	UI	1.4973	1.4861	0.0002	0.7428
$T_t^b$	Uncond. Transfer	1.1718	1.1705	-0.0000	0.5851
$T_t^a$	Liquidity Assist.	0.4774	0.4744	-0.0572	0.0951

**Table 3**      Fiscal multipliers for model with limited entry