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## Economic stimulus through bank regulation: Government responses to the COVID-19 crisis

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### ABSTRACT

In this paper, we estimate the effects of the COVID-19 pandemic on the banking system and the real economy and simulate potential policy responses. We combine machine learning algorithms, namely a Random Regression Forest and a Long Short Term Memory neural network, with an agent-based framework to calculate the expected results of the pandemic, according to different scenarios regarding financial stability. We then simulate government responses to this crisis and find that traditional demand and supply stimuli are outperformed by our suggestion of relaxing bank regulation. We examine two alternatives of our suggested policy and find that they result in optimised outcomes for most variables examined. Our findings have important policy implications as authorities are formulating post-crisis recovery plans amidst budgetary constraints.

### 1. Introduction

As economic systems everywhere experience the effects of the preventive lockdowns, we are still at a loss as to what the next day will hold. Policymakers are currently focused on containing the spread of the SARS-CoV-2<sup>1</sup> virus through vaccinations and on boosting the capacity of healthcare systems. On the other hand, a lot of attention has also been paid to finding a permanent medical solution to the disease caused by the virus, which has been termed COVID-19, in order for achieve the return to normality. From an economic point of view, policymakers and academics alike are trying to determine the extent of losses due to the lockdown policies and the preventive measures, as well as suggest possible measures that can be taken to re-ignite trade, industry and financial systems and to restore economic growth. The International Monetary Fund (IMF) reports a contraction of 3.3% for 2020 for world GDP (IMF, 2021), despite earlier predictions for a 3.0% drop (IMF, 2020b) or even for 3.3% growth (IMF, 2020a).

In this paper, two important aspects of this crisis are discussed. Firstly, we complement an agent-based model with machine-learning algorithms to predict the outcome of the COVID-19<sup>2</sup> crisis on the banking sector based on different scenarios. Secondly, we compare the potential outcomes of different policies that can be used to tackle the current crisis and propose the optimal policy according to different scenarios. We compute household utility and firm production functions using a Random Regression Forest (RRF) process on data from the United States and estimate predictions on bank stability using a Long Short Term Memory (LSTM) neural

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network on stability indicators proposed by Elnahass et al. (2021). We then feed these results into an agent-based model in order to demonstrate the possible economic and financial effects of the COVID-19 crisis and examine the outcome of possible government policies aimed at restarting the economy.

As researchers have been focusing on both the potential effects of the pandemic and the suggested policies for recovery, a multitude of recommendations has been presented. However, all have one common factor: they carry a (significant) cost. Indeed, not many economies can bear to further increase their deficits at such a critical time, but there is one policy that does not carry a budget cost, at least in terms of requiring public funds: deregulation of the banking sector, commonly a taboo topic, both in academic and in political discussions. Bank deregulation has been touted as a potential source of economic growth, by increasing not only the availability of financing for firms and households (Polyzos and Samitas, 2015; Samitas and Polyzos, 2015), but also bank efficiency, due to improved competition in the financial sector (Brown et al., 2019; Valverde et al., 2003). What is more, reduced competition due to regulation can actually deteriorate financial stability (Beck et al., 2006). We assert that, moral hazard issues notwithstanding (Bratis et al., 2015), this policy instrument can outperform alternative policies in times of crisis, both in terms of effectiveness and in terms of cost. In addition, debt servicing or amortisation relief measures that have been put into place in many countries are considered similar to demand and supply stimulus measures, by increasing disposable income for households and firms. As such, they do not have the generalised effect that recovery policies should entail. To clarify this further, despite the arguments against heavy regulation, this paper does not oppose bank regulation in general, but rather supports a temporary regulatory relief policy that can help restart economic systems after the deep crisis brought on by the pandemic. This is demonstrated by our findings, which can be used by policymakers, in cooperation with central and commercial banks, to speed up recovery in the post-COVID economy.

Our paper contributes to three aspects of the current literature. Firstly, we propose a DSGE agent-based model for the banking sector that can be used for policy simulations. Second, we discuss the economic consequences of the COVID-19 pandemic, through the channel of financial instability. Despite multiple macroeconomic models discussing economic disasters (Gabaix, 2012; Gourio, 2012; Barro, 2009; Barro and Ursua, 2008a; Gabaix, 2008), few – if any – focus on the financial sector as the underlying transmission channel. Lastly, we propose and evaluate different policy responses to the oncoming crisis, resulting not only in immediate policy suggestions but also on a new discussion of how bank regulation can be used as a macroeconomic policy instrument.

The rest of this paper is structured as follows. Section 2 presents the relevant literature, Section 3 discusses the different methodologies employed, Section 4 presents our findings and Section 5 concludes with policy implications.

## 2. Literature review

In the financial literature, researchers will commonly treat crises as surprises and try to build forecasting models, such as Early Warning Systems (EWS) which would help predict the so-called “known unknowns”, which are these risks that can be planned for. However, the current crisis is a major “unknown unknown”; from an economic perspective, such a sudden and deep shock in both the demand and the supply side could not have been easily predicted, let alone planned for. As such, the current crisis differs gravely from previous significant crises, such as the 1970s energy crisis, the financial crises of the 1930s and of 2007–09 or even the Dotcom crisis. The 1970s crisis represented primarily a supply crisis of rising production costs, while the other crises originated in the financial sector, before affecting the real economy. The COVID-19 pandemic has dealt a concurrent blow to both supply and demand and will trigger detrimental effects to the financial sector.

Consequently, applying the proper post-crisis policy response is more important than ever. Policymakers are in uncharted waters and need solid suggestions as to the potential cure. One of the major unknown unknowns has been the outbreak of the SARS-CoV-2 virus and the resulting COVID-19 pandemic. This virus is related to the SARS virus, SARS-CoV-1, which caused a similar, albeit far more constrained, outbreak in 2003. The outbreak of 2003 originated in the Guangdong province of China and gradually spread in a total of 29 countries killing 774 people out of a total of 8096 cases, resulting in a mortality rate of 9.6% (WHO, 2004), as opposed to the current pandemic where the mortality rate currently stands at 2.08%. The COVID-19 disease has affected 169,604,858 people in a total of 235 countries worldwide, resulting so far in 3,530,837 deaths (WHO, 2021).<sup>3</sup>

As a result, the current pandemic has had an immediate effect on the global economy due to the preventive lockdown policies implemented all over the world. Whilst the 2003 epidemic mainly affected the tourism industry, the results of COVID-19 span all areas of economic activity (Fotiadis et al., 2021; Polyzos et al., 2020b). Many fear that the worst is yet to come, as the economic systems are only now attempting to resume their normal activities, with China leading the way, despite heavy losses (Wall Street Journal, 2020). The current crisis is of particular interest, given its starting point, since China plays a central role not only to the Southeast Asia region (Apostolakis, 2016), but to the global economic environment as well (Liow et al., 2018). In addition, the increasing interconnectedness of financial institutions suggests that spillovers are more frequent and can account for a greater extent of market volatility, especially in times of crisis (Diebold and Yilmaz, 2014).

Even though output losses of the current crisis are already the subject of numerous papers (Baker et al., 2020; Maliszewska et al., 2020; Makridakis and Hartley, 2020; Yang et al., 2020), the effects on the banking sector have not been examined thoroughly. In addition, most researchers focus on the immediate losses (Elnahass et al., 2021; Zaremba et al., 2021), while we focus on the next day and the policies that should be implemented to restore economic systems back on a positive track. We postulate that commonly suggested policies, such as demand or supply stimuli (OEAD, 2020), carry a significant burden to public finances and suggest that

<sup>3</sup> Figure accurate on 1 June 2021.

authorities should loosen regulatory capital requirements for banks. This “financial stimulus” can increase the funds that banks make available to both firms and households and can result in the desired demand and supply boosts simultaneously and at a lower cost for public finances.

A common concept among political scientists and economists alike is that crisis prevention is something few governments invest in (Wu et al., 2020; Klomp, 2019; Cole et al., 2012; Reeves, 2011; Healy and Malhotra, 2009) despite the fact such incidents, though rare, have long lasting effects (Caruso, 2017). Indeed, disaster spending can even vary according to government ideology (Klomp, 2019). On the other hand, such events can even benefit the population, as relief spending could possibly alleviate pre-existing problems, in addition to those it was originally aimed at (Park and Wang, 2017). Governments will commonly underinvest in disaster prevention and prediction (Wu et al., 2020) and this will usually make them more susceptible to the negative effects of such crises. Often, especially in emerging economies, an unforeseen crisis can attract a great deal of foreign aid. This, however, further encourages underinvestment since governments see little need to spend on preparation and mitigation plans, if the country can wait for the crisis and someone else will pay the bill (Clarke and Dercon, 2019).

Currently, apart from the medical responses to COVID-19, a big part of the discussion revolves around the imminent economic disaster and possible government actions to deal with it. Such actions are designed on two pillars: measurement of damages and policies for recovery. The measurement of the social and economic impact of disasters is a matter that has been difficult to approach, as there is no standard methodology for this task (Pelling et al., 2002). Zapata-Martí (1997) describes the European Commission for Latin America and the Caribbean (ECLAC) methodology, which distinguishes between the direct damages, indirect damages and other secondary effects.

Barro (2009, 2006) presents an extensive discussion on “rare events” and disasters and suggest measurement of the resulting output losses. These studies suggest that the definition of “rare” corresponds to events such as the two World Wars, the Great Depression or even the Asian financial crisis (late 1990s) and other similar events. Thus, a framework for measurement of the financial consequences of such events is necessary. Barro and Ursua (2008a) suggest that using the peak-to-trough measurement method for consumption crises will result in failure to distinguish temporary from persistent economic declines, since it fails to take into account the strong (expected) post-crisis recovery; a dynamic approach would be more applicable. Gabaix (2008) shows that *ex ante* disaster management relates to a significant extent to the time-varying probability of that disaster occurring. This probability has been approximated in Barro and Ursúa (2008b) and in Isoré and Szczerbowicz (2017).

For the second pillar, the policy response to an output or a financial crisis is often a point discussed by researchers. A thorough discussion on existing research pertaining to financial risk management and policy uncertainty can be found in Hammoudeh and Mcaleer (2015). The authors emphasise that the difficulties surrounding financial risk management intensify insurmountably when there is economic policy uncertainty. Thus, it is important for policy makers to have an *ex ante* well-defined plan for dealing with the repercussions of external events, as uncertainty can aggravate the negative consequences (Sun et al., 2017). Often it can be the uncertainty shocks *per se* that have a devastating effect on the economy (Alexopoulos and Cohen, 2015) or the banking sector (Hu and Gong, 2019). Economic policy uncertainty can also have spillover effects among interdependent economic systems (Tsai, 2017).

Focusing on the financial sector, Sanches (2018) develops a dynamic general equilibrium model in order to examine the optimal policy responses to banking crises and finds that the outcome of such events depends heavily on the cost of liquidating long term assets. Baldacci et al. (2009) show that fiscal policy can help in resolving financial instability more quickly, with increased government expenses being the best choice. Levine et al. (2016) show that the negative effects of these crises, as well as the contagion effect towards the real economy, can be mitigated by implementing shareholder protection laws.

Despite the different policy suggestions, there is one common factor: all policies carry a cost. Indeed, not many economies can bear to further increase their deficits at such a critical time, but there is however one policy that does not carry a budget cost, at least in terms of requiring public funds: deregulation of the banking sector. Bank deregulation has been touted as a potential source of economic growth, by increasing not only the availability of financing for firms and households (Polyzos and Samitas, 2015; Samitas and Polyzos, 2015), but also bank efficiency, due to improved competition in the financial sector (Brown et al., 2019). What is more, reduced competition due to regulation can actually deteriorate financial stability (Beck et al., 2006).

However, as stated earlier, banking regulation is commonly a taboo topic, both in academic and in political discussions. Banks are regulated in order to protect shareholders and depositors alike (Koch-Medina and Munari, 2016) but also because banking instability can have significant adverse effects to the economic environment (McIlroy, 2008). On the other hand, Dungey et al. (2018) suggest that crisis contagion is unidirectional from the non-financial towards the financial sector only, which is a novel finding given the banking sector's generally accepted role as a financier of economic growth. Devereux and Dwyer (2016) study data from numerous banking crises and find that most of them do not result in output losses and, even if they do, these losses are insubstantial. In our modelling approach, we indeed consider the direction of the crises from the real economy towards the banking sector. Laeven (2019) suggests that increased regulation has resulted in banks increasing their capital ratios significantly and this comes with a reduction in available funds for corporate and consumer loans.

### 3. Methodology and data

#### 3.1. Agent-based model specification

We employ an agent-based model that simulates the US economy. It includes a production/goods market, the financial sector, household preferences and the government sector. The agent-based model is based on the Dynamic Stochastic General Equilibrium (DSGE) model of Colombo et al. (2016) but has been extended to an agent-based setup (LeBaron and Tesfatsion, 2008) in order to

account for heterogeneity in the ecosystem of modern economics (Jump et al., 2019). Indeed, DSGE models have been argued to carry drawbacks in describing complex economic systems (Buncic and Piras, 2016; Fagiolo and Roventini, 2012). Agent-based modelling is a good fit for our task because, unlike DSGE models, it features a bottom-up approach, by simulating the behaviour of each individual agent and then aggregating the results. This setup is used commonly in the banking and financial literature (Calimani et al., 2019; Boyd et al., 2019; De Jong et al., 2010) and has been used to simulate other crises as well (Cardaci, 2018; Krug et al., 2015; Polyzos et al., 2020a). The algorithmic steps are given in Appendix A, based on Polyzos et al. (2020a).

We note that our model does not consider some features of the real economy such as the shadow banking sector, prices of financial assets and collateral value dynamics. In addition, especially in times of an economic meltdown, such as the one brought forth by the COVID-19 pandemic, it is very difficult to model and account for the time-varying default risk, both in financial institutions and in the other economic agents. What is more, the interconnectedness of financial institution is modelled principally through interbank loans, which is admittedly a simplification. However, our modelling approach encompasses the main features of the financial system and of the real economy and has been established in the literature as an appropriate methodology (Farmer and Foley, 2009), especially when simulating uncertain scenarios. Consequently, we believe that our model's findings are not hindered by these simplifications.

In the agent-based model described below, we identify three separate periods: the training/setup period, the crisis period and the post-crisis period, similarly to Yang et al. (2020). In the training period, the learning algorithm described in Section 3.2.1 builds the production functions of firms and the utility functions of households. This step is important because these functions govern the behaviour of the aforementioned agents. In the crisis period, we propose a baseline scenario, given the measures proposed by Elnahass et al. (2021) which we extend using the LSTM process described in Section 3.2.2. This algorithm can also produce scenarios for extreme outcomes, using the neural network's bias coefficient, which we implement in order to perform scenario analysis. We measure the potential outcomes of the pandemic using these scenarios.

Finally, in the post-crisis period, we implement four different policies, namely a demand stimulus, a supply stimulus and two versions of a financial stimulus. The first two are OECD suggestions (OECD, 2020), but we argue that there is a significant cost attached to them. The demand stimulus can be simulated by increasing household wealth in an effort to boost consumption (Loayza and Pennings, 2020), while the supply stimulus can be implemented by directly financing the expansion of firm productive capacity (Guerrieri et al., 2020). We implement the finance stimulus with a temporary regulatory relief on the banking sector in an effort to increase the funds that banks make available to both households and banks. We assert that this type of financial stimulus comes with a significantly smaller cost for public finances and can be equally, if not more, effective, as it can simultaneously boost demand and supply.

We simulate two types of deregulation ("low" regulation and "moderate" regulation), using regulatory capital data from US banks from 1980 to 2018 (Wharton Research Data Services, 2020a). We follow Naceur et al. (2018) and split this data into three subperiods, namely from January 1992 to June 1995 (based on an event-free window with the implementation of Basel I), which we term "Low Regulation" period, from September 2005 to November 2007 which we term "Moderate Regulation" period (based on the implementation of Basel II), and from January 2014 to November 2015, which we term "Increased Regulation" period, which replicates the current regulatory status in the banking sector and is used as a baseline scenario in the simulations. We run our agent-based simulations using the sub-period data as indices of deregulation for the banking sector. It must be noted that deregulation also carries an increased risk of financial instability (Claessens et al., 2013), which we discuss in our findings. The regulatory relief, which is explained in more detail below, affects capital requirements directly and thus credit constraints and loan rates indirectly. Naturally, the way in which banks respond to the regulatory changes, given their transient nature, may differ and this is captured through the banks' optimisation problem.

It must be noted at this point that a major issue in bank regulation is the implementation of the countercyclical capital buffers (CCB). Given their advantage of allowing banks to run down regulatory capital in bad times, CCB's have been shown to make regulation less procyclical, while keeping the long-run incentives of capital regulation to address macroprudential risk (Montagnoli et al., 2021). In an actual implementation of the policy, relaxing CCB's could be a more time-consistent and less moral hazard-prone way of providing some temporary regulatory relief that banks would pay for by accumulating capital in good times. This has been tested in initial version of our work and the results showed that the relief provided by CCB is not adequate (on its own) to spur the economy to recovery.

### 3.1.1. Banks

Banks have a central role in our modelling approach. The role of the financial sector in facilitating economic activity is widely accepted. Banks generate economic growth in two ways: by financing the expansion of the productive capacity of firms and by financing consumption (Greenwald and Stiglitz, 1993). In our model, banks fulfil this role in the typical fashion of collecting funds from economic agents with cash surpluses and channelling them to those with cash deficits. They collect deposits at period  $t$  and pay interest rate  $r_d$  at period  $t + 1$ .

In the loan market, banks receive interest rate  $r_l$ , based on their cost of capital. They compete for loans in a symmetric Cournot-Nash game (Boyd et al., 2019), but have asymmetric information when borrowers request funds. Banks cannot know the borrower's underlying success probability and they can only observe the realisation of the financed project at time  $t + 1$ , when they receive interest only in case of success.

Thus, the profit function of the bank is as follows:

$$\Pi_b = \sum L_t r_{l,t} p_t - \sum D_t r_{d,t} \quad (1)$$

where  $p_i$  is a binary variable for each financed project's success ( $i$ ) with different and unknown (to the bank) distributions for each borrower, while  $L$  and  $D$  are loan assets and deposit liabilities respectively. The bank seeks to maximise  $\Pi$  in each time period according to Eq. (1), based on the choice variables  $L$  and  $r$  and given  $D$ . It must be noted that the loans supplied in  $L$  can be consumer, corporate or interbank loans, each carrying a different interest rate and probability of default.

Bank regulation is specified according to the supervisory framework, which is set by the regulator as follows:

$$Reg_{b,t} = \{CapReqVector_t, LiqC_{b,t}\} = \{t1, CapB, CCB_t, LCR_{b,t}\} \quad (2)$$

The vector in Eq. (2) is set for each bank  $b$  in each time period  $t$  and contains a Tier 1 capital requirement ( $t1$ ), the capital conservation buffer ( $CapB$ ), and the countercyclical capital buffer for the given time period ( $CCB_t$ ) as well as the amount resulting from implementing the liquidity coverage ratio on the given bank in the given time period ( $LCR$ ), as calculated based on the bank's assets.

For banking crises, we follow [Laeven and Valencia \(2010\)](#) and [Laeven and Valencia \(2018\)](#) since the current pandemic represents a systemic banking crisis and not an isolated distress event. We follow this approach as it is commonly accepted and helps address the controversy surrounding the definition of banking crises.

### 3.1.2. Producers – Goods market

The goods market included in the model represents the transfer of wealth from households to firms. We build this component *à la* [Greenwald and Stiglitz \(1993\)](#), in order to describe the relationship between production and capital demand. The market always clears at the end of each period. This market performs two functions. First, it represents total output and can thus be monitored to determine the GDP costs of the crisis and the pursuant recovery. Second, it will indicate the results of government policies to boost supply. Note that we are building a closed economy and thus all consumption reflects domestic production. This is a simplification that we believe does not influence our result, particularly given the pandemic nature of the current crisis. Since the market always clears, any increase in supply will be absorbed by demand, given steady consumption preferences from households. This simplification, also used by [Greenwald and Stiglitz \(1993\)](#), does not limit the applicability of our findings.

Firms incur costs during the production process and these costs need to be paid for either through sales revenue or through financing. Firms also seek financing in order to expand their productive capacity, which will lead to economic growth. Total output at time  $t$  has been produced at time  $t-1$  and the resulting production costs must be paid at time  $t$ . Thus, total production will be equal to:

$$Production_t = \sum_{\forall f \in F} Capacity_{f,t-1} = \sum_{\forall g \in G} ValueOfGoods_{g,t} \quad (3)$$

Since price changes and production costs are irrelevant (similarly to [Greenwald and Stiglitz, 1993](#)), firms can maximise profits only by increasing production at the lowest possible financing cost. Hence the role of the financial sector is paramount both for economic growth (i.e. increasing capacity) and for profit maximisation.

The production (capacity) function in (3), optimised by a Random Regression Forest for each firm, loosely follows [Schneider et al. \(2010\)](#) but maintains only observable components.

$$C = \gamma_e \cdot \mathbf{x}_e + \gamma_f \cdot \mathbf{x}_f + \varepsilon \quad (4)$$

where  $\mathbf{x}_e$  is a column vector of  $n$  possible economy-wide causes for the latent variable, with  $\gamma_e$  being their coefficients for these causes,  $\mathbf{x}_f$  is a column vector of  $m$  possible firm-specific causes for the latent variable, with  $\gamma_f$  being the coefficients for these causes and  $\varepsilon$  is the error term. In this manner, the latent variable  $C$  is determined by a set of causes that include both firm-specific (i.e. differ for each firm) and economy-wide (i.e. same for each company) factors. We calculate a separate  $\gamma_f$  vector for each firm using the RRF process and thus eliminate errors, rendering the  $\varepsilon$  term irrelevant, as each agent has a proprietary production function. Firm-specific causes are simulated using aggregated financial ratios from the US economy as listed in the Fama-French 49 Industries framework ([Wharton Research Data Services, 2020b](#)) while economy-wide data has been retrieved from the [World Bank \(2020\)](#) and can be seen in detail in [Appendix B](#). The variables used in the RRF process include most commonly used indicators about the macroeconomic status of a country. Naturally, our model can potentially suffer from the omitted-variable bias, but we believe that the multitude of input variables that are used in the RRF minimises this risk.

### 3.1.3. Households

The households in the system operate under Epstein–Zin utility preferences ([Epstein and Zin, 1989](#)), so that our model can capture the effects of uncertainty during this crisis ([Sun et al., 2017](#)). Such utility preferences can take into account static consumption preferences and also aggregate future utility in the presence of uncertainty. The typical household thus has a constant elasticity of substitution between current and future consumption. The basic equation proposed by Epstein–Zin is as follows:

$$U_{t,h} = [(1 - \beta_h)c_{t,h}^\rho + \beta_h \mu_{t,h} U_{t+1,h}^\rho]^\frac{1}{\rho} \quad (5)$$

where  $\beta$  represents time preferences and  $\rho$  determines the elasticity of intertemporal substitution, thus linking utility preferences back to the banking sector through liquidity ([Bayoumi, 1993](#)). The effects of uncertainty are captured by the  $\mu_t$  coefficient and are approximated by Epstein–Zin as follows:

$$\mu_t U_{t+1} = (E_t U_{t+1}^\alpha)^\frac{1}{\alpha} \quad (6)$$



where  $\alpha$  represents the household's risk aversion. Note that both  $\alpha < 1$  and  $\rho < 1$ .

We augment the Epstein-Zin utility function in Eq. (5) and introduce a health status indicator for the economy, following Yang et al. (2020). The authors suggest that the health status indicator can influence utility by impacting personal health either directly (due to infection) or indirectly (due to limited access to medical resources). The outbreak of a pandemic will thus affect household consumption goods and services (Barro, 2006).

Thus, combining Eqs. (5) and (6) and augmenting by the health status indicator, we get:

$$U_{t,h} = \left[ (1 - \beta_h) c_{t,h}^\rho + \beta_h (E_t U_{t+1,h}^\alpha)^\frac{\rho}{\alpha} \right]^\frac{1}{\rho} - \varphi_h h_s \quad (7)$$

where  $h_s$  is the health status indicator (which takes the value 1 during the pandemic and 0 otherwise) and  $\varphi$  represents the health preferences of each household. We choose to introduce the health status in the utility function (rather than the consumption function) since the pandemic has a direct negative effect on utility, which is complemented by the indirect effects through consumption. This is confirmed by Yang et al. (2020).

We approximate the parameters  $\alpha$ ,  $\beta$ ,  $\rho$  and  $\varphi$  using bootstrapping on Gallup poll data for the United States and we proceed to calculate individual preferences for each household using the RRF process discussed in Section 3.2.1. We perform sensitivity analysis on these parameters. Thus, our model can extend the approach of Li and Liu (2018) and capture preference heterogeneity on health risk (Yang et al., 2020), uncertainty (Sun et al., 2017), risk aversion and intertemporal substitution (Epstein and Zin, 1989), thus incorporating the effects of the disasters on consumption (Barro, 2006). Note that we do not need to specify any structure on how households provide labour at what wage rate, in order to model unemployment, since in our approach the labour market's limitations are on the demand side.

### 3.1.4. Government

The government collects taxation on all income generated by the aforementioned agents with zero ability for tax-evasion or shadow activities. Taxation funds are used as income substitution for those who are unemployed (unemployment benefits) or as spending on public goods. Normally, reduced public goods spending or increased unemployment could have adverse effects on household happiness, but this goes beyond the scope of our analysis. We proxy these effects by monitoring government spending on both public goods and unemployment benefits during the post-crisis, in order to demonstrate the trade-off between the two government-funded policies (demand and supply stimulus) and bank deregulation. Note that the tax rate can be variable, but we assume that tax rates will not be increased during the implementation of expansionary measures as this would act countercyclically.

### 3.1.5. Formal model notation

In this section, we present the notation of the agent-based model, as presented in Polyzos et al. (2020a). The model implements multiple simulation periods and is based on the four distinct types of economic agents presented above. The notation that is used is as follows:

- N1.  $t \in T = \{1, \dots, T\}$ 11.: The model runs on a group time periods of order  $|T|$
- N2.  $h \in H = \{1, \dots, H\}$ 21.: The artificial economy includes a set of households of order  $|H|$ . Households are initialised with different initial cash endowments and different preferences for holding cash, as follows:  $\forall h \in H : CB_{h,t=0} = U(1, 10)$  and  $\forall h \in H : PB_{h,t=0} = U(1, 10)$ . The precautionary demand for money (PB) signifies the amount of money that households choose to keep outside of deposit accounts. This would be a fraction of their initial cash. In addition, some households behave in a risk-loving manner, opting for higher interest rates for their deposits even if the bank offering them is in distress. So, for each household, the available balance is given by the difference of the cash balance and the precautionary demand. Thus:  $\forall h \in H, t \in T : AvB_{h,t} = CB_{h,t} - PB_{h,t}$
- N3.  $b \in B = \{1, \dots, B\}$ 31.: The artificial economy includes a set of banks of order  $|B|$ . Banks receive an endowment of cash equal to a random amount, as follows:  $\forall b \in B : CB_{b,t=0} = U(1, 10) * |H|$
- N4.  $f \in F = \{1, \dots, F\}$ 41.: The artificial economy includes a set of firms of order  $|F|$ . Firms have a random productive capacity, as follows:  $\forall f \in F : Capacity_{f,t=0} = U(1, 10) * (|H|/|F|)$
- N5.  $bc \in BC = H \cup F$ 51.: The set of potential bank retail customers in the economy (i.e., firms and households)
- N6.  $e \in E = BC \cup B = H \cup F \cup B$ 61.: Set of all economic agents in our system
- N7.  $fa \in FA = \{1, \dots, FA\}$ 71.: The active financial assets traded at any given time  $t$
- N8.  $eb \in EB \subseteq E$ 81.: The set of bankrupt economic agents (the agent type can be a bank, firm, or household). This a subset of set  $E$  and is initially empty. This set can be further subset into the subsets of bankrupt households ( $EB_H$ ), firms ( $EB_F$ ) and banks ( $EB_B$ ).

It must be noted that once an agent goes bankrupt, she will not participate in any financial transactions in the artificial economy. Thus, in the simulation steps described later in this section, sets  $E$ ,  $H$ ,  $F$ , and  $B$  actually contain only the active agents of the corresponding sets. These sets are defined as the difference of the sets at time  $t = 0$  from  $EB$ . Consequently, the active agent sets are as follows:

- N9.  $h \in H = H_0 - EB_H$
- $f \in F = F_0 - EB_F$
- $b \in B = B_0 - EB_B$

$$e \in E = E - EB = (H_{t=0} - EB_H) \cup (F_{t=0} - EB_F) \cup (B_{t=0} - EB_B)$$

N10.  $g \in G_t = \{1, \dots, G_t\}$ : This set contains all the goods available for sale at time  $t$ . These goods are produced at time  $t-1$ .

N11. Total production (i.e., the total value of goods traded) at time  $t$  equals the total capacity of active firms at time  $t-1$ .

$$Production_t = \sum_{\forall f \in F} Capacity_{f,t-1} = \sum_{\forall g \in G} Value_{g,t}$$

N12.  $un \in UN \subseteq H$ : The set of unemployed households. This is a subset of  $H$  and its members change every period.

In addition, the following assumptions hold.

A.1  $\forall e \in E : a \in A_e \subseteq FA$ : All economic agents carry a proprietary list of assets, which is a subset of  $FA$ .

A.2  $\forall e \in E : l \in L_e \subseteq FA$ : All economic agents carry a proprietary list of liabilities, which is a subset of  $FA$ .

A.3  $\forall fa \in FA : \exists! e \in E : fa \in A_e$  and  $\forall fa \in FA : \exists! e \in E : fa \in L_e$

For all financial assets, exactly one agent carries the item in her assets and exactly one agent carries the item in her liabilities.

We should note here that the banks' asset vectors are further divided into three subgroups according to the asset's liable agent. These groups can then be used to calculate the sum of weighted assets, since a different asset weight is assigned according to the type of the liable agent (bank, firm, or household).

$$A.4 \forall g \in G_t : \exists! h \in H : g \in Exp_e \text{ and } \forall g \in G_t : \exists! f \in F : g \in Production_f$$

For all goods in the market at the end of time period  $t$ , only one household has purchased the item (and thereby derived utility from it) and only one firm has produced the item at time  $t-1$ .

The corollary of assumption A4 is that the goods market must always clear domestically at the end of each period, since for simplicity purposes, we are simulating a closed economy.

The regulator implements the vector of market rules, which includes the capital adequacy ratios (the basic Tier 1 ratio, the capital conservation buffer, and the countercyclical capital buffer) as well as the liquidity coverage ratio (LCR). The LCR, when applicable, is calculated separately for each bank in each time period and is set equal to the total outflow of funds from deposit accounts in the last time period. The resulting rule vector imposes the minimum requirements for each banking institution, thereby affecting the funds that the institution makes available to other agents in the system. The rule vector is the policy implementation tool for the various regulatory scenarios simulated in our work.

The rule vector is the following.

$$N13. r_{b \in B, t \in T} = \{CapReqVector_t, LiqC_{b,t}\} = \{t1, CapB, CntCapB_t, LiqC_{b,t}\}$$

The vector for each bank in each time period contains a Tier 1 capital requirement ( $t1$ ), the capital conservation buffer, and the countercyclical capital buffer for the given time period as well as the amount resulting from implementing the LCR on the given bank in the given time period ( $LiqC$ ). This amount,  $LiqC$ , is calculated for each bank at each time step (see [Appendix A](#) for further details). The rules are applied in sets.

The regulator also implements the vector by which the assets of a bank are weighted. The weight vector depends on the type of rule set and is fixed throughout each simulation.

N14.  $w = \{w_{b \in B}, w_{h \in H}, w_{f \in F}\}$ : The weight vector  $w$  contains weights for each type of asset, which may be different from each other.

N15. Hence, the sum of weighted assets of the bank can be calculated using the following equation:

$$wa_{b \in B, t \in T} = \sum_{\forall b \in B} \begin{cases} a_{b,t} \times w_b \text{ if } \exists b' \in B : a_{b,t} \in L_{b',t} \\ a_{b,t} \times w_h \text{ if } \exists h \in H : a_{b,t} \in L_{h,t} \\ a_{b,t} \times w_f \text{ if } \exists f \in F : a_{b,t} \in L_{f,t} \end{cases}$$

The sum of the bank's weighted assets is the sum of the products of each asset in the bank's asset set with the corresponding weight (for that asset) from the weight vector  $w$ .

$$N16. \forall b \in B, t \in T : AvB_{b,t} = CB_{b,t} - \left[ \sum_{\forall i \in CapReqVector_t} (CapReqVector_{i,t} \times wa_{b,t}) \right] - LiqC_{b,t}$$

For each bank, the available balance is calculated by subtracting regulatory funds for the bank's cash reserves. The sum in the statement above is the sum of the products of each imposed capital buffer rule with the sum of the weighted assets of the bank, as calculated in N15. This amount is subtracted from the bank's cash balance, since it cannot be used to purchase assets.

The above notation serves in describing the algorithmic steps and for formulation preference functions for the behaviour of households. For example, when households place their excess cash balance in a deposit account, only risk-loving households may opt to invest the money in a high-risk security (if any banks offer the product) or a deposit, with equal probability for each case. Banks in more urgent need of cash issue these high-yield securities and we assume a signalling behaviour here. Households are considered to be

sophisticated investors and are thus aware of the reason why banks issue high-yield securities. Thus, only specific categories of households will participate in this market. This assumption is consistent with [Diamond \(1997\)](#) and [Allen and Gale \(2004\)](#), who suggest limited market participation.

Meanwhile, rational, risk-averse households stick to normal deposit products. Once the choice of product is made, a random bank is chosen, with banks that offer higher interest rates having more chances of being picked.

Hence, the expected reward function of each asset for the depositor is as follows:

$$Q_n E(R)_{a,h \in H,t} = Amt_{a,t-1} \times ir_a \times (1 - PD_{b \in B:a \in L_b}) \quad (8)$$

where PD is the probability of default of the bank that carries the asset in its liabilities. The probability of default is different for each institution, depends on the regulator's solution to bank distress, and is equal to

$$PD_{b,t} = f_b(r_{b,t}) \quad (9)$$

Combining Eqs. (8) and (9) and, we obtain

$$E(R)_{a,h \in H,t} = Amt_{a,t-1} \times ir_a \times (1 - f_b(r_{b,t})) \quad (10)$$

Eq. (10) signifies the importance of regulation for the utility received by depositors in the banking sector, a setup similar to social planning in [García-Palacios et al. \(2014\)](#).

On the borrower side, these deposits are used by banks to finance investment projects for firms, which aim to increase productive capacity. Firms that do not have an active investment project will propose one to the banking system, seeking financing. Investment projects carry a random return (this can be considered similar to the internal rate of return, IRR), which will help the firm increase productive capacity, as argued by [Chen and Matousek \(2020\)](#). For a project to be accepted, the firm must find a willing financier for the venture, with a cost of capital lower than the project's return. Also, each firm carries a random probability that its projects will fail.

If the firm is unable to find funding for investment projects, it gradually loses productive capacity. In this way, high interest rates tend to reduce long-term economic growth and may eventually lead to bank distress. Therefore, the productive capacity for each firm at any given time is expected to be equal to

$$Capacity_{f \in F,t} = Capacity_{f,t-1} + \begin{cases} U(\text{Min}(IRR), \text{Max}(IRR)) \times (-1), & \text{without active investment project} \\ IRR_{pr,f} \times (1 - PF_f), & \text{with active investment project} \end{cases} \quad (11)$$

If the firm fails to find financing for its current project, its productive capacity is reduced by a random amount, with uniform distribution between the minimum and maximum IRRs of all active projects in the system. We should note that firms produce the artificial economy's goods according to their capacity and taxes are collected on production, since the market always clears. Thus increased taxation carries a production cost due to the reduction of available income both on the firm and the consumer side.

### 3.2. Learning machines

We implement two learning machines to fit our empirical data and complement the DSGE agent-based model. We compute employ a Random Regression Forest (RRF) to build household utility and firm production functions. In addition, we create prediction scenarios regarding on bank stability using a Long Short Term Memory (LSTM) neural network based on the stability indicators in [Elnahass et al. \(2021\)](#). The use of the machine learning methodologies is apposite in order to capture the heterogeneity of the data (RRF) and in order to build forecast scenarios based on the limited data that is currently available (LSTM). Indeed, by using firm and household data from the US, we create individualised function for each economic agent, rather than estimating a single econometric model.

#### 3.2.1. Random Regression Forest (RRF)

Our agent-based model includes two behavioural functions, namely the households' utility function and the firms' production function. We calculate individual functions for each agent, based on data from the United States using a machine-learning process called Random Regression Forest (RRF), according to [Breiman \(2001\)](#). Random regression forests and random decision forests belong to the wider category of ensemble techniques, which combine more than one calculation algorithms to reach the desired goal. Random Forests are generally used as a prediction tool to compute non-parametric forecasts from many predictor variables when the underlying functional form is unknown. This approach gives us the flexibility to grow many deep trees, with a potentially large forecast variance, and is thus crucial in permitting our models to have the capacity to approximate non-linear functions of many predictors. Alternative methodologies, such as the Lasso Regression or the Bayesian Model Averaging approach were also considered but it was deemed that they added unnecessary complexity to our calculations. As the volume of data and the number of the functions was quite significant, the superior efficiency of RRF in terms of calculation speed made it an ideal methodology to implement. In addition, the aggregation over the different ensemble trees, which RRF offers, adds to the efficiency of our forecasts. Finally, calculating individualised RRF-optimised functions for each agents permits us to account for the heterogeneity in the underlying economic systems.

A random forest is a collection of  $m$  tree-structured classifiers or regressions  $\{\omega(x, \theta_k), k = 1, \dots, m\}$  where the  $\{\theta_k\}$  are independent random vectors of causal factors with identical distributions ([Breiman, 2001](#)). Each tree is allowed to cast a single, equally weighted vote for the most popular class at input  $x$ . Despite being designed for classification problems, random forests can be expanded for regression tasks simply by augmenting the random vector  $\theta$  of predictors so that the tree predictor  $\omega(x, \theta)$  takes on numerical values. The training set is considered as independently drawn from the distribution of the random vector  $Y, X$ . Thus, the expected squared



error of the numerical predictor  $h(x)$  is

$$E_{X,Y}(Y - \omega(X))^2 \quad (12)$$

The process minimises errors for each predictor, computes a regression function at each tree and then proposes a prediction based on the averages of the  $m$  trees. In order to select the inputs for each tree, the algorithm uses bootstrapping and random feature selection. Further details on this process can be found in [Ho et al. \(1994\)](#). Regression forests are used to compute non-linear regressions of dependent variables given independent input.

We use two datasets for our regression problems. Firstly, regarding household utility, we employ data on happiness from the Gallup World Poll database, which includes a set of questions posed to individuals in the United States and computes a happiness index of each individual. This data covers the period from 2005 to 2018, as Gallup conducts yearly surveys, asking people essentially about how their lives are going and what determines their utility functions. The data includes numerous indicators for each individual and thus we are able to feed the RRF algorithm with many independent variables. The dependent variable here is an unweighted average of the response values of households to the questions under the Gallup-Sharecare Global Well-Being Index, normalised in order to deal with the different range of values in the index. This approach is aimed at reconciling reported and evaluated happiness levels ([Kahneman et al., 1999](#)).

Secondly, regarding production functions, we download industry-level data from the Financial Ratios Suite of [Wharton Research Data Services \(2020b\)](#). We use the Fama-French 49 Industries framework in order to simulate all the sectors of an economic system. We proxy firm output (the dependent variable) with revenue and use a mix of company-specific and country-wide factors as independent inputs. The RRF process then builds individualised production functions for each firm in our artificial economy, by calculating  $\gamma_e$  and  $\gamma_f$  from Eq. (4). Economy-wide data for the United States was sourced from the [World Bank \(2020\)](#) and are presented in [Appendix B](#).

In order to determine the inputs for each process, we implement the random subspace feature selection of [Ho \(1998\)](#). The random forests of [Breiman \(2001\)](#) use randomly sampled subspaces of the input variables, where each tree casts a single vote on the final, combined predictor. [Ho et al. \(1994\)](#) demonstrate that combining multiple trees produced in randomly selected subspaces improves prediction accuracy and using the strong law of large numbers, we can deduce that predictions will converge and thus overfitting will not be a problem ([Ho, 1998](#); [Breiman, 2001](#)). The number of different trees needs to be sufficiently large and that requires a large number of observations, to avoid overfitting. Therefore, the RRF algorithm can only be applied when there is a multitude of observations available. In this way, random regression forests solve the problem of dimensionality by taking advantage of the high dimensionality and improving accuracy as complexity increases ([Ho, 1998](#)).

The RRF process constructs many decision trees, growing each one from a different set of training data, using randomly selected samples. Once a new prediction is requested, each tree in the forest gives a forecasted value (a vote for the output) and the result is the average of all votes. In classification algorithms (random decision trees), the class prediction is determined by majority votes among the forest of trees. Consequently, each tree is used in essence as a data structure and builds a predictor for a specific subsample of the data set. So instead of describing a clearly motivated hypothesis, the trees group the data and summarise the subsamples, which were selected randomly and then optimised using specific sampling criteria, such as information gain or variance minimisation ([Chen and Liu, 2005](#)). This ensures the absence of statistical correlation between the trees in the forest and thus model variance will be reduced when these trees are combined ([Ho, 1998](#)).

### 3.2.2. Long Short Term Memory (LSTM)

One of the potential determinants of the recovery outcomes after the COVID-19 crisis is the actual effect of the pandemic on the economy and on the financial system. We follow the approach of [Elnahass et al. \(2021\)](#) in order to determine the financial stability effects of the crisis. We create three scenarios (baseline, pessimistic, optimistic) by extending the accounting performance measures proposed (namely return on assets, return on equity, return on average assets, return on average equity and cost to income), using a Long Short Term Memory (LSTM) approach ([Schmidhuber and Hochreiter, 1997](#)). This algorithm belongs to the category of deep learning methodologies and is able to adapt to long-term dependencies ([Gers et al., 1999](#)) and overcome the errors of similar algorithms in the back-propagation of information contained in recent input events ([Bengio et al., 1994](#)). In this manner, LSTM networks are able to utilise the information contained in recent input and this information is usable for long periods of time after the input time, thus making it appropriate for our model. LSTM is essentially a special case in the group of recurrent neural networks, which utilise sequential information by selectively passing inputs across time steps during data element processing ([Cho et al., 2014](#)).

The LSTM topology features a recurrent learning unit inside the network and, in addition, several decision gates that utilise two important attributes: the longer states from the starting units and the shorter states from the last unit of information. This feature has permitted LSTM networks to achieve great success in solving time series forecasting problems ([Law et al., 2019](#)). The general setup follows that of RNN networks and includes an input and an output layer, with many hidden layers in between. However, the process involves an attention mechanism which can assign different weights to the various inputs of the model, thus permitting it to learn the importance of new input during data processing. A stateful LSTM methodology suggests that cell states are preserved after each iteration and are simply updated with the new information.

The modelling approach includes building a forecasting network  $\theta$  which will predict  $n$  future values based on a vector of  $T$  previous values of the same data series. The model is as follows:

$$\{\hat{y}_t\}_{t=T+1}^{T+n} = \theta(\{y_t\}_{t=1}^T) \quad (13)$$

The decision functions at each gate (forget gate  $f$ , include gate  $i$  and output gate  $o$ ) and the hidden layer ( $h$ ) are as follows:

$$f_t = \sigma(W_f \cdot (h_{t-1}, y_t) + b_f) \quad (14)$$

$$i_t = \sigma(W_i \cdot (h_{t-1}, y_t) + b_i) \quad (15)$$

$$o_t = \sigma(W_o \cdot (h_{t-1}, y_t) + b_o) \quad (16)$$

$$h_t = o_t \times \tanh(C_t) \quad (17)$$

where  $\sigma$  represents a sigmoid function,  $W_{f,i,o}$  represents the weight vector of inputs,  $h_{t-1}$  is the hidden layer from previous periods,  $y_t$  is the new input vector and  $b_{f,i,o}$  is the bias of each gate. The bias coefficient is a common feature of all machine learning functions and can either be set beforehand or calculated during the training phase.

In order to determine the new candidate values (vector  $C_t$ ) that can be added to the neural cell's state, LSTM uses the following equations. These are determined as follows:

$$C_t = \tanh(W_C \cdot (h_{t-1}, y_t) + b_C) \quad (18)$$

$$C_t = f_t \times C_{t-1} + i_t \times C_t \quad (19)$$

Thus, the new cell state,  $C_t$ , is as follows:

$$C_t = \sigma(W_f \cdot (h_{t-1}, x_t) + b_f) \times C_{t-1} + \sigma(W_i \cdot (h_{t-1}, x_t) + b_i) \times \tanh(W_C \cdot (h_{t-1}, x_t) + b_C)_t \quad (20)$$

The algorithm is trained and calibrated by employing the differential evolution algorithm of [Storn and Price \(1997\)](#), which is a population-based optimisation algorithm that performs well in reaching global optima. The commonly used gradient-based algorithms, being local search methods, carry the risk of convergence to local optima ([Askarzadeh and Rezazadeh, 2013](#)). In cases where the initial weights are located, either randomly or through normalisation, near local optima, the algorithm would fail to reach the global optimum. The differential evolution algorithm is population-based and thus does not face this problem.

## 4. Findings

### 4.1. Training models

#### 4.1.1. Household utility

This section presents the accuracy rates of predictions in the household utility functions. As mentioned earlier, we implement an RRF on data from the Gallup poll. This results in a different utility function for each household of our simulation process. The Gallup World Poll is a yearly cross-sectional survey which is designed to represent the resident population of each country aged 15. The survey has been conducted since 2006 and compiles the data collected into a single report. In order to mine household utility, we construct an unweighted average of the response values of households to the questions under the Gallup-Sharecare Global Well-Being Index, normalising the values to account for the different ranges of the questions. The Global Well-Being Index can only take two values (Struggling and Thriving) and thus reduces the explanatory power of the model, so an average of the given answers is required. Since reported and evaluated levels of happiness often diverge ([Kahneman et al., 1999](#)), this method is better suited at reconciling these differences. The full set of questions can be found in [Gallup \(2018\)](#).

The data is split into subsamples in order to confirm the accuracy of the algorithm. Following [Pérez-Benito et al. \(2019\)](#), we compare the result of the RFF to a linear multi-variate regression and calculate three metrics on prediction accuracy, viz. the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Rooted Mean Square Error (RMSE). The formulae for the metrics are given below:

$$MAPE = \frac{1}{N} \sum_{t=1}^N \frac{|y_t - \hat{y}_t|}{y_t} \quad (21)$$

**Table 1**

Comparison of accuracy performance metrics for household utility.

|      | MLR    |             | RFF    |             |
|------|--------|-------------|--------|-------------|
|      | Value  | Improvement | Value  | Improvement |
| MAPE | 18.35% | 0.00%       | 12.55% | 31.61%      |
| MAE  | 0.0352 | 0.00%       | 0.0252 | 28.41%      |
| RMSE | 0.0458 | 0.00%       | 0.0361 | 21.18%      |

Note: This table demonstrates the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Rooted Mean Square Error (RMSE) of the RFF and of the Multiple Linear Regression (MLR) model when calculating household utility. The improvement percentage column compares the performance of RFF to MLR as the benchmark model. The actual and predicted values used in the calculation of MAE and RMSE have been normalised in the range [0,1].

$$MAE = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t| \quad (22)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2} \quad (23)$$

where  $y_t$  and  $\hat{y}_t$  are the observed and fitted values of the variable at time  $t$ , respectively. We demonstrate the results in Table 1.

#### 4.1.2. Production functions

Similarly to the calculation of household utility functions, we calculate a production function for each individual firm incorporating both economy-wide and firm-specific causes. Our training sample includes aggregated data from the US economy as listed in the Fama-French 49 Industries framework and we use data mined from [Wharton Research Data Services \(2020b\)](#) for the period from 2000 to 2018. We proxy production using revenue from the firms' income statements. Economy-wide data for the United States has been retrieved from the [World Bank \(2020\)](#). The accuracy metrics of our training model are given in Table 2.

#### 4.2. Model setup

Our model setup includes three distinct periods. First, the model training period, which lasts for 24 periods (months). During this period, we instantiate the economic agents using the individual production functions (for firms) and the individual utility functions (for households) calculated using the RRF methodology (Section 3.2.1) on US economy data. The model's training simulates the period from March 2018 to February 2020 and is common for all scenarios examined. Our model is trained on data up to February 2020 as we place the beginning of the crisis in March 2020, despite some difficulties in computing this date, since there are conflicts between the various levels of government, as well as between the different states. Most statewide stay-at-home orders were issued after 20 March 2020, with New York leading the way and other states following suit. Consequently, we can place the beginning of the crisis in March (Baker et al., 2020) and thus using training data up to February 2020 is appropriate.

We then execute a benchmark scenario of no COVID-19 outbreak in order to be able to perform comparisons with the outbreak scenarios. We record key variables 20 periods after the end of the training period, for comparison purposes. We consider different scenarios for the effects of the pandemic, by performing an LSTM prediction on the performance measure proposed by Elnahass et al. (2021) regarding the effects of COVID-19 crisis on financial stability. We perform different sets of simulations based on each of these scenarios. Regarding the size of the economic disaster, there is mixed evidence in the relevant literature (Barro, 2006; Gourio, 2012). Barro and Ursúa (2008b) suggest a mean disaster size of 10% with risk persistence equal to 0.6, which would be a moderate scenario. Isoré and Szczerbowicz (2017), on the other hand, use a baseline disaster size of 22% with 0.9 persistence, which we adopt in our approach.

We simulate three types of policy response, as discussed earlier. These are a demand stimulus, a supply stimulus and two variations of a finance stimulus, with the latter being achieved through relaxing bank regulation. For the finance stimulus, the two scenarios examined are "Low Regulation" and "Moderate Regulation", as discussed in Section 3.1. We also execute a set of simulations for each scenario where authorities do not respond at all to the measures and simply adopt a *laissez-faire* approach, allowing the economy to self-heal. This is also for comparison purposes. Each set of simulations consists of 1000 repetitions of the same scenario, resulting in a total of 16,000 simulations that produced our empirical results.

#### 4.3. Economic consequences of the COVID-19 crisis

Our assessment of the damages caused by the economic consequences of the COVID-19 crisis is focused on three pillars: the banking sector, real economic activity and household utility/happiness. We present the outcomes of the crisis, as induced by our LSTM scenarios of financial instability, in the tables below. The variable values are recorded at the beginning of the lockdown period and then recorded again at the end of the crisis period. We then revisit these variables one year later. The percentage changes against the no-crisis benchmark are displayed for each variable in the panels. The no-crisis benchmark scenario produced simulation values using 1000 simulations where no external crisis has occurred in the artificial economy.

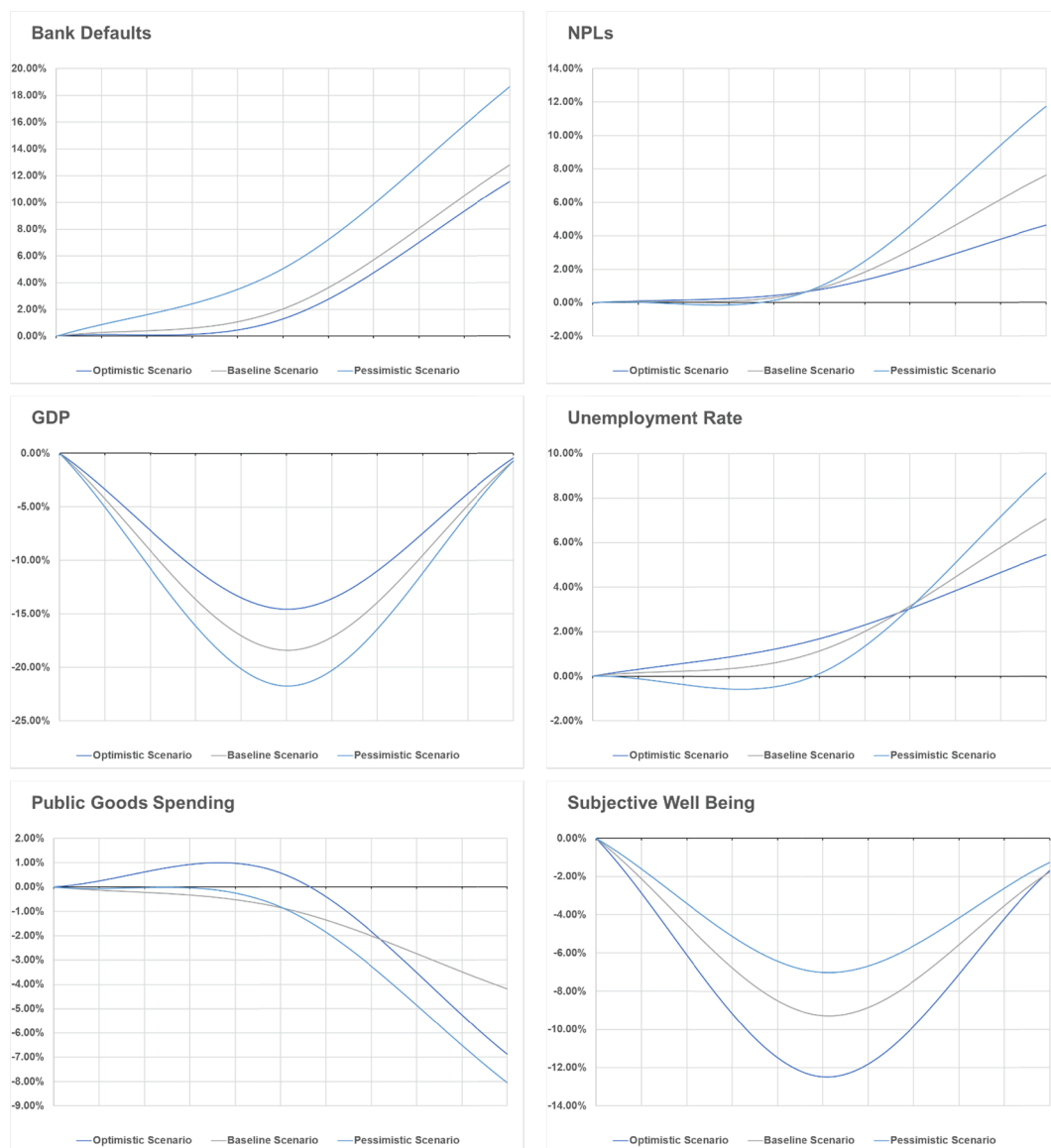
We present the impulse response functions of some key variables in Fig. 1. We must note that these are non-converging despite the fact that the model will reach an equilibrium after a few periods. This is because, as the model progresses, further events will influence these variables and thus result in a non-zero reverting function. The effects of the COVID-19 pandemic and of the preventive measures are channelled to economic activity both through the demand and through the supply side. This has been brought on by the lockdown measures, which, on the one hand, have significantly reduced the demand for some goods and services, whilst, on the other, have reduced the performance and productivity of workers. Adding uncertainty to the above, we can see how the pandemic has created a deep economic crisis, with persistent, long-run effects.

Table 3 discusses the banking sector and shows the average changes in the variables vis-à-vis the no-crisis benchmark. The scenarios (Optimistic, Baseline, Pessimistic) are based on LSTM forecasts on the banking performance measures of Elnahass et al. (2021). The *Crisis End* values show the change in the variables when comparing the end of the crisis to the corresponding period in the benchmark scenario. Similarly, the *Year Later* values represent comparisons with 12 periods after the preventive measures are lifted,

**Table 2**  
Comparison of Accuracy Performance Metrics for Firm Production Functions.

|      | MLR    |             | RFF    |             |
|------|--------|-------------|--------|-------------|
|      | Value  | Improvement | Value  | Improvement |
| MAPE | 15.35% | 0.00%       | 9.66%  | 37.07%      |
| MAE  | 0.0289 | 0.00%       | 0.0198 | 31.49%      |
| RMSE | 0.0374 | 0.00%       | 0.0265 | 29.14%      |

Note: This table demonstrates the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Rooted Mean Square Error (RMSE) of the RFF and of the Multiple Linear Regression (MLR) model when calculating firm production functions. The improvement percentage column compares the performance of RFF to MLR as the benchmark model. The actual and predicted values used in calculation of MAE and RMSE have been normalised in the range [0,1].



**Fig. 1.** Impulse Response Functions for Key Variables. Note: This figure shows the impulse response functions of key variables for different scenarios on the effects of the COVID-19 lockdowns. The values are recorded at the beginning and at the end of the lockdowns and then one year later. The percentage changes against the no-crisis benchmark are displayed for each variable in the panels. The impulse response functions are non-zero reverting, due to the progression of the model and further variables influencing the final outcome.

**Table 3**

Projected consequences of the COVID-19 crisis on the Banking sector.

|                    | Crisis End |          |             | Year Later |          |             |
|--------------------|------------|----------|-------------|------------|----------|-------------|
|                    | Optimistic | Baseline | Pessimistic | Optimistic | Baseline | Pessimistic |
| Bank Defaults      | +1.29%     | +2.03%   | +5.07%      | +11.55%    | +12.78%  | +18.64%     |
| Banks in Distress  | +7.14%     | +24.89%  | +19.59%     | +23.46%    | +27.10%  | +39.15%     |
| NPLs               | +0.78%     | +0.86%   | +0.96%      | +4.62%     | +7.64%   | +11.74%     |
| Low Risk Deposits  | +3.35%     | +4.21%   | +4.67%      | −0.59%     | −2.66%   | −3.42%      |
| High Risk Deposits | −50.38%    | −46.39%  | −51.28%     | −60.78%    | −78.52%  | −79.28%     |
| Consumer Loans     | −2.67%     | −8.56%   | −7.31%      | −5.73%     | −9.34%   | −13.93%     |
| Interbank Loans    | +8.27%     | +10.05%  | +10.20%     | +5.77%     | +3.37%   | +4.55%      |
| Corporate Loans    | −3.71%     | −6.78%   | −7.60%      | +5.36%     | +5.64%   | +7.12%      |

Note: This table depicts the average changes in the banking sector monitored variables vis-à-vis the no-crisis benchmark over the entire simulation set, regardless of the policy tool implemented. The scenarios (Optimistic, Baseline, Pessimistic) were computed using LSTM forecasts on the bank performance measures proposed by [Elnahass et al. \(2021\)](#). The Crisis End values show the change in the variables when comparing the end of the crisis to the corresponding period in the benchmark scenario, while the Year Later values represent comparisons with 12 periods after the end of the crisis.

regardless of the policy tool implemented. We achieve this by averaging the recorded values over the simulations with each policy tool.

The empirical results demonstrate that the main effects of the crisis are mostly evident in the long run, rather than the short run. We note an increase in bank defaults and NPLs (we will see the extent to which this relates to specific policy choices in [Section 4.4](#)) which intensifies in the long run. We also note a flight-to-safety effect, as depositors switch from high- to low-risk deposits, both during the crisis and in the year later.<sup>4</sup> Finally, there is an interesting change in the composition of bank loan portfolios. After the crisis ends, banks seem to have an increased exposure to the interbank market and a reduced exposure to both the corporate and the consumer loan market. This suggests increased financial instability ([Carlson and Wheelock, 2016](#)). One year later, the resulting instability has not yet settled, as the interbank exposure of banks is still increased, when compared to the no-crisis scenario, while corporate loans have increased. At the same time, banks seem to have a reduced exposure to consumer loans. We believe that as banks move funds towards corporate loans to finance economic recovery (attested by the increased number of investing firms in [Table 4](#)) and given their increased exposure to the interbank market as a stabilisation mechanism, their available funds for consumer loans are limited. This could potentially thwart recovery efforts as it may reduce consumer demand in the goods market.

[Table 4](#) presents the differences recorded in the real economy variables against the no-crisis benchmark. As can be expected, we see that the longer the lockdown measures, the greater the damage, both in the short run and in the long run. During the crisis period, GDP drops from between 14.58% and 21.75% when compared to the no-crisis simulations. However, it is important to note that regardless of the policy choice, the responses work and help drive GDP towards the no-crisis benchmark. It should be noted here that we executed a simulation set where no policy was implemented after the COVID-19 crisis. The GDP loss for this simulation set was recorded to be 6.11% on average, a figure higher than IMF calculations (2021), which of course have been calculated based on expectations of policy responses.

In addition, public goods spending (the funds that governments make available to public goods for the economy) is significantly decreased on average over entire the simulation set. We will examine the policies that drive this result in the next section. We also note that wages seem to be reduced and that there does not seem to be a pattern with respect to duration. We also note the increased number of capacity-expanding firms. As we will see below, this result is driven by the “Financial Stimulus” policies, which significantly increase the ability of firms to find financing for their investment projects.

[Table 5](#) presents the average changes in the monitored variables for household utility. Again, the changes represent comparisons to the no-crisis benchmark regardless of the policy tool implemented and they are calculated as an average over the entire simulation set. We introduce here the distinction between the vulnerable and non-vulnerable population class. This follows [Giarda \(2013\)](#) who shows that a certain part of the population is more susceptible to unemployment risks, in case of economic or financial crises. This part of the population represents roughly 15% of the total. It must be noted that this vulnerability relates only to unemployment risks and does not relate to the COVID-19 crisis *per se*, even though this population group may be more susceptible to the health risks of the pandemic. As [Giarda \(2013\)](#) points out, the increased vulnerability to economic crises can be attributed primarily to social factors which are beyond the scope of this paper.

There are two important conclusions to be discussed here. First, there is a reduction in subjective well-being, as calculated by the individual utility functions, which is greater in the short term rather than the long term. This finding is in line with relevant literature ([Di Tella et al., 2003](#)) on subjective well-being, that suggests that in the case of crises, there is a direct negative effect from the crisis itself. In addition, the negative effects of the crisis are symmetrical across population classes in the short run, but asymmetrical in the long run, since the vulnerable classes seem to suffer more in the long run. Second, there is an increase in unemployment, which is graver in the long run, regardless of the policy implemented and affects the vulnerable classes to a greater extent. It is important to note that the average increase in unemployment in the “no-action” simulations is 21.25%, thus government policies seem to be effective on average.

<sup>4</sup> For a discussion on the distinction between low- and high-risk deposit products, see [Samitas and Polyzos \(2015\)](#).



**Table 4**

Projected consequences of the COVID-19 crisis on the real economy.

|                              | Crisis End |          |             | Year Later |          |             |
|------------------------------|------------|----------|-------------|------------|----------|-------------|
|                              | Optimistic | Baseline | Pessimistic | Optimistic | Baseline | Pessimistic |
| Firms with Active Investment | −0.53%     | −0.52%   | +1.47%      | +3.25%     | +3.92%   | +3.78%      |
| GDP                          | −14.58%    | −18.41%  | −21.75%     | −0.46%     | −0.74%   | −0.76%      |
| Average Wage                 | −0.86%     | −0.10%   | −0.35%      | −3.50%     | −2.23%   | −3.26%      |
| Public Goods Spending        | +0.57%     | −0.85%   | −0.82%      | −6.89%     | −4.20%   | −8.05%      |

Note: This table depicts the average changes in the monitored variables of the real economy vis-à-vis the no-crisis benchmark over the entire simulation set, regardless of the policy tool implemented. The scenarios (Optimistic, Baseline, Pessimistic) were computed using LSTM forecasts on the bank performance measures proposed by Elnahass et al. (2021). The Crisis End values show the change in the variables when comparing the end of the crisis to the corresponding period in the benchmark scenario, while the Year Later values represent comparisons with 12 periods after the crisis ends.

**Table 5**

Projected consequences of the COVID-19 crisis on household utility.

|                       | Crisis End |          |             | Year Later |          |             |
|-----------------------|------------|----------|-------------|------------|----------|-------------|
|                       | Optimistic | Baseline | Pessimistic | Optimistic | Baseline | Pessimistic |
| Subjective Well Being | −12.48%    | −9.27%   | −7.01%      | −1.70%     | −1.78%   | −1.27%      |
| Vulnerable            | −12.39%    | −9.15%   | −6.71%      | −2.30%     | −2.78%   | −1.39%      |
| Non-Vulnerable        | −12.49%    | −9.29%   | −7.07%      | −1.59%     | −1.60%   | −1.25%      |
| Unemployment Rate     | +1.68%     | +1.13%   | +0.11%      | +5.45%     | +7.05%   | +9.11%      |
| Vulnerable            | +1.54%     | +0.69%   | −0.46%      | +6.10%     | +7.66%   | +9.69%      |
| Non-Vulnerable        | +1.69%     | +1.22%   | +0.21%      | +5.31%     | +6.91%   | +8.95%      |

Note: This table depicts the average changes in monitored variables for household utility vis-à-vis the no-crisis benchmark over the entire simulation set, regardless of the policy tool implemented. The scenarios (Optimistic, Baseline, Pessimistic) were computed using LSTM forecasts on the bank performance measures proposed by Elnahass et al. (2021). The Crisis End values show the change in the variables when comparing the end of the crisis to the corresponding period in the benchmark (no-crisis) scenario, while the Year Later values represent comparisons with 12 periods after the crisis ends. The vulnerable and non-vulnerable distinction follows Giarda (2013) who shows that a certain part of the population is more susceptible to unemployment risks, in case of economic or financial crises.

#### 4.4. Potential policy outcomes

After examining the short- and long-run effects of the COVID-19 crisis, we can now move to the projected outcomes of potential government policies. As mentioned earlier, we simulate four different policies. These are the demand stimulus, a supply stimulus and two versions of the financial stimulus, one with low regulation and one with medium regulation. In this section, we are not concerned with the scenarios presented before and thus our results represent averages over three different durations simulated. We examine the potential outcome in each of three pillars discussed in the previous section.

Table 6 presents our findings with respect to the banking sector. We calculate the average changes in the monitored variables vis-à-vis the no-crisis benchmark. The snapshot period is one year after the crisis period has ended. We note that both types of financial stimulus, using deregulation, are at least equally effective when compared to the demand and supply stimulus. The financial stimulus actually favours financial stability, as attested by the lower number of banks in distress and the lower number of bank defaults, despite the higher number of NPLs. We believe that this effect is due to the fact that deregulation gives banks the flexibility to function in this difficult environment. We also see that the financial stimuli mainly increase the volume of corporate loans, thus favouring long-term growth, as opposed to short-term consumption, for example. However, we do see the effect of the increased financial instability in the

**Table 6**

Policy outcomes on the banking sector.

|                    | Demand Stimulus | Supply Stimulus | Financial Stimulus |                   |
|--------------------|-----------------|-----------------|--------------------|-------------------|
|                    |                 |                 | Low Regulation     | Medium Regulation |
| Bank Defaults      | +17.46%         | +21.48%         | +9.70%             | +8.65%            |
| Banks in Distress  | +31.69%         | +34.62%         | +30.65%            | +22.65%           |
| NPLs               | +5.69%          | +4.47%          | +11.85%            | +9.99%            |
| Low Risk Deposits  | −0.95%          | −1.10%          | −3.69%             | −3.15%            |
| High Risk Deposits | −80.45%         | −81.84%         | −65.56%            | −63.57%           |
| Consumer Loans     | −15.87%         | −13.45%         | −3.66%             | −5.69%            |
| Interbank Loans    | +0.87%          | +0.93%          | +7.55%             | +8.91%            |
| Corporate Loans    | +4.65%          | −3.21%          | +12.87%            | +9.84%            |

Note: This table shows the average changes in the banking sector monitored variables vis-à-vis the no-crisis benchmark one year after the crisis has ended. The numbers are averages for each policy under the different scenarios of economic consequences of the COVID-19.

increase of interbank loans; this, nonetheless, is managed effectively by banks. The differences in bank portfolios according to each policy choice is demonstrated graphically in Fig. 2.

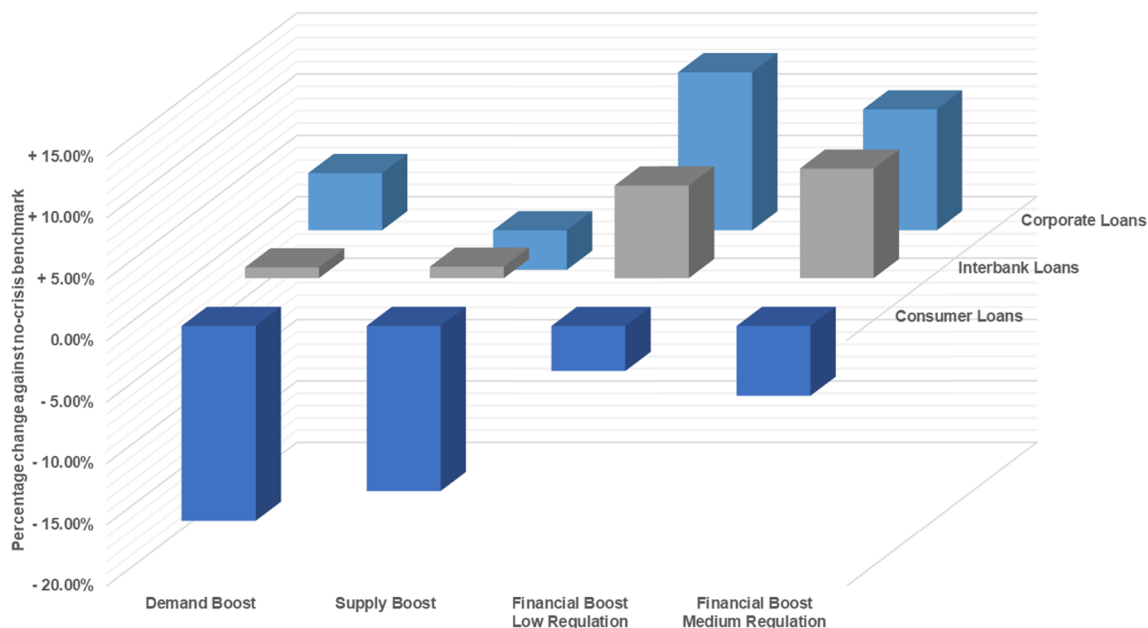
In Table 7, we see the expected policy outcomes of the four different policies. The important variable here is GDP and the outcome is clear. The financial stimulus through deregulation results in increased GDP when compared to the no-action benchmark scenarios (where the banking sector is under “increased regulation”). This finding agrees with the literature that suggests that increased bank regulation is associated with GDP costs and lower bank efficiency (Barth et al., 2013; Majerbi and Rachdi, 2014). In addition, the demand and supply stimulus policies fail to return GDP to their no-crisis levels, with the supply stimulus recording a drop as high as 5.10%.

We believe that this effect is demand-driven: despite increased production, demand is not strong enough to sustain economic growth. Since in our model the market clears at each step, this finding should also suggest lower productive capacity for firms. Indeed, we see that the supply stimulus results in a reduced number of firms with an active investment project (i.e. firms that are currently expanding their productive capacity). This would result in reduced productive capacity, when compared to alternatives, despite the supply boost given to firms through the government policies. In other words, government financing for firms seems to simply reduce corporate loans and not increase productive capacity.

By implementing traditional macroeconomic policies, governments should expect a GDP loss from anywhere between 2.53% and 5.10%, according to our empirical findings, a result which is in line with IMF figures for 2020 and the early predictions for 2021 (IMF, 2020b, 2021). Moreover, we establish the increased cost of these policies, which is evident through the reduced funds available for public goods. We note that these amounts exclude the funds routed to government relief and recovery plans. We see that public goods spending is greatly reduced under these policies, while it will be increased when a financial stimulus is implemented. This is not an unexpected result and clearly demonstrates the budgetary strains of the commonly suggested recovery policies. If we factor in the increased costs related to public health, the budgetary constraints could be further amplified.

Finally, Table 8 shows the expected outcomes in household utility. This table includes suggestive evidence of possible inefficiencies of bank deregulation as a macroeconomic policy. In terms of subjective well-being, we see that the demand stimulus provides the best results, both overall and in both population classes, most likely due to its impact on personal wealth levels (Senik, 2014; Giarda, 2013; Van Praag et al., 2003), which are increased or, at least, maintained to pre-crisis levels. The financial stimulus also provides positive results overall, but the effect is asymmetric across the population classes since the vulnerable population experiences a loss in subjective well-being. This is partly associated with increased unemployment risk (mostly evident in the “Medium Regulation” scenario) but also relates to the resulting financial instability. Reduced consumer loans in the financial stimulus scenarios result in a deterioration of available income, which is not offset by government funds, as in the demand stimulus. The non-vulnerable class also enjoys lower unemployment risk in all scenarios, except for the supply stimulus case, a finding which is intuitively expected.

An interesting question that arises here is the mechanism with which bank deregulation helps combat the demand and supply problems described earlier. We have demonstrated how relaxing the regulatory framework encourages corporate loans which favour long-term growth. This can be achieved even during the crisis, since deregulation seems to help reduce financing costs and thus can



**Fig. 2.** Policy Outcomes for Bank Loan Portfolios. Note: This figure demonstrates the policy outcomes for bank loan portfolios, measured as the average percentage change of the variables under each policy against the no-crisis benchmark. The numbers are averages under the different scenarios of economic consequences of the COVID-19.

**Table 7**

Policy outcomes on the real economy.

|                              | Demand Stimulus | Supply Stimulus | Financial Stimulus |                   |
|------------------------------|-----------------|-----------------|--------------------|-------------------|
|                              |                 |                 | Low Regulation     | Medium Regulation |
| Firms with Active Investment | +0.85%          | −4.71%          | +8.65%             | +9.82%            |
| GDP                          | −2.53%          | −5.10%          | +2.82%             | +2.19%            |
| Average Wage                 | −2.85%          | −3.46%          | −2.69%             | −2.98%            |
| Public Goods Spending        | −17.56%         | −18.25%         | +5.45%             | +4.84%            |

Note: This table shows the average changes in the monitored variables for the real economy vis-à-vis the no-crisis benchmark one year after the crisis has ended. The numbers are averages for each policy under the different scenarios of economic consequences of the COVID-19.

**Table 8**

Policy outcomes on household utility.

|                       | Demand Stimulus | Supply Stimulus | Financial Stimulus |                   |
|-----------------------|-----------------|-----------------|--------------------|-------------------|
|                       |                 |                 | Low Regulation     | Medium Regulation |
| Subjective Well Being | +3.29%          | −13.09%         | +1.34%             | +2.14%            |
| Vulnerable            | +5.49%          | −9.91%          | −2.35%             | −1.86%            |
| Non-Vulnerable        | +2.90%          | −13.66%         | +1.99%             | +2.85%            |
| Unemployment Rate     | +11.11%         | +19.42%         | −2.32%             | +0.60%            |
| Vulnerable            | +12.55%         | +16.97%         | −0.80%             | +2.55%            |
| Non-Vulnerable        | +10.86%         | +19.68%         | −2.59%             | +0.26%            |

Note: This table shows the average changes in the monitored variables for household utility vis-à-vis the no-crisis benchmark one year after the crisis has ended. The numbers are averages for each policy under the different scenarios of economic consequences of the COVID-19.

facilitate positive NPV values for firms, even with reduced demand. Taking on new investment projects can boost employment, thus reversing the demand shock of the pandemic and improving the outcomes in societal happiness. Hence, this approach tackles both the demand and supply issues at once. On the other hand, a pure demand stimulus does not seem to tackle the supply issues of the pandemic, while a supply stimulus appears to fail in boost corporate investments and thus unemployment.

Before completing this section, we believe it is useful to demonstrate a comparison of key variables in terms of the average outcomes across all policies when compared to the “no-response” benchmark, which is the case where the crisis occurs but authorities do not intervene and allow the economy to recover on its own. These are displayed in Fig. 3, where we can see that there is a clear argument in favour of government intervention after such a severe crisis. The no-response alternative is indeed catastrophic and it is imperative that governments not only focus on the immediate response to the crisis, but also formulate plans for the next-day recovery.

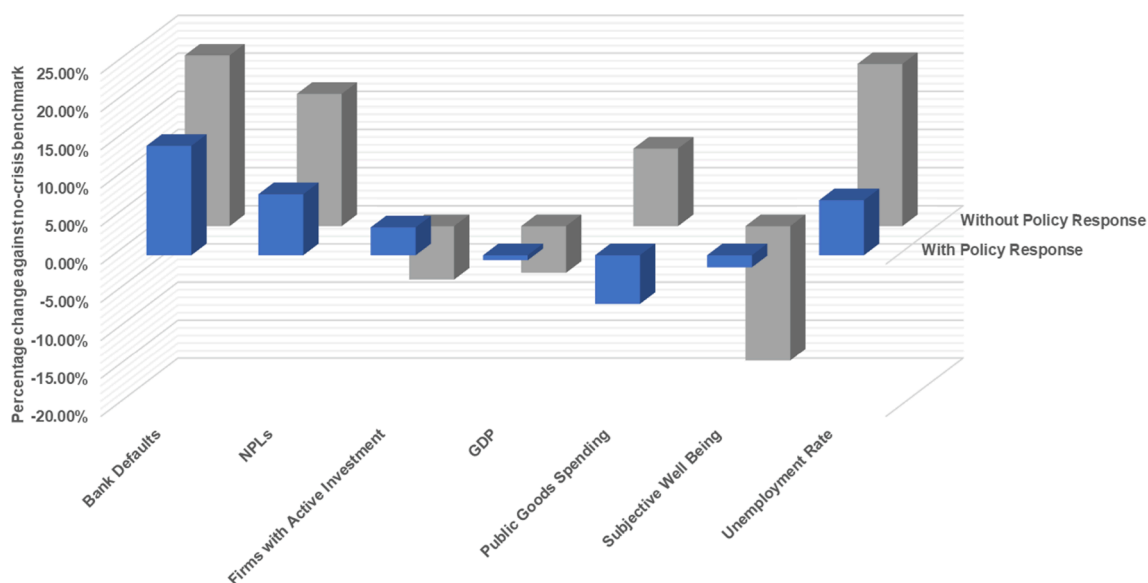
We can see that the “no response” outcomes are far graver, with the year-later increase in bank defaults and NPLs being 22.38% and 17.33%, respectively, as opposed to 14.32% and 8.00% on average over the scenarios with policy responses. The drop in GDP without a policy response is projected to be 6.11% as opposed to 0.66% and the percentage increase in unemployment is estimated 21.25% as opposed to 7.20% with a policy response. The only variable that increases if there is no policy response is public spending, but this outcome is driven by the increased unemployment figures, which result in increased unemployment benefit payments.

We sum up policy outcomes in Table 9. According to our findings, the optimal policy, despite its limitations, is implementing a financial stimulus, by lowering the regulatory framework to a minimum. We note that our “Low Regulation” framework simulates the loose regulatory policies of Basel I. We see that this policy has the most positive outcomes, surpassing the “Medium Regulation” framework by additionally reducing overall unemployment, as well as reducing the unemployment risk of the vulnerable population. The financial stimulus policies do result in increased financial instability, but the increased flexibility reduces bank defaults, when compared to alternatives. They result in GDP improvement when compared both to alternative policies and to the no-crisis benchmark and this improvement is driven by ameliorating productive capacity through increased financing. They pose a smaller burden on the federal budget, thus permitting increased government spending on public goods.

## 5. Conclusions

This paper has presented the expected consequences of the COVID-19 crisis on the banking sector and on the real economy and has examined four possible alternative policy responses, namely the demand stimulus, the supply stimulus and two types of financial stimulus, using deregulation. The financial stimulus scenarios examine deregulation as a less costly policy response to this crisis, which is more effective than the alternatives, as deregulation can boost both demand and supply simultaneously. We find that many of the negative effects of the crisis are not evident in the short run and that the long-run effects, in some cases, are more severe. We note thought the potential risks of such a policy. Should deregulation lead to a system-wide banking crisis, the final cost will ultimately be borne by households. We take this into account through variables monitoring financial stability and show that the benefits of the policy outweigh the costs in increased instability.

Based on our findings, the suggested policy is to lower the regulatory framework to a minimum, thus implementing a strong economic stimulus through the financial sector. More specifically, our findings suggest that maintaining only some basic requirements



**Fig. 3.** Comparison of Outcomes after the COVID-19 Crisis. Note: This figure demonstrates key variables in terms of their respective average outcomes across all policies when compared to the “no-response” benchmark. The “no-response” benchmark is the case where even though the crisis occurs, authorities do not intervene and allow the economy to recover on its own.

**Table 9**

Summary of policy recommendations.

| Policy                                         | Positive Outcomes                                                                                                                                                                                                                                                                                                                                                                                                            | Negative Outcomes                                                                                                                                                                                                                                                                                                             |
|------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Financial Stimulus<br><i>Low Regulation</i>    | <ul style="list-style-type: none"> <li>• Lower bank defaults with respect to alternatives</li> <li>• Increased GDP with respect to no-crisis benchmark</li> <li>• Reduced unemployment overall and in both classes</li> <li>• Higher public goods spending</li> <li>• More corporate loans</li> <li>• More firms with investment projects</li> <li>• Smaller flight-to-safety effect with respect to alternatives</li> </ul> | <ul style="list-style-type: none"> <li>• Higher NPLs</li> <li>• More interbank loans, suggesting financial instability</li> <li>• Reduced subjective well-being for the vulnerable class</li> </ul>                                                                                                                           |
| Financial Stimulus<br><i>Medium Regulation</i> | <ul style="list-style-type: none"> <li>• Lower bank defaults with respect to alternatives</li> <li>• Increased GDP with respect to no-crisis benchmark</li> <li>• Higher public goods spending</li> <li>• More corporate loans</li> <li>• More firms with investment projects</li> <li>• Smaller flight-to-safety effect with respect to alternatives</li> </ul>                                                             | <ul style="list-style-type: none"> <li>• Higher NPLs</li> <li>• Increased unemployment for the vulnerable class</li> <li>• More interbank loans, suggesting financial instability</li> <li>• Reduced subjective well-being for the vulnerable class</li> </ul>                                                                |
| Demand Stimulus                                | <ul style="list-style-type: none"> <li>• Increased subjective well-being overall and in both classes</li> <li>• Smaller reduction in deposits with respect to alternatives</li> <li>• Less interbank loans with respect to alternatives</li> </ul>                                                                                                                                                                           | <ul style="list-style-type: none"> <li>• More bank defaults</li> <li>• GDP loss with respect to no-crisis benchmark</li> <li>• Reduced number of firms with investment projects</li> </ul>                                                                                                                                    |
| Supply Stimulus                                | <ul style="list-style-type: none"> <li>• Smaller reduction in deposits with respect to alternatives</li> <li>• Less interbank loans with respect to alternatives</li> </ul>                                                                                                                                                                                                                                                  | <ul style="list-style-type: none"> <li>• More bank defaults</li> <li>• GDP loss with respect to no-crisis benchmark</li> <li>• Increased unemployment overall and in both classes</li> <li>• Reduced subjective well-being overall and in both classes</li> <li>• Reduced number of firms with investment projects</li> </ul> |

on Tier-1 capital, while lowering the remaining capital requirements of Basel III, would provide the banking sector with the necessary flexibility to effectively finance economic recovery. The reduction of regulation needs to be implemented as a cooperation between governments and banks as it needs to have clear goals towards economic recovery.<sup>5</sup> Despite the cost in increased financial instability,

<sup>5</sup> For example, regulators could exclude corporate loans directly aimed at COVID-19 recovery from the bank's weighted assets. This can be achieved both directly (with an explicit directive) or indirectly (implementing for example full government guarantee for such loans which would reduce their coefficient to zero).

the deregulation policies result in GDP improvement when compared both to alternative policies and to the no-crisis benchmark. This finding is in line with recent literature on the topic (Lyu et al., 2021). In addition, this policy poses a smaller burden on the federal budget (potential banking crises notwithstanding) and permits increased government spending on public goods. This could include, for example, increased budget for healthcare or could be targeted at the vulnerable population classes, who can experience reduced subjective well-being under these policies.

A worrying outcome of the demand stimulus is the increased subjective well-being. This outcome can be troubling since it suggests that the demand stimulus can be used as a political tool for near-sighted governments aiming at re-election. Indeed, presenting bank deregulation as a recovery tool may be a difficult political task, whilst touting relief cheques can be much easier. Despite the fact that both demand and supply stimuli do not seem to present any other advantage over the financial stimulus, except for lower interbank loans, they may be pushed forward for political purposes. In addition, the simulations on the supply stimulus suggest that relief financing for firms does not seem to boost productive capacity nor does it help in maintaining employment levels. Consequently, we believe that this alternative, if implemented, should be coupled with strict rules on employee layoffs and on how the financing will be used.

Furthermore, it should be noted that both demand and supply stimulus policies come with an increased budgetary cost. In our simulations, we do not account for the increased costs for healthcare, due to the pandemic. Thus, the budgetary constraints of these policies could be even greater. Governments could resort to increasing public debt to cover the costs of these recovery policies, but this case could result in contractionary budgets for the coming years, in an effort to repay these loans or even to cover interest payments. Despite increasing government deficits worldwide and no (visible) plans to repay public debt, it is difficult to suggest that piling on further debt is a desired policy. We note here that we do not suggest that bank deregulation is a zero-cost policy since there can be increased costs for monitoring and, potentially, for bailouts. Furthermore, bailouts may carry significant political costs, particularly in times of economic recessions. However, as mentioned above, our simulations show that bank deregulation outperforms alternative policies in terms of the desired outcomes. Hence, it is up to the commanders-in-chief to assume this (possible) political cost, in order to guide the economies to recovery.

Our findings come with certain limitations. Firstly, we acknowledge that the agent-based framework cannot be argued to cover all the features of the real economy, as mentioned earlier. We implement a simplified version of the economic system, which however covers the fundamental functions of the monetary system and hence the simplification does not diminish the validity of our findings. In addition, our proposal is for a short-term relaxing of bank regulations. Thus, there could be increased costs associated with changing regulation, both on the side of banks and on the side of authorities. In addition, easing regulation will not necessarily force banks to increase financing to the economy. Indeed, if bankers are worried about either financial or economic instability or if they expect regulation to return to its previous levels without prior warning from regulators, it is possible that internal credit models may not be changed at all, thus severely mitigating the expected effects. In addition, the resulting instability could result in federal funds required for rescuing banks. In our model, banks in distress are rescued using bail-ins. In case of a more generalised instability, this may not be enforced by policymakers. The increased rescuing costs could offset any federal budget benefits of these policies. Finally, deregulation could arguably lead to a new Great (or even greater) Financial Crisis. We do not suggest deregulation as a cut in monitoring; indeed, higher monitoring of bank activities should be implemented as banks could try to take advantage of reduced regulation to boost short-term profits. Increased monitoring could suggest increased costs for policymakers, thwarting the expected positive effects of the financial stimulus.

## CRedit authorship contribution statement

**Stathis Polyzos:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Aristeidis Samitas:** Conceptualization, Formal analysis, Validation, Investigation, Resources, Writing – original draft, Writing – review & editing, Project administration. **Elias Kampouris:** Methodology, Validation, Formal analysis, Writing – review & editing, Visualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Algorithm steps

### 1. System Initialisation:

Banks receive a random amount of initial cash equal to the product of a random variable times the number of households in the system

$$\forall b \in B : CB_{b,t=0} = U(1, 10) * |H|$$

Firms start with an initial random productive capacity equal to the product of a random variable times the number of households over the number of firms in the system

$$\forall f \in F : Capacity_{f,t=0} = U(1, 10) * (|H|/|F|)$$

Households receive a random amount of initial cash and their precautionary cash demand is initialised.

The simulation steps follow the order given below.

## 2. Simulation Step at Time $t$

The LCR is calculated for each bank. The required amount is the difference of deposit funds from the last period to the current one. If the outflow of funds is negative, the LCR is zero.

Assuming that the deposits of a bank at any given time are given by

$$d \in D_{b \in B, t \in T} \subseteq L_{b, t}$$

the amount required to satisfy the LCR rule is given by

$$LiqC_{b \in B, t \in T} = 100\% \times \begin{cases} 0, & \text{if outflow is negative} \\ \sum_{d \in D_{b \in B, t \in T}} d_{b, t-1} - \sum_{d \in D_{b \in B, t \in T}} d_{b, t} \end{cases}$$

Interest is added to all loans in the list of financial assets

$$\forall \lambda \in \Lambda \subseteq FA : Amt_{\lambda, t} = Amt_{\lambda, t-1} \times (1 + ir_{\lambda})$$

where  $\Lambda$  is the subset of financial assets that represents a loan asset,  $Amt$  is the amount remaining in the loan, and  $ir$  is the interest rate for the particular security.

Add household income (wages or unemployment benefits) and subtract expenditure

$$\forall h \in H : CB_{h, t} = CB_{h, t-1} + Wage^{def}(=f(Production_{t-1}, |H|)) + UnemploymentBenefit^{def}(if h \in UN) - Expenditure^{def}(=g(Wage))$$

Household wages are a function of last period's total production (by firms) and the number of households in the system. In addition, it is important to note that unemployment benefits are paid from government funds collected via taxation and the Tobin tax, if implemented (see step 1.12).

Banks make payments for high-risk securities as follows:

$$\forall b \in B : \forall i \in I \subseteq A_{i, t} : Amt_{i, t} = Amt_{i, t-1} \times (1 + ir_i)$$

In this step, the amount remaining in each security is added to the CB of the asset holder and subtracted from the CB of the liable bank. When paying out a security yield, the liable bank uses its CB value, not the AvB value

Economic agents (banks, firms, and households) pay their loan obligations

$$\forall \lambda \in \Lambda \subseteq FA : Amt_{\lambda, t} = Amt_{\lambda, t-1} - Pmt_{\lambda} = Amt_{\lambda, t-1} - InitialAmount \times \left( ir + \frac{ir}{(1 + ir)^n - 1} \right)$$

Payment  $Pmt$  is subtracted from the CB of the liable economic agent and added to the CB of the asset holder (bank). When repaying loans, the liable economic agents use their CB value, not the AvB value, since the precautionary demand (which leads to the AvB value) is not taken into account when repaying a loan. If CB does not fully cover the obligation, households have to dip into their savings (money in deposit accounts), until either all savings are withdrawn from banks or no more outstanding payments remain.

Households place their excess cash balance in a deposit account.

Bank customers seek financing. In this step, any firms or households that have liabilities with missed payments or that have a negative available balance seek funds from the marketplace. Banks are selected according to the lowest interest rate offered for loans and agents ask for the full financing required. Banks in turn offer the amount they can (i.e., their AvB figure at time  $t$ ) and if the required amount is not covered, the next bank in the ordered list is chosen. Banks finance the firm or household if the banking system can cover their full financing needs. If, at the end, the customer's full financial needs are not met, then no loans are taken out.

Banks seek financing. In this step, any banks that have liabilities with missed payments or that have a negative available balance seek funds from the marketplace. Financing banks are chosen in random order and the initial bank asks for the full financing it needs. Financing banks in turn offer the amount they can (i.e., their AvB figure at time  $t$ ) and if the bank is not covered, the next random bank is chosen to seek the remaining financing from. Banks finance the initial bank if the banking system can cover their full financing needs.



Any agents (banks, households, or firms) that still have missed payments are candidates for default. The default criteria differ for banks and households and naturally, the consequences for the specific agent and the entire system are different. Banks with one missed payment are immediately candidates for default while for firms and households, the threshold is placed at three missed payments. The criteria for banks are stricter, since it is not acceptable for a financial institution to be unable to make payments for its liabilities.

The government produces public goods, using the remaining funds collected from taxation in the last period. In this way, there is a trade-off between bank bailouts, unemployment benefits, and public goods. If the government chooses to rescue a bank, it has less to spend on public goods. However, if the bank fails and unemployment rises as a result of the ensuing crisis, there is less money available for public goods.

Banks re-examine their interest rate policy. The average weighted cost of capital is used as the main deposit rate, which is increased further if the bank approaches the distress zone.

Firms propose investment projects and seek financing.

The regulator re-examines the countercyclical capital buffer. The decision to increase the percentage for the countercyclical capital buffer is taken when three consecutive growth periods have been achieved. Similarly, it is decreased after three consecutive recession periods. This is a limited approach to the implementation of the policy (Claessens et al., 2013).<sup>6</sup>

Individual and societal subjective well-being are calculated, according to each household's own happiness function, using our machine-optimised happiness function.

The system recalculates each household's employment status. During an economic downturn (i.e., a reduction of GDP), there is increased chance of a negative change in households' employment status (i.e., from employed to unemployed), while the opposite occurs during economic expansion. In addition, there is increased probability of a negative change for vulnerable households and a decreased probability of a positive change, similar to Giarda (2013).

Statistics are collected.

The system progresses to the next time period.

## Appendix B. Economy-wide variables for the random regression forest

| Code              | Indicator Name                                                               |
|-------------------|------------------------------------------------------------------------------|
| BX.KLT.DINV.CD.WD | Foreign direct investment, net inflows (BoP, current US\$)                   |
| BX.TRF.PWKR.CD.DT | Personal remittances, received (current US\$)                                |
| DT.DOD.DECT.CD    | External debt stocks, total (DOD, current US\$)                              |
| DT.ODA.ALLD.CD    | Net official development assistance and official aid received (current US\$) |
| DT.TDS.DECT.EX.ZS | Total debt service (% of exports of goods, services and primary income)      |
| EG.USE.ELEC.KH.PC | Electric power consumption (kWh per capita)                                  |
| EG.USE.PCAP.KG.OE | Energy use (kg of oil equivalent per capita)                                 |
| EN.ATM.CO2E.PC    | CO2 emissions (metric tons per capita)                                       |
| EN.POP.DNST       | Population density (people per sq. km of land area)                          |
| FS.AST.DOMS.GD.ZS | Domestic credit provided by financial sector (% of GDP)                      |
| GC.REV.XGRT.GD.ZS | Revenue, excluding grants (% of GDP)                                         |
| GC.TAX.TOTL.GD.ZS | Tax revenue (% of GDP)                                                       |
| IC.REG.DURS       | Time required to start a business (days)                                     |
| IQ.SCI.OVRL       | Overall level of statistical capacity (scale 0–100)                          |
| IT.CEL.SETS.P2    | Mobile cellular subscriptions (per 100 people)                               |
| MS.MIL.XPND.GD.ZS | Military expenditure (% of GDP)                                              |
| NE.EXP.GNFS.ZS    | Exports of goods and services (% of GDP)                                     |
| NE.GDI.TOTL.ZS    | Gross capital formation (% of GDP)                                           |
| NE.IMP.GNFS.ZS    | Imports of goods and services (% of GDP)                                     |
| NV.AGR.TOTL.ZS    | Agriculture, value added (% of GDP)                                          |
| NV.IND.TOTL.ZS    | Industry, value added (% of GDP)                                             |
| NY.GDP.DEFL.KD.ZG | Inflation, GDP deflator (annual %)                                           |
| NY.GDP.MKTP.CD    | GDP (current US\$)                                                           |
| NY.GDP.MKTP.KD.ZG | GDP growth (annual %)                                                        |
| NY.GNP.ATLS.CD    | GNI, Atlas method (current US\$)                                             |
| NY.GNP.MKTP.PP.CD | GNI, PPP (current international \$)                                          |
| NY.GNP.PCAP.CD    | GNI per capita, Atlas method (current US\$)                                  |
| NY.GNP.PCAP.PP.CD | GNI per capita, PPP (current international \$)                               |
| SI.DST.FRST.20    | Income share held by lowest 20%                                              |
| SI.POV.DDAY       | Poverty headcount ratio at \$1.90 a day (2011 PPP) (% of population)         |
| SI.POV.NAHC       | Poverty headcount ratio at national poverty lines (% of population)          |
| SM.POP.NETM       | Net migration                                                                |
| SP.POP.GROW       | Population growth (annual %)                                                 |

(continued on next page)

<sup>6</sup> Despite its limitations, this implementation is consistent with the basic motivation behind its introduction in Basel III whereby banks are forced to accumulate capital during expansionary periods in order to ensure liquidity under recessionary periods.

(continued)

| Code              | Indicator Name                                      |
|-------------------|-----------------------------------------------------|
| SP.POP.TOTL       | Population, total                                   |
| SP.URB.GROW       | Urban population growth (annual %)                  |
| TG.VAL.TOTL.GD.ZS | Merchandise trade (% of GDP)                        |
| TT.PRI.MRCH.XD.WD | Net barter terms of trade index (2000 = 100)        |
| TX.VAL.TECH.MF.ZS | High-technology exports (% of manufactured exports) |

### Appendix C. Relative standard errors of simulated recorded values

|                              | No Crisis | No Policy Response | Demand Stimulus | Supply Stimulus | Financial Stimulus |                   |
|------------------------------|-----------|--------------------|-----------------|-----------------|--------------------|-------------------|
|                              |           |                    |                 |                 | Low Regulation     | Medium Regulation |
| Bank Defaults                | 8.77%     | 8.14%              | 7.74%           | 7.90%           | 9.52%              | 8.43%             |
| Banks in Distress            | 14.56%    | 12.72%             | 12.47%          | 15.26%          | 16.82%             | 14.83%            |
| NPLs                         | 5.87%     | 6.89%              | 5.45%           | 6.52%           | 5.96%              | 6.41%             |
| Low Risk Deposits            | 13.53%    | 14.16%             | 15.02%          | 15.03%          | 17.28%             | 17.06%            |
| High Risk Deposits           | 5.42%     | 4.65%              | 6.18%           | 6.40%           | 4.98%              | 5.18%             |
| Consumer Loans               | 14.87%    | 14.36%             | 14.38%          | 12.31%          | 16.81%             | 15.18%            |
| Interbank Loans              | 9.77%     | 10.93%             | 8.27%           | 11.45%          | 12.01%             | 8.98%             |
| Corporate Loans              | 8.16%     | 7.46%              | 9.47%           | 8.11%           | 7.85%              | 7.97%             |
| Firms with Active Investment | 11.32%    | 10.33%             | 10.13%          | 10.70%          | 11.45%             | 13.45%            |
| GDP                          | 11.99%    | 10.50%             | 10.91%          | 11.85%          | 12.24%             | 12.32%            |
| Average Wage                 | 7.34%     | 8.46%              | 8.50%           | 8.13%           | 7.47%              | 7.80%             |
| Public Goods Spending        | 15.62%    | 13.11%             | 14.78%          | 12.97%          | 19.79%             | 19.84%            |
| Subjective Well Being        | 5.49%     | 6.35%              | 5.97%           | 5.68%           | 5.25%              | 5.38%             |
| Vulnerable                   | 5.15%     | 5.79%              | 5.94%           | 4.85%           | 5.43%              | 4.96%             |
| Non-Vulnerable               | 15.40%    | 14.39%             | 13.02%          | 12.33%          | 19.92%             | 14.43%            |
| Unemployment Rate            | 11.15%    | 10.35%             | 10.08%          | 11.46%          | 10.06%             | 13.24%            |
| Vulnerable                   | 6.88%     | 8.20%              | 6.55%           | 5.73%           | 8.62%              | 7.12%             |
| Non-Vulnerable               | 13.50%    | 16.09%             | 15.38%          | 13.50%          | 15.93%             | 16.37%            |

**Note:** This table presents the relative standard error (RSE) of the simulations. The RSE is equal to the standard error divided by the mean and expressed as a percentage.

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