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Authors:
Benedetti Fasil, C.
Impullitti, G.
Licandro, O.
Sedláček, P.

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Contact information
Name: Simone Salotti
Address: Edificio Expo, C/Inca Garcilaso 3, 41092 Sevilla (Spain)
Email: simone.salotti@ec.europa.eu
Tel.: +34 954488406

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This technical report is dedicated to the loving memory of Cristiana, whose untimely passing did not allow her to see the completion of this project she created.

Heterogeneous Firms, R&D Policies and the Long Shadow of Business Cycles*

Cristiana Benedetti-Fasil
JRC European Commission

Giammario Impullitti
University of Nottingham, CEP and CEPR

Omar Licandro
University of Nottingham and Barcelona GSE

Petr Sedláček
University of Oxford and CEPR

June 25, 2021

Abstract

Growth and business cycles have a long tradition of being studied separately. However, events such as the Great Recession raise concerns that severe downturns may have detrimental implications for growth. If so, what policies may help alleviate such long-lasting effects of large recessions? To study these questions, we develop a tractable general equilibrium model of endogenous growth featuring heterogeneous firms, financial constraints and a range of innovation policies. A preliminary analysis suggests that counter-cyclical tax credits may serve as a powerful automatic stabilizer alleviating the long-lasting negative effects of severe cyclical downturns.

Keywords: Firm dynamics, innovation policy, endogenous growth, business cycles.
JEL Classification: F12, F13, O31, O41.

*The views expressed in this paper do not necessarily reflect those of the European Commission. Benedetti-Fasil: cristiana.benedetti-fasil@ec.europa.eu, Impullitti: giammario.impullitti@nottingham.ac.uk, Licandro: Omar.Licandro@nottingham.ac.uk, Sedláček: petr.sedlacek@economics.ox.ac.uk.

1 Introduction

There is a long tradition in macroeconomics of studying growth and business cycles separately. However, events such as the financial crisis of 2009 give rise to concerns that severe cyclical downturns may have persistent negative effects through their impact on long-run growth. Indeed, many countries have failed to revert back to their original growth paths following the Great Recession. A connection between business cycles and growth may then give a strong mandate to policy, as the costs of even modest and temporary cyclical fluctuations could be high (Lucas, 2003; Barlevy, 2007).

This paper presents a tractable general equilibrium model in which business cycles and productivity growth are connected. In addition, we embed a wide range of governmental policies supporting innovation with the goal of understanding how different policies impact growth and cyclical fluctuations. Recent research has shown that entry, exit, and firm heterogeneity play an important role in shaping long-run growth patterns and the aggregate effects of macroeconomic shocks (Klette and Kortum, 2004; Akcigit and Kerr, 2016; Clementi and Palazzo, 2016; Sedláček and Sterk, 2017). Firms' characteristics have also been shown to matter for the effects of policies promoting innovation and long-run growth (Acemoglu et al., 2018). We thus incorporate firm dynamics and heterogeneity in our model.

Specifically, our framework features heterogeneous firms which produce differentiated varieties of goods using unskilled labor and capital. These goods are then sold to the household on a monopolistically competitive market. Firms also invest into improving their productivity by hiring skilled labor to conduct R&D. Importantly, firm differ not only in their production efficiency, but also in their efficiency with which they can conduct R&D. While the former evolves over time along with successful R&D efforts, the latter is a permanent characteristic.

The investment into R&D is subject to a financial friction which necessitates obtaining external funding for a fraction of the R&D costs. If successful in their R&D efforts, the efficiency with which they produce output increases. Knowledge spillovers, typical of Schumpeterian growth models (Aghion and Howitt, 1992; Grossman and Helpman, 1991), imply that the innovation process drives sustained productivity growth. In addition, the production efficiency of all firms is also affected by an aggregate, mean-reverting, shock, the source of short-run fluctuations in this economy. Apart from wage and capital costs needed in production and R&D, firms also pay a fixed operating cost which is stochastic. In some cases, these costs are so large then businesses opt to shut down. Finally, an endogenous mass of entrants penetrates the market and replaces businesses which have shut down. Therefore, our model features endogenous aggregate growth, exogenous cyclical fluctuations and endogenous firm-level dynamics of entry, growth and exit.

The model includes several market failures leading to inefficient investment in innovation and suboptimal growth, thereby motivating policy intervention. First, as typical in endogenous growth models, when an innovation is introduced it benefits consumers immediately as they can buy goods at a lower price, but it also benefits consumers in the future as all later innovations build upon past innovations. This is the *intertemporal spillover effect* which leads to underinvestment in innovation, as current innovator do not take into account the benefits of future innovation building on their technology. With business cycle fluctuations this dynamic externality has a new feature. Benefits accruing to other firms occur in the future, as they need time to improve upon or imitate an idea, or they must wait for a patent to expire. A firm's incentive to undertake R&D is thus heavily dependent on the short-term benefits that accrue to it. A planner would instead take into account that R&D done during recessions will benefit other innovative firms when macroeconomic conditions improve. Firms do not take these effects into account, thereby failing to exploit the opportunity provided by downturns of innovating at lower costs. This distorsion is stronger the more procyclical profits are. Hence, with cyclical fluctuations intertemporal knowledge spillovers lead to more underinvestment during recessions and less during booms (Barlevy, 2007).

Second, a firm's innovation increases skilled labor demand, thereby increasing skilled wages and the cost of innovation for other firms. Eventually some firms, those who cannot catch up with the average growth pace of the economy, exit the market. This *selection/business stealing effect* is not taken into account by the innovating firms and produces overinvestment in innovation. Finally, credit constraints constitute an additional reason for firms to underinvest in innovation.

To tackle these market failures we consider a wide set of policies widely used in advanced economies to stimulate growth. The policy modelling is particularly targeted to reproduce the innovation policy tools of the EU Framework Program and the Cohesion Funds, one of the largest growth policy program in the world. Government levy a uniform corporate tax and lump-sum tax to fund innovation policies. These consist of a tax credit for R&D, direct innovation subsidies via grants, and zero-interest loans aimed at reducing the credit constraints. While all firms can access the R&D tax credit, firms need to apply to subsidies and loans. Firm quality is private information and the government can only observe a signal via current firm productivity/size. Since the probability of obtaining a grant or a loan is proportional to the signal and firms must pay application costs, not all firms obtain policy support. Both incumbent firms and entrants have access to grants and loans while tax credits are only available to the former.

We parametrise the model to reproduce key aggregate and cross-sectional facts of the French economy. The model matches key long-run growth statistics at the firm and aggregate level, along some key business cycle facts. We first analyze the model without policies and focus on the model's implications for long-run growth but also for business cycles and the connection between the two. A key ingredient of this analysis is a solution method which allows us to solve this complex model efficiently.[1] The results show that, consistent with the literature, more than half of overall long-run growth is driven by *selection* (Lentz and Mortensen, 2008). Specifically, because firms differ in their ability to conduct R&D, resources gradually flow from relatively inefficient businesses to more efficient firms, increasing growth. The second most important driver of aggregate growth is *creative destruction* whereby exiting incumbent firms are replaced by innovative entrants.

Next, we document that the model does relatively well in replicating the cyclical dynamics of key macroeconomic aggregates. Importantly, however, our model also features cyclical fluctuations in the aggregate growth rate. This is because R&D effort responds to changes in production efficiency, rising when the economy is in a boom and when there are greater benefits to be reaped from innovation. This pro-cyclical nature of R&D, which is consistent with the data, together with the endogenous movements in the firm distribution, imply that aggregate growth is also slightly pro-cyclical.[2]

As in Barlevy (2007), in our model the pro-cyclicality of R&D comes from the heavy dependence of R&D incentives on the short-run profits of the innovating firms which dominates the "opportunity cost" channel according to which firms should innovate more in downturns as the foregone output and sales are lower (Aghion and Saint-Paul, 1998; Aghion et al., 2010). Barlevy (2007) shows that if production fixed costs are large, profit are strongly procyclical and so is R&D. Precisely, free entry requires that for innovation incentives to be larger in booms profits must be more pro-cyclical than the cost of R&D. Firm heterogeneity strengthens the pro-cyclical forces in our model, as fixed costs imply that low productivity firms are more sensitive to profit fluctuations as they are more likely to exit. If marginal firms do some R&D, their exit reduces aggregate innovation effort.

This connection between business cycles and growth is also quantitatively important. Estimating the model on data for real GDP we show that it does well in replicating the time-path of GDP following the Great Recession. In particular, it mimics the very persistent drop in output and the lack of a recovery to the original time path. The reason for this is that the severe recession was accompanied by a period of subdued growth. Without a strong bounce back, this growth is never recovered and the economy is permanently on a lower *level* of output.

Finally, we consider the effect of policies on business cycles and growth. While we model the full set of policies, in this draft we only present results on tax credits, a prominent tool of innovation policy in many countries, and we restrict the analysis to a uniform credit rate for all firms.[3] Our model suggests that tax credits can be an effective tool to promote aggregate growth as they increase the inefficiently low level of R&D. Moreover, if tax credits are made to be counter-cyclical, they have the potential to act as an automatic stabilizer and reduce the

[1] Towards this end, we adapt the method proposed in Sedláček and Sterk (2017).

[2] Empirical evidence on the procyclicality of R&D can be found in Griliches (1990); Comin and Gertler (2006); Barlevy (2007); Ouyang (2011); Aghion et al. (2012) among others.

[3] Future drafts will cover grant and loans, as well as size-dependent policies.

permanent losses from large recessions. Intuitively, as the dynamic externality produced by knowledge spillovers is at the root of R&D cyclicality, and the decentralised economy features stronger underinvestment in innovation, a role for counter-cyclical innovation policy naturally emerges. Although we only focus on innovation policies in this paper, a corollary of our results is that in the absence of counter-cyclical R&D policy instruments, stabilisation policies, when viable, can play a larger role than in business cycle models with exogenous productivity.

Literature review. The paper is related to several lines of research in the literature. First, our work is related to the recent literature bridging the growth and the business cycle approach to macroeconomic analysis.[4] A key challenge that all models linking business cycle and growth have to face is to reproduce the pro-cyclicality of innovation observed in the data. The theoretical underpinning of pro-cyclical innovation is also fundamental in shaping the role of growth and in particular of technical change for the propagation and persistency of short-run fluctuations. Aghion et al. (2010) introduce credit constraints to offset the opportunity cost channel linking innovation and business cycle. A negative productivity shock reduces current cash flow, which in turn reduces firm capacity to borrow to finance investment improving productivity in the future. In other words, in downturns firms perceive innovation as a riskier activity as they expect to hit their borrowing constraint and therefore reduce their productivity-enhancing investment. Another explanation for the pro-cyclicality of R&D is endogenous labor supply (Fatas, 2000). If labor supply is pro-cyclical, then R&D will be pro-cyclical as well, as firms will not be willing to divert already scarce resources away from production.[5]

In our model both credit constraints and endogenous labor supply contribute to the pro-cyclicality of R&D, although its main driving force is the intertemporal knowledge spillovers and fixed production costs, as in Barlevy (2007). Moreover, firm heterogeneity adds an extensive margin and reallocations that strengthen the pro-cyclicality and consequently the propagation and persistency of short-run fluctuations. These microeconomic features of our economy can potentially generate new cost of business cycle not obtainable in the standard models with exogenous productivity considered in Lucas (2003) and in the endogenous growth representative version (e.g. Barlevy, 2004).[6]

Limited attention in the growth and business cycle literature has been devoted to the role of innovation policies in taming the costs of short-run fluctuations. Barlevy (2007) suggests that counter-cyclical R&D subsidies would be effective in reallocating research from booms to recessions thereby correcting the dynamic inefficiencies generated by cycles. Nuno (2011)

[4]See Fatas (2000), Barlevy (2004, 2007), Comin and Gertler (2006), Aghion et al. (2009, 2010, 2014), Nuno (2011), Anzoategui et al. (forthcoming), Bianchi et al. (2019), Benigno and Fornaro (2018), Vinci and Licandro (2020), and Cozzi et al. (2021), among others.

[5]Pro-cyclicality of R&D can also be obtained assuming that innovation is produced with goods, not labor. If more goods are produced during booms there are more resources available for R&D. Aghion and Saint-Paul (1998) and Comin and Gertler (2006) follow this route.

[6]In ongoing extensions of our baseline analysis we are exploring the welfare implications of the model.

shows that if both investment in R&D and physical capital are distorted in the market economy, counter-cyclical R&D subsidies have no effect on welfare. While fixed permanent subsidies to capital and R&D that restore the Pareto optimal steady state produce large welfare gains. Aghion et al. (2010) study the role of credit in smoothing business cycle fluctuations by facilitating innovation. Financial systems that ease credit constraints allow firms to borrow and make investments during recessions when the costs of investing are low but collateral values are also low. Benigno and Fornaro (2018) provide a Keynesian growth theory, building a New Keynesian model with innovation-driven growth and showing how pessimistic expectations can lead to persistent slumps with high unemployment and weak growth, a 'stagnation trap'. Severe depressions of aggregate demand reduce firms' profits thereby weakening their incentives to innovate and reducing productivity growth. Productivity growth affects households' future income, and a fall in future income generates a further reduction in current aggregate demand. Weak demand pushes the interest rate to the zero lower bound and monetary policy is unable to restore growth and full employment. By affecting expected future growth, substantial subsidies to innovation instead can push the economy out of the stagnation trap. We contribute to this line of research introducing firm heterogeneity and exploring its role in shaping aggregate effects of a rich set of innovation policies.[7]

Bloom et al. (2019) presents a survey of the empirical literature on innovation policy, condensing it in a *toolkit* for innovation policy makers. The policies are ranked by means of a composite index of the strength and quality of the evidence and the magnitude of the effects. Other criteria are whether the effects are likely to take place in the short or in the long run and whether they will affect inequality. The R&D tax credit and direct public funding of research seem to be more effective in the short run while human capital policies are more effective in the long run. Competition and trade policies seem to have a small impact on innovation but they are cheaper in terms of public budget. The R&D tax credit and trade policy tend to increase inequality, as the boost the relative supply of skilled labor, while human capital policy have the opposite effect. We complement this line of work assessing the impact of a rich set of innovation policies in a dynamic general equilibrium framework. Our paper belongs to the emerging new quantitative growth theory literature, where frontier endogenous growth models are taken structurally to micro and macro data and used for quantitative analysis (e.g. Lentz and Mortensen, 2008; Akcigit and Kerr, 2016). Our work is particularly related to Acemoglu et al. (2018) who present a quantitative assessment of the effects of R&D subsidies in an endogenous growth model where firms are heterogeneous in productivity (Klette and Kortum (2004)) and in innovation capacity. Tying the model closely to US micro data and focusing on the steady state equilibrium, they show that R&D subsidies to incumbents achieve modest increase

[7] Ates and Saffie (2018) develop an endogenous growth model with heterogeneous firms and aggregate risk to study the productivity effect of financial crises. They show that credit shortages give rise to a quantity/quality trade off, as firms born during the crises are fewer but produce higher quality goods.

in growth, subsidies to entrants and to fixed operating costs reduce growth.[8] The most effective policy proves to be a tax on the fixed operation costs of incumbents, which reduces the share of low-innovation type of firms and increase the share of high-innovation firms.[9] We complement this analysis focusing on a wider set of policies, casting our experiment in a framework which can be potentially used to analyse the interaction between innovation policies and business cycle fluctuations.

Finally, we make contact with the literature on the relationship between financial systems and innovation-led growth and in particular with the research on credit frictions in endogenous growth models.[10] Typically, this line of research shows both theoretically and empirically that lower financial frictions, or better access to credit, have an unambiguously positive effect on economic growth and in particular on innovation-driven growth [Levine (2005)]. Recent research incorporating firm-level modelling and data has highlighted a negative effect operating via *selection*. Introducing credit constraints in a simplified version of Klette and Kortum (2004), Aghion et al. (2018a) show that better access to credit has a direct positive effect on incumbent firms' innovation incentives and a negative effect on innovation by entrants. These two offsetting effects can potentially generate an inverted-U relationship between credit constraints and productivity growth, which is also uncovered in French firm-level data. Exploiting a policy change that improved access to credit, they show that firms affected by this policy increase their productivity growth but also experience lower exit rates, especially those firms that were less productive before the policy change. While they focus on a simple deterministic steady-state model and reduced-form econometric analysis we propose a structural quantitative approach which allows us to asses counterfactual scenarios.

The rest of the paper is structured as follows. The next section introduces the baseline model. Section 3 introduces the financial friction and innovation policies. Section 4 describes the parametrization and solution method. Section 5 provides the main quantitative analysis of the baseline model. Section 6 focuses on the link between business cycles and growth, using the Great Recession and the current COVID-19 pandemic as examples. Finally, Section 7 provides results of the policy analysis and Section 8 concludes.

[8] The positive direct effect of subsidies to incumbents on their innovation is in part offset by lower entry. First, higher incumbents' innovation increases creative destruction thereby reducing the value of entry; secondly, it increases the demand for skilled workers and their wage, thereby increasing the cost of entry. Subsidising incumbents fixed operating costs reduces the exit rate, thereby producing a negative selection effect which increases the proportion of low-innovation type firms and reduces growth. Finally, subsidising entry has negative effects on growth as it discourages innovation by incumbents.

[9] The analysis is limited to closed economy. For quantitative analyses of R&D subsidies in open economy see Impullitti (2010), Akcigit et al. (2018), and Borota et al. (2019). Ferraro et al. (2020) set up a quantitative growth model to capture historical patterns of US tax policies and assess the impact of a rich set of fiscal policies on growth. They show that cutting taxes on capital gains increases long-run growth, while tax cuts on corporate income and dividends have the opposite effects.

[10] There is an extensive theoretical and empirical literature exploring several channels through which financial frictions can affect innovation and growth. For a recent survey see (Aghion et al., 2018b)

2 Model

This section builds a tractable general equilibrium endogenous growth model with heterogeneous, credit constrained firms. Businesses hire labor and capital to produce output at a given efficiency level. However, they can also invest into R&D in order to improve their technology. These forces, together with government taxes and a policy supporting innovation, then jointly determine the endogenous rate of growth of the aggregate economy.

In this model firms endogenously enter, exit and conditional on survival they grow over their life-cycle. Throughout their life-cycles firms may invest into developing better production technologies. However, a fraction of these costs must be paid upfront for which firms borrow from financial intermediaries under constraints. Finally, the model also includes a government which levies corporate taxes on firms, lump-sum taxes on households and in return provides support in the form of grant, loans and tax-credit to firms' technology investments.

We first describe the baseline model and only then turn to incorporating frictions and policies. In what follows, aggregate variables are denoted by upper-case letters, while firm-specific variables are denoted by lower-case letters.

2.1 Households

The representative household comprises a continuum of individuals of measure one. An exogenous fraction S_t of family members works as skilled labour, the complement as unskilled. The labor market pays wages $W_{s,t}$ and $W_{u,t}$ to skilled and unskilled workers, with $N_{s,t}$ and $N_{u,t}$ being the time each of them allocate to work, respectively.

The representative household take prices as given and chooses consumption C_t, investment into physical capital I_t, and the supply of labor for both skilled and unskilled family members $N_{s,t}$ and $N_{u,t}$. The per-period utility of the representative household is given by

$$\ln C_t - \upsilon_s S_t \, \frac{N_{s,t}^{1+\theta}}{1+\theta} + \upsilon_u (1 - S_t) \, \frac{N_{u,t}^{1+\theta}}{1+\theta}, \tag{1}$$

where $\upsilon_u > 0$ and $\upsilon_s > 0$ are the disutilities of labor for the un-skilled and skilled, respectively, and $\theta > 0$ is the Firsch elasticity. Households buy intermediate goods y_j and use them to produce a composite good that they consume or invest. The technology to produce the composite good is

$$C_t + I_t = \left(\int_{j \in \Omega_t} y_{j,t}^{\frac{\eta-1}{\eta}} \, \mathrm{d}j \right)^{\frac{\eta}{\eta-1}}, \tag{2}$$

where $y_{j,t}$ denotes the quantity of variety j, $\eta > 1$ is the elasticity of substitution between varieties and Ω_t is the endogenous mass of varieties in the economy.

The representative household maximizes the net present value of life-time utility, with subjective discount factor $\beta \in (0,1)$, subject to the following budget constraint

$$\int_{j \in \Omega_t} p_{j,t} y_{j,t} \mathrm{d}j = W_{s,t} N_{s,t} S_t + W_{u,t} N_{u,t} (1 - S_t) + K_t R_t + \Pi_t - T_t, \tag{3}$$

which states that total income stems from employment, renting out of capital to firms at rate R, from the ownership of firms, where Π represents aggregate profits net of corporate taxes, and T is a lump sum tax. Total income is spent on consumption and investment into physical capital, where $I_t = K_{t+1} - (1-\delta)K_t$, δ is the depreciation rate and K is the stock of capital. In addition, $\int_{j \in \Omega_t} p_{j,t} y_{j,t} \mathrm{d}j = P_t \big(C_t + I_t\big)$, implicitly defining the aggregate price level $P_t^{1-\eta} = \int_{j \in \Omega_t} p_{j,t}^{1-\eta} \mathrm{d}j$, which we normalize to 1 implying that p_j is the relative price of variety j and that all the factor prices in the above budget constraint are real.

The optimality conditions for y_j, N_s, N_u and I are, respectively, given by

$$y_{j,t} = p_{j,t}^{-\eta} (C_t + I_t), \tag{4}$$

$$W_{s,t} = \upsilon_s C_t N_{s,t}^{\theta}, \tag{5}$$

$$W_{u,t} = \upsilon_u C_t N_{u,t}^{\theta}, \tag{6}$$

$$\frac{1}{C_t} = \beta \mathbb{E} \frac{1}{C_{t+1}} \left(R_{t+1} + 1 - \delta \right). \tag{7}$$

2.2 Incumbent firms

Firms produce individual varieties j using labor and capital. They must also pay stochastic operation costs which induce endogenous exit. In addition, they can invest into improving the efficiency with which they produce their corresponding varieties. The timing of events for firms is the following: at the beginning of each period firms observe the operation cost and decide whether to remain in operation or not. Conditional on survival, they produce, invest in innovation and hire labor and capital. At the end of the period, innovations are realised and firms also exit for exogenous reasons.

Technology. Production of the individual variety j happens according to technology

$$y_{j,t} = A_t q_{j,t} k_{j,t}^{\alpha} n_{y,j,t}^{1-\alpha}, \tag{8}$$

where A is the aggregate state of technology, which follows a stochastic process that we specify later, q_j is firm specific productivity, k_j is capital and $n_{y,j}$ is unskilled labor used in the production of variety j; $\alpha \in (0,1)$.

Let us denote by $n_{r,j,t}$ the number of skilled workers employed by firm j to undertake an

R&D project at t. The probability of success is

$$x_{j,t} = \Big(\gamma_j \; n_{r,j,t}\Big)^{\psi}, \tag{9}$$

where $\psi \in (0,1)$ and $\gamma_j > 0$ are measures of innovation efficiency. Upon success, a firm's productivity improves according to $q_{j,t+1} = (1+\lambda)q_{j,t}$, with $\lambda > 0$. We assume that some firms are more efficient in delivering a successful innovation than others and that this heterogeneity is permanent. Hence, γ takes one of two values (high and low), γ_H and γ_L and χ is the share of high-type firms.[11]

Optimal decision rules. The value at the beginning of period t of a firm j with productivity $q_{j,t}$, conditional on aggregate productivity A_t, but before the firm observes the realization of the fixed production cost ϕ, is given by

$$V_j(q_{j,t}, A_t) = \int_{\phi} \max \Big\{ \widetilde{V}_j(q_{j,t}, A_t) - \phi W_{u,t}, 0 \Big\} \; \mathrm{d}F(\phi), \tag{10}$$

where ϕ is an i.i.d. stochastic operation cost (expressed in units of unskilled labor) the firm has to pay to produce in $t+1$, whose distribution is $F(\phi)$ with mean $\overline{\phi}$ and standard deviation σ_{ϕ}. Conditional on survival firms choose prices, employment (in production and R&D) and capital to maximize

$$\widetilde{V}_j(q_{j,t}, A_t) = \max_{p,n_c,n_r,k} (1-\tau)\pi_{j,t} + (1-\rho)\; \mathbb{E}\beta_t V_j(q_{j,t+1}, A_{t+1}), \tag{11}$$

where $\tau > 0$ is a corporate tax, $\pi_{j,t} = p_{j,t}y_{j,t} - R_t k_{j,t} - n_{y,j,t}W_{u,t} - n_{r,j,t}W_{s,t}$ are profits and $\mathbb{E}V_j(q_{j,t+1}, A_{t+1}) = x_{j,t}V_j(q_{j,t}(1+\lambda), A_{t+1}) + (1-x_{j,t})V_j(q_{j,t}, A_{t+1})$ is the continuation value, $\beta_t = \beta C_t/C_{t+1}$ the discount factor, and ρ is an exogenous exit rate.

Exit decisions are taken at the beginning of the period, just after observing the operation cost ϕ. For any q, it exits a cutoff function that determines the operation costs below which firms optimally exit. The cutoff function reads

$$\widetilde{\phi}_t(q) = \widetilde{V}(q, A_t)/W_{u,t}, \tag{12}$$

which is different for firms with different productivity. The endogenous survival rate associated with the above exit condition is simply the CDF of the operation costs evaluated at the cutoff, $\Phi_t(q) = F(\widetilde{\phi}_t(q))$.

The first order conditions for capital and unskilled labor read

$$R_t = \frac{(\eta-1)\alpha}{\eta} \; \frac{y_{j,t}}{k_{j,t}} \; p_{j,t} \quad \text{and} \quad W_{u,t} = \frac{(\eta-1)(1-\alpha)}{\eta} \; \frac{y_{j,t}}{n_{y,j,t}} \; p_{j,t}. \tag{13}$$

[11] Heterogeneity in research has been similarly modelled in e.g. Acemoglu et al. (2018) and Akcigit et al. (2019).

The optimal pricing behavior emerging from combining these two conditions is

$$p_{j,t} = \frac{\eta}{\eta - 1} \underbrace{\left(\frac{R_t}{\alpha}\right)^{\alpha} \left(\frac{W_{u,t}}{1-\alpha}\right)^{1-\alpha} \frac{1}{A_t q_{j,t}}}_{\text{MPC}}, \tag{14}$$

a standard case of a constant markup over marginal production costs (MPC).

The optimal R&D decision is given by

$$(1-\tau)W_{s,t} = \psi \frac{x_{j,t}}{n_{r,j,t}} \mathbb{E}\beta_t (1-\rho) \Big[V\big(q_{j,t}(1+\lambda), A_{t+1}\big) - V\big(q_{j,t}, A_{t+1}\big) \Big], \tag{15}$$

where optimal investment into R&D simply balances the marginal costs of adding an extra R&D worker, the after-tax wage costs $(1-\tau)W_s$, with the expected marginal benefits. The latter are represented by the increase in the probability of success multiplied by the expected gain of being successful, represented by the term in square brackets.

2.3 Startups

In order to enter at period $t+1$, at period t a potential startup has to pay a fixed entry cost, undertake R&D activities and be successful in discovering a new variety, which allow them to become incumbents.

The entry process. The entry process entails two stages, all taking place at t, after which a successful startup enters and becomes an incumbent at $t+1$. First, potential entrants have to pay an initial research cost $\theta W_{s,t}$ to build a prototype. After paying this cost, a prototype with productivity $q_{j,t} = \overline{q}_t(1+\lambda_{e,j})$ is built, where $\overline{q}_t$ is the average productivity of the economy at period t. The idiosyncratic component of the prototype's productivity, $\lambda_{e,j}$, is drawn from the distribution $F_\lambda(\lambda_e)$ with zero mean and standard deviation σ_e. Second, potential entrants use their prototypes to search for new varieties of the composite good. Entrant j discover a new variety with probability

$$x_{j,t} = \left(\gamma_e \overline{n}_{r,t}^{\kappa} n_{r,j,t}^{1-\kappa}\right)^{\psi}, \tag{16}$$

$\gamma_e > 0$. As with incumbents, γ_e can take on two values (high and low), γ_H and γ_L, with the share of high-type startups being again χ. Potential startups benefit from the research effort of incumbents through $\overline{n}_r$, a form of knowledge spillover. In case of success, the productivity of the new variety at $t+1$ is $q_{j,t+1} = q_{j,t}(1+\overline{\lambda}_e)$.[12]

[12]Parameter $\overline{\lambda}_e$ is introduced for quantitative purposes as it helps mapping the observed difference in average productivity between startups and incumbents.

Free entry and optimal decision rules. Assuming free entry, we obtain

$$\theta W_{s,t} = \int_{\lambda_e} \widetilde{V}_e\big(\overline{q}_t(1+\lambda_e)\big)\ \mathrm{d}F_\lambda(\lambda_e),$$

where $\widetilde{V}_e$ is the value of entrants described below. The mass of potential entrants E_t, and the mass of next period new startups M_{t+1} are related through

$$\underbrace{\int_{j\in E_t} x_{j,t}\mathrm{d}j}_{\overline{x}_{e,t}E_t} = M_{t+1},$$

where $\overline{x}_{e,t}$ is the average probability of success of potential entrants.

After potential entrants draw the productivities q_j of their prototypes, they have to choose their research effort $n_{r,j}$. The value function of a potential entrant reads

$$\widetilde{V}_e(q_{j,t}, A_t) = \max_{n_{r,j,t}} \quad -(1-\tau)n_{r,j,t}W_{s,t} + (1-\rho)\ \mathbb{E}\beta_t V(q_{j,t+1}, A_{t+1}). \tag{17}$$

If the research project is successful the potential startup enters with productivity $q_{j,t+1} = q_{j,t}(1+\bar{\lambda}_e)$, becoming an incumbent at $t+1$. Its expected value is $\mathbb{E}V(q_{j,t+1}, A_{t+1}) = x_{j,t}V(q_{j,t+1}, A_{t+1})$, with $V(q_{j,t+1}, A_{t+1})$ given by (10). The value of being unsuccessful is zero. The optimal decision for R&D investment by entrants can be written as

$$(1-\tau)W_{s,t} = (1-\kappa)\psi\frac{x_{j,t}}{n_{r,j,t}}\mathbb{E}\beta_t(1-\rho)V(q_{j,t+1}, A_{t+1}). \tag{18}$$

2.4 Equilibrium

The labor market clears every period t both for skilled workers,

$$N_{s,t}S_t = \int_{j\in\Omega_t\cup E_t} n_{r,j,t}\ \mathrm{d}j + \theta E_t$$

where labor demand takes into account that skilled labor is by startup both for entry, producing the prototype, and for post-entry innovation, and unskilled workers

$$N_{u,t}(1-S_t) = \int_{j\in\Omega_t} n_{y,j,t}\ \mathrm{d}j + \phi\Omega_t,$$

where Ω_t is the mass of incumbents and E_t the mass of potential entrants. The market for capital also clears every period t, as well,

$$K_t = \int_{j\in\Omega_t} k_{j,t}\ \mathrm{d}j.$$

Finally, profits (net of the R&D cost of both incumbents and potential entrants) are distributed to households

$$\Pi_t = \int_{j \in \Omega_t} \pi_{j,t} \, \mathrm{d}j.$$

In the next section we extend the model to include frictions and governmental policies supporting R&D. At this point, however, corporate taxes are not being used for any such policies and therefore they are simply redistributed back to the household in the form of lump-sum transfers.

Balanced growth path. When the economy is on the balanced growth path (BGP), all aggregates grow at the same rate g. Using the definition of output in (2) and the production technology (8), we can write

$$C_t + I_t = \left(\int_{j \in \Omega} y_{j,t}^{\frac{\eta-1}{\eta}} \, \mathrm{d}j \right)^{\frac{\eta}{\eta-1}} = \overline{q}_t K_t^{\alpha} \left(\int_{j \in \Omega} \left(\frac{q_{j,t}}{\overline{q}_t} \left(\frac{k_{j,t}}{K_t} \right)^{\alpha} n_{y,j,t}^{1-\alpha} \right)^{\frac{\eta-1}{\eta}} \mathrm{d}j \right)^{\frac{\eta}{\eta-1}}$$

where

$$\overline{q}_t = \frac{1}{\Omega} \int_{j \in \Omega} q_{j,t} \, \mathrm{d}j.$$

Since at a BGP the distributions of capital k_j/K and productivity $q_j/\overline{q}$, relative to the corresponding means, are stationary, the big term in parenthesis will be constant. Moreover, consumption, investment and capital will be all growing at the same rate g. Consequently, the stationary growth rate is given by $(1+g)^{1-\alpha} = \overline{q}_{t+1}/\overline{q}_t$, with

$$(1+g)^{1-\alpha} = \frac{\overline{q}_{t+1}}{\overline{q}_t} = \frac{1}{\Omega} \left(\int_{j \in \widehat{\Omega}} \frac{q_{j,t}}{\overline{q}_t} (1 + \lambda x_j) \mathrm{d}j + (1 + \overline{\lambda}_e) \int_{j \in M} x_j (1 + \lambda_{e,j,t}) \mathrm{d}j \right), \tag{19}$$

where $\widehat{\Omega}$ is the set of survival incumbents. The last equality directly results from the definition of q_{t+1}, i.e., after substituting the $q_{j,t+1}$ terms by their equilibrium values,

$$\overline{q}_{t+1} = \frac{1}{\Omega} \int_{j \in \Omega} q_{j,t} \, \mathrm{d}j = \int_{j \in \widehat{\Omega}} q_{j,t} (1 + \lambda x_j) \mathrm{d}j + (1 + \overline{\lambda}_e) \bar{q}_t \int_{j \in M} x_j (1 + \lambda_{e,j,t}) \, \mathrm{d}j.$$

3 Financial frictions and innovation policies

Next, we extend the baseline model described in the previous section to include a financial friction and several policies supporting R&D.

3.1 Financial frictions

Firms tap into financial markets to fund part of their innovation expenditures. We assume that firms must obtain outside capital to fund a fraction d_j of their direct R&D costs and that this financial dependence varies across firms, that is d_j is distributed $D(d)$ in the support $(0, 1)$. Therefore, firm j needs to borrow $d_j\, n_{r,j,t} W_{s,t}$ from financial intermediaries. Financial markets imperfections imply that firms are credit constrained in their innovation efforts. Due to imperfect contractability, firms repay their loans only with probability $\mu \in (0, 1)$. In this case, the lender receives $\Gamma_{j,t}$ and with the complement probability $1 - \mu$, firms default on their loans. In order for lenders to be willing to participate, it must be that the repayment $\Gamma_{j,t}$ is sufficiently large. In particular, it must be that the returns from lending to firms are at least as large as the returns from investing in the market at a rate $\widetilde{r}$, which is a strictly positive, exogenous intra-period cost. Formally, this results in the following incentive compatability constraint

$$(1 + \widetilde{r}) d_j\, n_{r,j,t} W_{s,t} \leq \mu \Gamma_{j,t}. \tag{20}$$

In equilibrium, free entry of financial intermediaries results in (20) holding with equality which yields the following expression for the value of the loan

$$\mu \Gamma_{j,t} = (1 + \widetilde{r}) d_j\, n_{r,j,t} W_{s,t}. \tag{21}$$

Consequently, financial markets add $\widetilde{r} d_j$ to the cost of each skilled worker employed in research.

3.2 Innovation policies

We consider three types of policies: tax credits, loans and grants. Moreover, we distinguish between policies to incumbents and entrants. These policies "only" change the costs of R&D for individual firms and therefore the optimal decisions described above are still valid, but with a different value for R&D costs. We describe this, along with the optimal choices regarding the innovation policies, below.

Incumbents. The government awards grants covering a constant fraction s, $s \in (0, 1)$, of the total direct cost $n_r W_s$ of a research project. Financial costs are explicitly excluded. The government also provides loans to finance a fraction m, $m \in \big(0, s(1 + \widetilde{r})/\widetilde{r}\big)$, of direct research costs $n_r W_s$. Public loans charge the rate factor $1/\mu$ conditional on the loan be repaid, which happens with probability μ. This makes the expected financial cost of research loans equal to zero. Finally, the government also uses a size-dependent tax-credit for R&D. Firms obtain a credit on their corporate taxes at rate $\tau_r(n_{r,j,t})$ for their R&D expenditure. Tax credits can be uniform across firms or may be oriented to promote R&D of small (large) firms, in which case $\tau_r'(n_{r,j,t})$ will be negative (positive). The total credit is $\tau_r(n_{r,j,t}) \tau n_{r,j,t} W_{s,t}$.

Therefore, R&D costs are

$$(1+\mathcal{I}_{j,t})\big(1-\varphi(n_{r,j,t})\big)\ n_{r,j,t}W_{s,t}, \tag{22}$$

where the indicator function $\mathcal{I}_{j,t} = \big\{-s+\widetilde{r}\max\{(d_j-s-m),0\}\big\}$. The tax credit factor $\varphi(n_{r,j,t}) = \tau_r(n_{r,j,t})\tau/(1-\tau)$ is such that using $(1+\mathcal{I}_{j,t})\big(1-\varphi(n_{r,j,t})\big)\ n_{r,j,t}W_{s,t}$ instead of simply $n_{r,j,t}W_{s,t}$ in all the optimal firm decisions described in Section 2.2, we obtain the new optimal choices in the presence of innovation policies.

Startups. We assume that policy supporting entrants different from the one supporting incumbents only parametrically and not conceptually. The government awards grants to potential startups covering a fraction s_e, $s_e > d_e$, of the direct research cost n_rW_s. It also provides loans to finance a fraction m_e, $m_e \in (0, d_e)$, of direct research costs n_rW_s. A firm awarded with a research loan requires additional funds for the fraction $d_e - m_e$ of direct research costs, that needs to be financed through financial intermediates. Public loans charge the subsidised rate factor $1/\mu_e$ that makes the expected financial cost of research loans equal to zero.

Government budget. The only difference to the equilibrium of our model without policies is that the direct cost of the innovation policy, which includes grants and loans to incumbents and startups, need to be financed with taxes to corporation profits (net of tax credits) and households' lump-sum taxes. We assume that the budget is balanced every period and therefore defined as:

$$G_t + L_t + G_{e,t} + L_{e,t} = \tau\Pi_t + T_t.$$

where G_t, L_t and $G_{e,t}, L_{e,t}$ are the total amount of government expenditure to cover grants and loans of incumbents and entrants respectively.

3.3 Distribution of firms

Let us denote by $\omega_t(q)$ the mass of firms with productivity q that are operative at period t. The total mass of operative firms is then $\Omega_t = \int \omega_t(q)\mathrm{d}q$. Where will they be in the distribution at period $t+1$? Notice that a fraction ρ of them will exogenously exit at the end of period t, and a fraction $1 - F\left(\widetilde{\phi}_{t+1}(q)\right)$ will endogenously exit to avoid paying the fixed operation costs. These are the possible situations in which they may be when moving to $t+1$ (let us suppress index t to simplify the notation).

At the beginning of period $t+1$, the operation cost will realize and among those that did not upgrade and survived to the exogenous death shock, a fraction $F\big(\widetilde{\phi}(q)\big)$ will optimally remain operative. There will also be a fraction $F_\lambda\left(\frac{q}{\overline{q}_t(1+\overline{\lambda})}\right)$ of the mass M_{t+1} of entrants that will start business with productivity q. We can now write the evolution law of the density $\omega_t(q)$. Let us use the notation $q_\lambda = \frac{q}{1+\lambda}$ and $\lambda_{q,t} = \frac{q}{\overline{q}_t(1+\overline{\lambda})}$ to refer to incumbents and potential startup that get productivity q if successful in research, respectively. The law of motion of the density $\omega_t(q)$ is then:

$$\omega_{t+1}(q) = (1-\rho)F\big(\widetilde{\phi}_{t+1}(q)\big)\Bigg(\underbrace{\Big(1-x_t(q)\Big)\omega_t(q)}_{\text{remain in } q} + \underbrace{x_t(q_\lambda)\omega_t(q_\lambda)}_{\text{upgrade to } q} + \underbrace{F_\lambda(\lambda_q)M_{t+1}}_{\text{entrants}}\Bigg). \tag{23}$$

The total mass of firms is given by

$$\Omega_t = \int_g \omega_t(g)\mathrm{d}g.$$

At the balanced growth path, the total mass Ω will be constant and the distribution ω_t/Ω will be moving to the right in a way that the mean $\overline{q}_t$ grows at rate g as defined in (19). In other terms, at a balanced growth path, there exists a stationary density function $\widehat{\omega}(\widehat{q})$ associated to $\omega_t(q)$ where $\widehat{q} = q/\overline{q}$.

4 Parametrization and solution

This section describes the parametrization of our model which is geared towards the French economy and the employed solution method. We begin with a simplified framework, with only financial frictions and corporate taxation, and we leave the discussion of innovation policies - their parametrization and analysis of their impact - to the next section.

4.1 Parametrization

While all model parameters impact the properties of the model, we group the discussion of their parametrization with the moments in the data which they most intuitively affect. All parameters, their values and targets are in Table 1.

Household parameters. We assume that the model period is one year and therefore set the discount factor, β, to 0.97, targeting a roughly 3 percent interest rate. The elasticity of substitution between varieties, η, is set to 5.8 implying a 20 percent markup which falls within the range in France documented in Bundesbank (2017) and is consistent with Akcigit et al. (2020). The capital depreciation rate, δ, is taken from the Penn World Tables and is set to 3.6 percent. The elasticity of labor supply, θ, is common to both labor types and is set to 1, a standard value in the macro literature. The disutility of labor for unskilled labor, υ_u, is set such that wages of the unskilled are normalized to 1. Finally, the disutility of labor of skilled labor, υ_s, is set such that wages of skilled are 1.36 times higher than that of the unskilled, consistent with the wage-skill premium documented in Verdugo (2014).

Research and development. Following Akcigit et al. (2020) we set the curvature in the research and development function, ψ, to 0.71. We assume there are two types of firms in regards to research and development: low and high types. The only difference between the two is the level of their research and development efficiency, γ. Low type efficiency, γ_L, is set such that the aggregate share of research and development spending relative to GDP is consistent with Eurostat data and equal to 2.2 percent. High type efficiency, γ_H, is set such that the model delivers a realistic ratio between startup size and average firm size. Taking Eurostat data, this ratio is 3.5 in the French economy. The rate at which firms with successful R&D projects grow, λ, is set such that the model replicates the 1.7 percent average growth rate of real GDP in France between 1980 and 2017. Finally, we assume that this rate is the same for startups, $\overline{\lambda}_e = \lambda$, and that there are no knowledge spillovers from aggregate R&D to individual firms, $\kappa = 0$.

Firms. The assumed Cobb-Douglas production function of firms is parametrized with $\alpha = 0.36$ mimicking the capital share in income taken from AMECO. In addition to wages and capital costs, firms must also pay stochastic costs of operation. These are assumed to be log-normal with mean, μ_F, and dispersion, σ_F. While the former is set such that the model delivers an average firm exit rate of 6 percent, the latter is parametrized such that the model delivers a realistic volatility of exit rates over the business cycle. Both these targets are taken from EUROSTAT business demographic data for France. The mean and dispersion of entrants' initial productivity levels is governed by a normal distribution with mean μ_E and dispersion σ_E. While the former is normalized around average firm productivity, the latter is set such that exit rates of startups are 2.8 times larger than the average. Finally, we assume that share of high type startups, χ, is such that the model produces a realistic share of small firms. Specifically, in the EUROSTAT data about 90 percent of businesses have less than 4 employees. We therefore target this share in the model by requiring that 90 percent of all firms are smaller than the average startup which have on average 3.6 workers in the data. The mass of low type entrants is set such that (stationarized) aggregate output is normalized to 1.

Frictions, taxes and aggregate shock. We set the corporate tax rate to 28 percent, roughly equal to the effective corporate tax in France. In addition, we assume that firms must obtain external funding for *all* their expenditures, $d = 1$, and this comes at an additional 5 percent cost over and above the rental rate. Finally, the aggregate production efficiency shock, A, is assumed to follow an AR(1) process with persistence ρ_A and dispersion of shocks σ_A such that the persistence and dispersion of the cyclical component of GDP matches the data. Note that real GDP in the model is not equal to Y, but is instead defined consistent with the data as $GDP = \int_i y_i di$.

Table 1: Parameter values

parameter		value
β	discount factor	0.97
η	elasticity of substitution	5.8
θ	elasticity of labor supply	1
υ_u	disutility of labor, unskilled	1.95
υ_s	disutility of labor, skilled	11.98
δ	capital depreciation rate	0.036
ψ	curvature in R&D	0.71
γ_L	R&D efficiency, low	0.16
γ_H	R&D efficiency, high	0.20
λ	innovation rate	0.339
α	returns to capital in production	0.36
μ_F	stochastic operational costs, mean	-4.27
σ_F	stochastic operational costs, dispersion	2.21
σ_E	dispersion of startup productivity levels	0.4
χ	share of high-type startups	0.92
M	mass of low type entrants	0.029
τ	corporate tax rate	0.28
d	share of expenditures requiring external funds	1
$\widetilde{r}$	rate of external funds	$1.05R$
ρ_A	aggregate production efficiency shock, persistence	0.57
σ_A	aggregate production efficiency shock, dispersion	0.008

4.2 Solution method

The structural model is a general equilibrium framework with heterogeneous firms and endogenous growth. Individual businesses must know the entire distribution of firm productivity and types in order to be able to forecast the development of the wage and rental rate, key variables in their optimization decisions. In addition, the presence of the aggregate shock makes these firm distributions time-varying rendering the solution of the model challenging.

The method employed in this paper follows that developed in Sedláček and Sterk (2017) and adapted to a model with (exogenous) growth in Sedláček (forthcoming). The procedure is based on first-order perturbation along the stationary steady state life-cycle dynamics of individual firms, which depend on the evolution of their firm-specific productivity values. Notice that without persistent idiosyncratic shocks and without adjustment costs, all firms with the same productivity level will make the same decisions. Therefore, it is possible to treat a particular distance from average productivity as a separate "firm type". Specifically, we allow for $I = 41$ such different values, centred around average productivity $\overline{q}$. To economize on notation, we can express the model compactly as:

$$\mathbb{E}_t f\left(y_{t+1}, y_t, x_{t+1}, x_t; \Upsilon, \zeta\right) = 0$$

where x_t is a vector containing the state variables and y_t is a vector containing the non-preditermined variables, Υ is a vector containing all parameters of the model and ζ is a scalar parameter pre-multiplying the covariance matrix of the shock innovations, as in Schmitt-Grohe and Uribe (2004). Importantly, the above is system of a finite number of expectational difference equations.

4.2.1 Solving for the steady state without aggregate uncertainty

One first solves for the equilibrium of a version of the model without aggregate uncertainty. That is, we find vectors $\overline{y}$ and $\overline{x}$ that solve $f\left(\overline{y}, \overline{y}, \overline{x}, \overline{x}; \Upsilon, 0\right) = 0$. As described in the main text, the calibration targets various parameters to match long-run statistics. The calibration procedure has the following steps:

1. given values for the technology types (i.e. technology gaps) and R&D types, the aggregate wage and rental rates (R, W_u and W_s) it is possible to compute firm-specific prices, capital and unskilled labor choices, implied levels of production, firm values, skilled labor choices and exit rates.

2. given firm values and exit rates from (1.) and a normalization of the mass of entrants, it is possible to back out the entry cost and to compute the distribution of firm masses across technology types.

3. given the mass of firms in all technology types from (2.) and their optimal choices from (1.) and (2.), it is possible to compute all aggregate variables.

4.2.2 Solving for the equilibrium with aggregate uncertainty

Next, one can solve for the dynamic equilibrium using first-order perturbation around the stationary steady state (including the steady state life-cycle patterns of firms) found in the previous step. The first-order approximated solutions, denoted by hats, have the following form:

$$\begin{aligned} \widehat{x}_{t+1} &= \overline{x} + \Theta\left(\widehat{x}_t - \overline{x}\right) \\ \widehat{y}_{t+1} &= \overline{y} + \Phi\left(\widehat{x}_t - \overline{x}\right) \end{aligned}$$

where Θ and Φ are matrices containing the coefficients obtained from the approximation. The perturbation procedure is standard and carried out in one step.

An advantage of perturbation methods is that the computational speed is relatively high and many state variables can be handled. An important prerequisite for perturbations to be accurate, however, is that deviations from the steady-state are not too large. For firm dynamics models like the one in this paper it may seem problematic because differences in employment levels across firms may be very large. The solution method adopted here, however, overcomes this problem since the steady state we perturb around contains the entire life-cycle profiles of firms. These growth paths, captured by the constants in the above equations, are themselves non-linear functions of technology types.

Hence, the fact that most newborn firms starts off much below their eventual sizes does not involve large accuracy losses since the same is true for the steady-state sizes of newborn firms. Similarly, the fact that the equilibrium features various firm types with very different optimal sizes does not reduce accuracy since we perturb around the growth path for each individual firm type.

5 Quantitative analysis

This section provides a quantitative assessment of the model. Our framework features both endogenous growth and business cycles and we therefore begin by discussing these properties separately. However, a key contribution of the paper is the ability to connect business cycle fluctuations to long-term growth and we do this at the end of this section. The next section then discusses the impact of policies on the model outcomes.

5.1 Long-run and cross-sectional properties

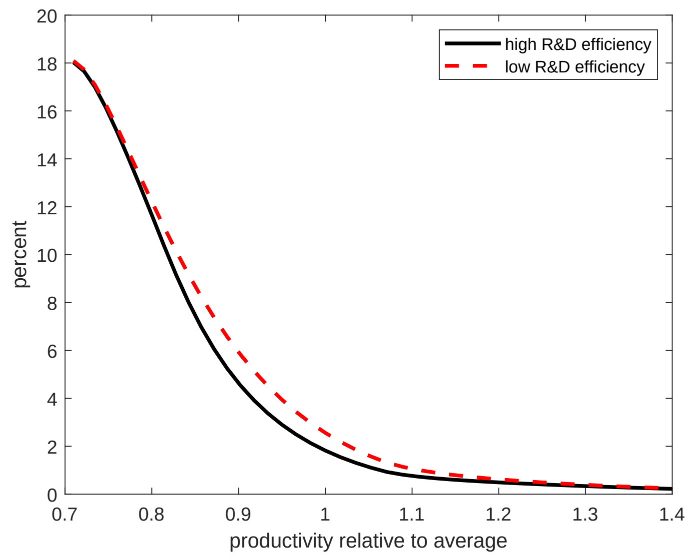
Let us begin by discussing some of the targeted firm dynamics properties. We will then move on to discussing the endogenous growth rate and its sources.

5.1.1 Firm dynamics

A key feature of the data is that startups are smaller than incumbent business. In the French economy, the average incumbent firm is 3.5 times larger than the average startup. In reality this may be driven by several factors. For instance the presence adjustment costs, larger financial frictions for young businesses, gradual customer acquisition, permanent size heterogeneity and subsequent selection and technology growth.

Our framework has the potential to speak to many of the above, but the baseline framework considers the final two reasons which are connected in our model. In particular, firms are characterized by either a low or a high R&D efficiency. The businesses with a high efficiency find it profitable to spend more on R&D and therefore they end up growing faster. This, in

Figure 1: Firm-level exit rates



Notes: Exit rates of low and high R&D efficiency businesses as a function of productivity (relative to average productivity).

turn, also improves their average survival probabilities. Specifically, the average exit rate of low type firms is 6.8 percent, while it is 5.5 percent on average for high type businesses.

The forces described above can be seen in Figure 1 which plots firm-level exit rates for the two types of businesses as a function of their productivity. The resulting effect is that average incumbent firms are 3.9 times larger than the average startup in our model.

5.1.2 Growth

The average growth rate of real GDP of 1.7 percent per year is a calibration target. We can, however, decompose the aggregate growth rate into several components to gain insight into its drivers. In particular, we can write the aggregate growth rate as

$$(1+g)^{1-\alpha} = \sum_m \underbrace{\sum_i (1+\lambda x_i(m))\omega_i(m)di}_{\text{incumbents}} + \underbrace{M(m)\sum_i (1+\overline{\lambda}_e x_i^e(m))p_i di}_{\text{entrants}}, \tag{24}$$

where we have made explicit that in our quantitative model there is a finite number of R&D types, low and high indicated by $m = \{L, H\}$, and that there is also a finite number of productivity levels (distances from average productivity) $i = 1, ..., I$. The stationary distribution of these productivity levels is given by $\omega_i(m)$, while at entry it is determined by p_i (the discretized version of the probability distribution $F(\lambda_e)$) and is common across types.

In addition to decomposing growth into the contributions of entrants (also called "creative destruction") and incumbents, we can further decompose the contribution of incumbents into the role of "selection" and "incumbent" R&D efforts. The former was dubbed by Lentz and

Table 2: Sources of growth (in percent)

	creative destruction	selection	incumbents	aggregate
level	0.8	0.9	0.03	1.73
share	45.3	53.9	0.8	100

Mortensen (2005, 2008) and refers to growth generated by a reallocation of resources from less to more productive firms. In our case, this amounts to resources reallocating from low to high efficiency type firms. Therefore, we can decompose growth into three components

$$(1+g)^{1-\alpha} = \sum_m \underbrace{\sum_i (1+\lambda x_i(m))p_i di}_{\text{incumbents}} + \underbrace{\sum_i (1+\lambda x_i(m))(\omega_i(m)-p_i) di}_{\text{selection}} + \underbrace{M(m)\sum_i (1+\overline{\lambda}_e x_i^e(m))p_i di}_{\text{creative destruction}}, \tag{25}$$

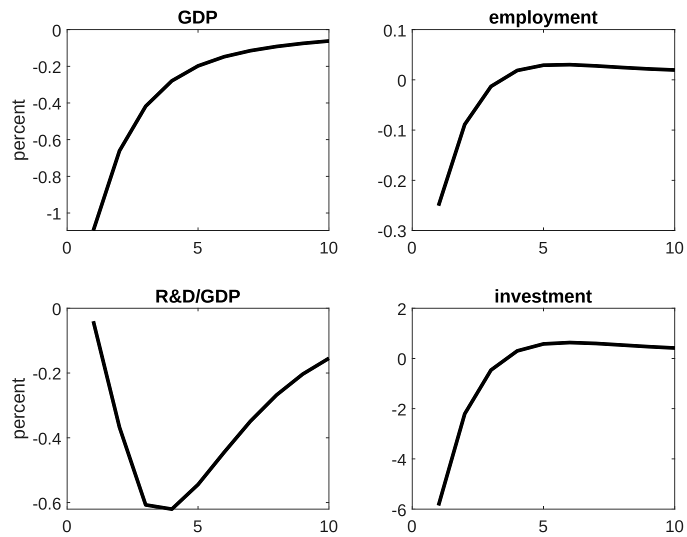
Table 2 shows the contributions of the different sources of growth in the stationary steady state. Specifically, creative destruction accounts for almost half of all growth as relatively unproductive businesses shut down and give way to new startups. Note that firm exit happens along the entire productivity distribution, but is more concentrated at the bottom (see Figure 1).

The most powerful force driving growth is selection. Slightly more than half of all growth is driven by a reallocation of resources from firms which are relatively less efficient in R&D to those that are better at it. Finally, only a very small share (less than one percent) of growth is driven by the fact that all firms try to conduct R&D and improve their productivity level. However, the change in the distribution of firms along their life-cycles is key.This decomposition is preliminary, it has to be checked and confronted to the data.

5.2 Business cycle properties

Let us now move on to examining the business cycle properties of the model. As was explained in the parametrization section, the model features a mean-reverting exogenous shock to the production efficiency of all businesses, A. This exogenous driving force is calibrated such that the model delivers the persistence and business cycle volatility of real GDP consistent with the

Figure 2: Impulse responses of aggregates



Notes: Impulse responses to a negative one-standard-deviation shock to aggregate production efficiency of firms.

data. In everything that follows, we use the Hodrick-Prescott filter with a smoothing coefficient of 100 to extract the cyclical components of empirical time series at an annual frequency.

Table 3 shows business cycle statistics of other key variables in the model. In addition, Figure 2 shows the impulse responses to a negative one-standard-deviation shock to aggregate production efficiency, A. In both we focus on key aggregate variables: GDP, employment, investment and R&D share in output.[13]

The table shows that - with the exception of investment - the cyclical components of other variables are all less volatile and less persistent than in the data. This is not uncommon in frameworks with heterogeneous firms, in which different businesses have somewhat different responses to shocks making the aggregate response somewhat dampened. The volatility of investment is, on the other hand, higher than in the data. Note, however, that our model does not include any form of adjustment costs which would help control the volatility of investment and which could also introduce a more realistic, hump-shaped, response of investment.

Finally, other sources of variation (e.g. financial or demand shocks) and other frictions (e.g. adjustment costs or search and matching frictions) may be important in matching the empirical movements over the business cycle. We leave these avenues for future research.

6 Link between business cycles and growth

Since the financial crisis, there has been much debate about the link between business cycle fluctuations and medium- to long-term growth. In addition, there is a much longer debate

[13]Real GDP, employment and investment are taken from the OECD database and for the sample period of 1980-2018. The R&D share in output is the "GERD" measure in Eurostat, for 2003-2017.

Table 3: Business cycle statistics

	real GDP	Employment	R&D/GDP	Investment
		Data		
standard deviation	0.014	0.007	0.020	0.056
autocorrelation	0.640	0.567	0.545	0.582
		Model		
standard deviation	0.014	0.003	0.014	0.065
autocorrelation	0.643	0.385	0.791	0.397

about the costs of business cycles, which have proven to be difficult to assess. An important conclusion in that strand of the literature is that if business cycles were linked to long-term growth, then deep recessions have the potential for being very costly for society (see e.g. Lucas, 2003). As such, a link between aggregate downturns and depressed long-run growth would provide strong support for a new role of stabilization policies and for policies sustaining long-run growth, innovation policies.

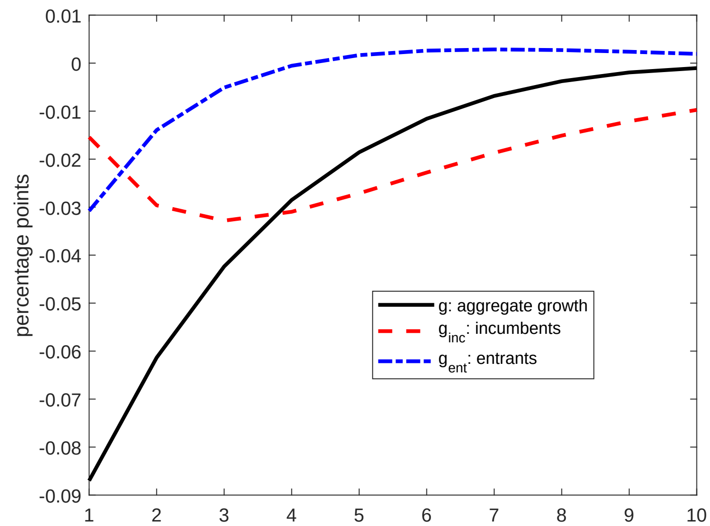
A key feature of our model is that it simultaneously speaks to both (endogenous) growth and business cycles. In this section we analyze this connection. In doing so, we will first document the general link between business cycles and growth. Next, we will utilize the features of the solution method which allows us to *estimate* the model on actual data. We will use this to show the model-predicted impact of the financial crisis and compare it to the data as a means of an "out-of-sample" test for the model. Finally, through the lens of our model, we will briefly discuss the possible impact the COVID-19 pandemic may have in the years to come.

6.1 Business cycles and growth

Let us begin with analyzing the general link between business cycles and growth. The model features several channels through which growth can be affected by cyclical fluctuations. These include the endogenous R&D decisions, and the endogenous distribution of firms. The latter is further impacted not only by endogenous firm entry, but also by endogenous firm exit, i.e. selection. All these interact together and shape the response of long-run growth to aggregate shocks.

In Figure 3, the area between the x-axis and the IRF for aggregate growth (the continuous line) represents the output loss generated by the shock. During the transition period, TFP grows at a low rate relative to the stationary solution moving TFP to a lower trend. These losses are never recovered, generating a permanent decline in output relative e to the previous balanced growth path. The movement to a lower trend will be discussed in more detail in the following subsection. This effect results from a fundamental property of endogenous growth models.

Figure 3: Impulse responses of aggregates



Notes: Impulse responses to a negative one-standard-deviation shock to aggregate production efficiency of firms.

Differently from the Neoclassical growth model, in this class of models when a temporary shock hits the economy output does not converge back to the previous balanced growth path. In our model, the slope of the BGP is endogenous, and its intercept critically depend on the effect that the transition has on initial conditions. The shock slows down growth for a while

productive capacity is destroyed which has a negative effect on the intercept of the balance growth path (see Figures 4 and 5).

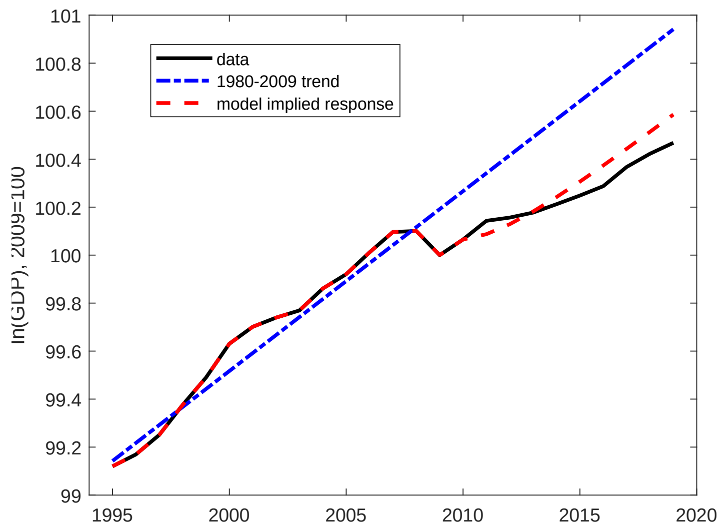
Figure 3 also plots two counterfactual responses: $g_{ent} = \sum_m M(m) \sum_i (1 + \lambda_e x_i^e(m)) p_i di$ and $g_{inc} = \sum_m \sum_i (1 + \lambda x_i(m)) \omega_i(m) di$. While the former shows how growth of incumbents is affected by the aggregate shock, the latter shows the same for entrants. Note that the two curves do not add up to the response of overall growth. This is because they combine in a non-linear fashion and with time-varying weights (see equation 24).

The impulse responses reveal that aggregate growth falls in response to a negative shock to aggregate production efficiency. The drivers behind this drop stem both from incumbents and entrants with roughly similar magnitudes. As mentioned before, the fact that recessions are connected with persistent drops in growth is concerning and may constitute a strong mandate for policy intervention. In the next subsection, we investigate the magnitude of these changes on the example of the financial crisis.

6.2 The impact of the financial crisis

Many countries experienced a persistent drag on the aggregate economy following the financial crisis in 2009-2010. Output levels dropped significantly and while the growth rates reverted back to pre-crisis levels, the lack of a strong bounce back meant that national economies found themselves at persistently lower levels. This was also the case of France.

Figure 4: Impulse responses of aggregates



Notes: Time paths of log real GDP in the data, according to a linear trend estimated on 1980-2009 and implied by our model estimated on 1980-2009.

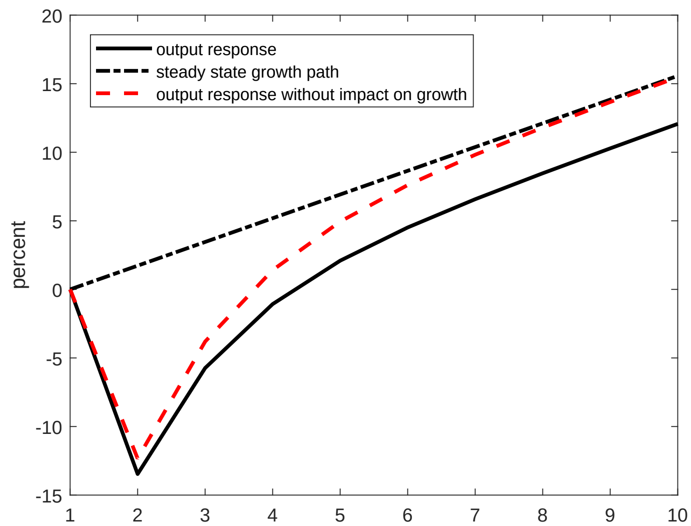
A key advantage of the employed solution method is that it allows us to *estimate* our model. Specifically, we use the cyclical component of log real GDP in the data from 1980 to 2010 to estimate the underlying shocks to production efficiency, A, using the Kalman filter. As a by-product, we obtain the implied time-paths of all variables in the model. Using these, we can then reconstruct the time-path for log GDP and allow it to "settle back" to the model's steady state from the point where it finds itself in 2010.

Figure 4 depicts the implied time-paths, where for clarity we only focus on the period between 1995 and 2019. In addition to the data and the model implied time-path, we also add a linear trend estimated on the sample between 1980 and 2010.

The figure shows that the model can replicate the persistent drag on real GDP in the data following the financial crisis. The large drop is followed by only a subdued recovery and features a permanent loss in the *level* of output due to the losses in productive capacity occurred during the Great Recession as described in the previous subsection. In the next subsection, we investigate the mechanism through which this happens in more detail on the example of the COVID-19 pandemic.

While the model, by construction, returns back to its original long-run growth *rate*, the data seems to suggest that even the rate might have dropped somewhat. This can be seen from the fact that the wedge between the real GDP data and the original linear trend keeps increasing, while it stabilizes in the case of the model prediction.

Figure 5: COVID-19 output growth path



Notes: Impulse responses to a negative shock to aggregate production efficiency of firms mimicking a roughly 14 percent drop in output.

6.3 The COVID-19 pandemic

The previous subsection showed how temporary downturns can have persistent effects in the productive capacity of the economy. In this subsection we investigate this further on the example of the current COVID-19 pandemic. Recent data suggests that French GDP contracted by 14 percent during the second quarter of 2020. This raises concerns about the possible long-lasting negative effects of such strong economic fallouts even if they are relatively temporary.

To analyze the potential for persistent losses in productive capacities, we analyze the impulse responses of output to a one time negative shock to production efficiency, A, which is set such that output drops by roughly 14 percent. Figure 5 shows these impulse responses. The figure shows three growth paths. First, the "output response" path which is the model implied response of output to the aggregate shock. Second, the past "steady state growth" path which is simply how output would have evolved without the aggregate shock. And finally, a counterfactual response of output which assumes that its growth rate is unaffected.

The key insight is that our model features permanent effects on the *level* of output as was suggested in the previous section. Following a temporary negative aggregate shock to the production efficiency, output drops (see the top left panel of Figure 2). In addition, output growth gets depressed for a long while as well (see Figure 3). These two combined result in the output growth path being permanently lower. While the growth *rate* recovers to its steady state value, there is no bounce-back and therefore the economy ends up on a permanently lower trajectory. In contrast, had there been no impact on growth, output would have reverted back to its long-run path (see "output response without impact on growth" in Figure 5). The above analysis suggests that even if 2020 were the only year impacted by the COVID-19 pandemic, the negative effect may be permanent and large. The model suggests that the level of GDP stays lower by 3 percentage points ten years after.

There are many caveats to Figure 5 and it should therefore be taken as only suggestive. For instance, modelling the current economic impact of the pandemic as a drop in production efficiency may not be suitable. Similarly, the persistence of the shock may be very different. Several countries have observed strong bounce-backs in the numbers of new firms starting up. Most notably, in the US the number of new business applications has recovered to almost pre-pandemic levels. These are important signs suggesting that the year 2020 may not be as bad as its second quarter.

On the other hand, there are several aspects not taken into account in the current analysis that could make the prediction even more dire. A key aspect is the growth potential of young businesses, which is assumed to be constant in our model. However, Sedláček and Sterk (2017) show that downturns give rise to cohorts of firms which are weaker in their growth potential which leads to a persistent drag on the aggregate economy in future years.

Applied to the specific question of the pandemic, Sedláček and Sterk (2020) develop a "Startup Calculator" which quantifies the persistent negative impact of a short-lived disruption among startups on aggregate employment. This has recently been adopted by the European Commission for several individual member states (see Benedetti-Fasil et al., 2020).

7 Policy analysis

In this section, we investigate how the presence of policies supporting R&D affect the economy. As with the previous sections, we will focus both on the long-run implications and on the business cycle. While our model incorporates several policy measures, in this section we focus solely on the impact of tax credits.

7.1 Tax credits

Tax credits reduce costs faced by firms. Specifically, after paying corporate taxes on profits, firms obtain a tax credit (or rebate) proportional to the size of their R&D investment and the corporate tax rate. For simplicity we will only study the case of a tax credit uniform for all firms. In our case, this amounts to obtaining a rebate equal to $\tau\tau_r n_r W_s$, where τ_r is the tax credit rate.

To analyze the impact of tax credits, we set τ_r such that the government budget is unaffected in the new stationary steady state. This is possible because tax credits are expansionary. Given that firms are taxed, the baseline model features inefficiently low R&D spending. Giving some of the tax collection back in the form of tax credits increases R&D and in turn size and profits. It is therefore possible to set tax credits such that the government budget is unaffected. This

Table 4: Sources of growth (in percent)

creative destruction	selection	incumbents	aggregate
	no tax credits, $\tau_r = 0$		
0.80	0.90	0.03	1.73
	positive tax credits, $\tau_r = 0.25$		
0.94	1.05	0.03	2.02

happens at a rate $\tau_r = 0.25$, i.e. 25 percent of R&D costs are tax deductible.

Note that we re-solve for the model equilibrium. This is necessary because as tax credits increase, so does equilibrium growth. However, the growth rate is important in firms' forward-looking decisions as it impacts discounting. Therefore, we solve for the fixed point growth rate consistent with a our value of tax credits.

7.1.1 Long-run implications

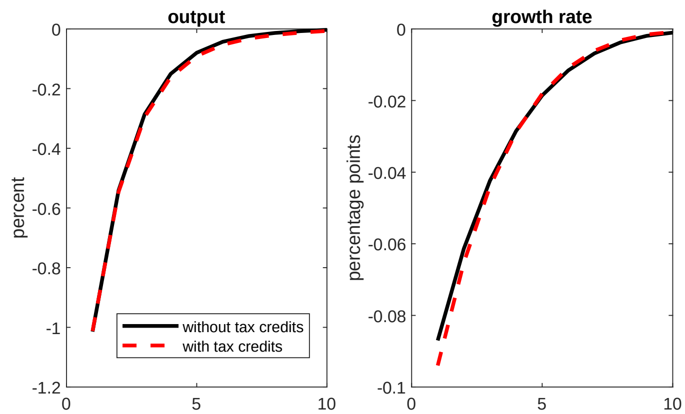
Table 4 shows the implications of tax credits for long-run growth. It documents that tax credits have a strong positive impact on aggregate growth which rises from 1.7 percent in the baseline without tax credits to 2 percent in the economy supported by tax credits. The drivers of growth remain essentially unchanged. Selection contributes more than a half and creative destruction contributes just under a half of aggregate growth. One reason for this outcome is that the tax credits specified in this exercise are common to all firms. In the current version of the model, startups are not directly eligible for this support. However, they do benefit from it indirectly via continuation values of incumbent businesses. If, for example, the tax credit were set to be size dependent, we may expect a somewhat differential impact on the drivers of growth.

7.1.2 Business cycle implications

The previous paragraphs have shown that tax credits are beneficial from the point of view of increasing long-run growth. We now turn to analyzing how they change short run dynamics.

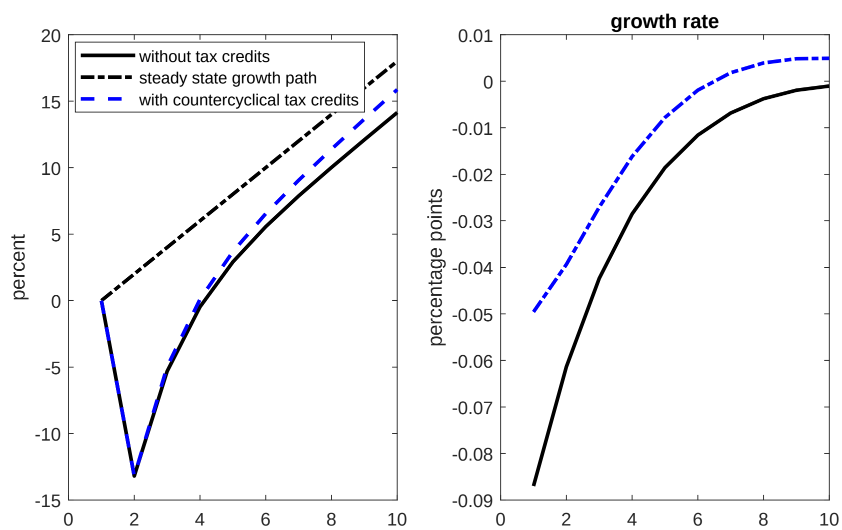
Towards this end, we inspect impulse responses of output to a large negative production efficiency shock. Specifically, we reconsider our COVID-19 example and compare the impulse responses in the baseline without tax credits to those of an economy supported by tax credits. Figure 6 shows how output and the aggregate growth rate respond in these two economies. While the response of output in the two economies is almost identical (in fact it is somewhat smaller in the economy with tax credits), the growth rate responds a little more in the economy with tax credits. Interestingly, these two effects almost exactly cancel out and the growth path of output is essentially the same in both economies.

Figure 6: Responses in economies with and without tax credits



Notes: Impulse responses to a negative shock to aggregate production efficiency of firms mimicking a roughly 14 percent drop in output. Responses from the baseline without tax credits and from an economy with tax credits set to $\tau_r = 0.25$.

Figure 7: Responses in economies without and with countercyclical tax credits



Notes: Impulse responses to a negative shock to aggregate production efficiency of firms mimicking a roughly 14 percent drop in output. Responses from the baseline without tax credits and from an economy with countercyclical tax credits set to $\phi = 0.25$.

An advantage of our numerical approach is that it is relatively straight forward to consider time-varying policies. In particular, we investigate the situation when tax credits roughly double during the large output drop of 14 percent, analyzed in our COVID-19 scenario.

Figure 7 shows the model implied growth paths with and without tax credits, together with the steady state growth path. As can be seen from the figure, counter-cyclical tax credits serve as an automatic stabilizer. The impact response was recalibrated to be the same in the two economies.

The subsequent growth path is, however, different in the two economies. Specifically, in the economy with counter-cyclical tax credits, the recovery is faster and with a smaller permanent loss. This is despite the fact that the aggregate long-run growth *rate* is unchanged. The reason for this starkly different growth path lies in the cyclical response of the growth rate shown in the right panel of Figure 7. In the economy with countercyclical tax credits, the growth rate temporarily "overshoots" its long-run value. This enables the economy to recover more lost ground through the crisis and end up with a less of a permanent loss.

8 Conclusion

In this paper we presented a tractable, general equilibrium, model with heterogeneous firms, aggregate uncertainty and endogenous growth. This framework is capable of connecting business cycle analysis with medium- to long-run implications on growth.

We parametrize this framework to the French economy and use it to analyze how cyclical downturns impact long run growth on the examples of the Great Recession and the current COVID-19 pandemic. Next, we introduce multiple governmental policies supporting innovation and investigate their implications on both long-run growth but also short-run dynamics following crisis. The results suggest that tax credits are a potentially powerful tool increasing long run growth. Moreover, if they are made counter-cyclical, they can serve as an automatic stabilizer, reducing the permanent losses from severe downturns.

Many questions remain open, however. What is the role of other governmental policies, often used in practice: e.g. loans and grants? We have modelled these policies but not explored them. How do these policies interact? What implications do these policies have on resource reallocation in economies and (intra-)national regions with large heterogeneity, i.e. what are the core/periphery dynamics? The model has the potential to explore the role of firm heterogeneity these and other key questions. For now, we leave these and other questions for future research.

References

Acemoglu, Daron, Ufuk Akcigit, Nicholas Bloom, and William Kerr, "Innovation, Reallocation and Growth," *American Economic Review*, 2018, *108* (11), 3450–3491.

Aghion, Philippe and Gilles Saint-Paul, "On the Virtue of Bad Times: An Analysis of the Interaction between Productivity Growth and Economic Fluctuations," *Macroeconomic Dynamics*, 1998, *2*, 322–344.

_ and Peter Howitt, "A Model of Growth Through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–351.

_ , Antonin Bergeaud, Gilbert Cette, Remy Lecat, and Helene Maghin, "The Inverted-U Relationship Between Credit Access and Productivity Growth," *Economica*, 2018, *86*, 1–31.

_ , David Hemous, and Enisse Kharroubi, "Cyclical Fiscal Policy, Credit Constraints, and Industry Growth," *Journal of Monetary Economics*, 2014, *62*, 41–58.

_ , Marios Angeletos, Abhijit Banerjee, and Kalina Manova, "Volatility and Growth: Credit Constraints and Productivity-Enhancing Investment," *Journal of Monetary Economics*, 2010, *57*, 24–67.

_ , Nicolas Berman, Laurent Eymard, Philippe Askenazy, and Gilbert Cette, "Credit Constraints and the Cyclicality of R&D Investment: Evidence from France," *Journal of the European Economic Association*, 2012, *10*, 1001–1024.

_ , Peter Howitt, and Ross Levine, "Financial Development and Innovation-Led Growth," in Thorsten Beck and Ross Levine, eds., *Handbook of Finance and Development*, Amsterdam: Edward Elgar, 2018.

_ , Philippe Bacchetta, Romain Rancierre, and Kennet Rogoff, "Exchange Rate Volatility and Productivity Growth: The Role of Financial Development," *Journal of Monetary Economics*, 2009, *56*, 494–513.

Akcigit, Ufuk and William Kerr, "Growth through Heterogeneous Innovations," *Journal of Political Economy*, 2016, *126* (4), 1374–1443.

_ , Douglas Hanley, and Nicolas Serrano-Velarde, "Back to Basics: Basic Research Spillovers, Innovation Policy and Growth," mimeo 2020.

_ , _ , and Stefanie Stancheva, "Optimal Taxes and R&D Policies," NBER Working Paper 22908 2019.

— , **Sina T. Ates, and Giammario Impullitti**, "Innovation and Trade Policy in a Globalized World," *NBER Working Paper*, 2018, (No. 24543).

Anzoategui, Diego, Diego Comin, Mark Gertler, and Joseba Martinez, "Endogenous Technology Adoption And R&D as Sources of Business Cycle Persistence," *American Economic Journal: Macroeconomics*, forthcoming.

Ates, Sina T. and Felipe Saffie, "Fewer but Better: Sudden Stops, Firm Entry, and Financial Selection," Federal Reserve Bank Working Paper 2018.

Barlevy, Gadi, "The Cost of Business Cycles under Endogenous Growth," *American Economic Review*, 2004, *94* (4), 964–990.

— , "On the Cyclicality of Research and Development," *American Economic Review*, 2007, *97* (4), 1131–1164.

Benedetti-Fasil, Cristiana, Petr Sedláček, and Vincent Sterk, "EU Startup Calculator: Impact of COVID-19 on Aggregate Employment," 2020.

Benigno, Gianluca and Luca Fornaro, "Stagnation Traps," *Review of Economic Studies*, 2018.

Bianchi, Francesco, Howard Kung, and Gonzalo Morales, "Growth, slowdowns, and recoveries," *Journal of Monetary Economics*, 2019.

Bloom, Nicholas, John van Reenen, and Heidi Williams, "A Toolkit of Policies to Promote Innovation," *Journal of Economic Perspective*, 2019, *33* (3), 163–184.

Borota, Teodora, Fabrice Defever, and Giammario Impullitti, "Innovation Union: Costs and Benefits of Innovation Policy Coordination," *CEP Discussion paper*, 2019, (1640).

Bundesbank, Deutsche, "Markups of Firms in Selected European Countries," Deutsche Bundesbank Monthly Report 2017.

Clementi, Gianluca and Dino Palazzo, "Medium-Term Business Cycles," *American Economic Journal: Macroeconomics*, 2016, *51* (6), 1823–1861.

Comin, Diego and Mark Gertler, "Medium-Term Business Cycles," *American Economic Review*, 2006, *96* (3), 532–551.

Cozzi, Guido, Beatrice Pataracchia, Philipp Pfeiffer, and Marco Ratto, "How Much Keynes and How Much Schumpeter?," *European Economic Review*, 2021, *133*, 103–660.

Fatas, Antonio, "Do Business Cycles Cast Long Shadows? Short-run Persistence and Economic Growth," *Journal of Economic Growth*, 2000, *5*, 147–162.

Ferraro, Domenico, Soroush Ghazi, and Pietro Peretto, "Implications of Tax Policy for Innovation and Aggregate Productivity Growth," *European Economic Review*, 2020, *130.*

Griliches, Zvi, "Patent Statistics as Economic Indicators," *Journal of Economic Literature*, 1990, *28.*

Grossman, Gene and Elhanan Helpman, "Quality Ladders in the Theory of Growth," *Review of Economic Studies*, 1991, *58.*

Impullitti, Giammario, "International Competition and U.S. RD Subsidies: A Quantitative Welfare Analysis,," *International Economic Review,*, 2010, *51* (4), 1127–1158.

Klette, Tor Jakob and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 2004, *112* (5), 986–1018.

Lentz, Rasmus and Dale Mortensen, "Productivity Growth and Worker Reallocation," *International Economic Review*, 2005, *46* (3), 731–749.

_ **and** _ , "An Empirical Model of Growth Through Product Innovation," *Econometrica*, 2008, *76* (6), 1317–1373.

Levine, Ross, "Finance and growth: Theory and evidence," in Philippe Aghion and Steve Durlauf, eds., *The Oxford Handbook of Innovation*, Vol. 1, Amsterdam: North-Holland, 2005, p. 865–934.

Lucas, Robert, "Macroeconomic Priorities," *American Economic Review*, 2003, *93* (1), 1–14.

Nuno, Galo, "Optimal Research and Development and the Cost of Business Cycles," *Journal of Economic Growth*, 2011, *16*, 257–283.

Ouyang, Min, "On the Cyclically ofR&D," *Review of Economics and Statistics*, 2011, *93*, 542–533.

Schmitt-Grohe, Stephanie and Martin Uribe, "Solving dynamic general equilibrium models using a second-order approximation to the policy function," *Journal of Economic Dynamics and Control*, 2004, *28* (4), 755–775.

Sedláček, Petr, "Creative Destruction and Uncertainty," *Journal of the European Economic Association*, forthcoming.

_ **and Vincent Sterk**, "The Growth Potential of Startups over the Business Cycle," *American Economic Review*, 2017, *107* (10), 3182–3210.

_ **and** _ , "Startups and Employment Following the COVID-19 Pandemic: A Calculator," *COVID Economics*, 2020, *13.*

Verdugo, Gregory, "The Great Compression of the French Wage Structure, 1969-2008," *Labour Economics*, June 2014, *28*, 131–144.

Vinci, Francesca and Omar Licandro, "Switching-Track after the Great Recession," 2020. CFCM Working paper 02/2020.

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