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How can green differentiated capital requirements affect climate risks? A dynamic macrofinancial analysis

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How can green differentiated capital requirements affect climate risks? A dynamic macrofinancial analysis*

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Abstract

Using an ecological macrofinancial model, we explore the potential impact of the 'green supporting factor' (GSF) and the 'dirty penalising factor' (DPF) on climate-related financial risks. We identify the transmission channels by which these green differentiated capital requirements (GDCRs) can affect credit provision and loan spreads, and we analyse these channels within a dynamic framework in which climate and macrofinancial feedback effects play a key role. Our main findings are as follows. First, GDCRs can reduce the pace of global warming and decrease thereby the physical financial risks. This reduction is quantitatively small, but is enhanced when the GSF and the DPF are implemented simultaneously or in combination with green fiscal policies. Second, the DPF reduces banks' credit provision and leverage, making them less fragile. Third, both the DPF and the GSF generate some transition risks: the GSF increases bank leverage because it boosts green credit and the DPF increases loan defaults since it reduces economic activity. These effects are small in quantitative terms and are attenuated when there is a simultaneous implementation of the DPF and the GSF. Fourth, fiscal policies that boost green investment amplify the transition risks of the GSF and reduce the transition risks of the DPF; the combination of green fiscal policy with the DPF is thereby a potentially effective climate policy mix from a financial stability point of view.

Keywords: stock-flow consistent modelling, climate change, financial stability, green financial regulation

JEL Codes: E12, E44, G18, Q54

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1. Introduction

Recent years have seen a growing interest in the role that the financial system could play in the fight against climate change. It has been argued that, by facilitating the financing of climate friendly activities, a green transformation of the financial system could contribute to the transition to a low-carbon economy. Suggestions for such a transformation include various types of central bank and financial regulation tools as well as climate-related financial disclosures (see Campiglio, 2016; Volz, 2017; Campiglio et al., 2018; NGFS, 2018).

In this paper, we focus on one of these suggestions linked with financial regulation. In particular, we study the proposal of using capital requirements as a means to promote the transition to a low-carbon economy. Two forms of green differentiated capital requirements (GDCRs) have been suggested in the related discussions (see Schoenmaker and Van Tilburg, 2016; Matikainen, 2017; EU HLEG, 2018; Dankert et al., 2018; Van Lerven and Ryan-Collins, 2018; D'Orazio and Popoyan, 2019; Berenguer et al., 2020). The first one is the so-called 'green supporting factor' (GSF), which implies that banks need to hold less capital for loans provided to support activities that can lead to the reduction of carbon emissions. The second form is the so-called 'dirty penalising factor' (DPF) whereby banks need to hold more capital against loans that finance high-carbon activities.

Although these proposals have recently received a growing attention, there is still a lack of a systematic attempt to evaluate their potential implications. Thomä and Gibhardt (2019) have estimated some potential effects of GDCRs on credit supply and the level of interest rates in the EU. However, their analysis is partial and static: it does not rely on a complete macroeconomic framework that permits the examination of both direct and indirect dynamic macroeconomic effects of such requirements. Moreover, they do not quantify the potential effects on climate-related financial risks. Punzi (2019) have explored some macroeconomic implications of the GSF, using a Dynamic Stochastic General Equilibrium (DSGE) model. However, their analysis does not pay explicit attention to climate-related financial risks.[1] Dunz et al. (2020) have explored the macroeconomic and financial effects of the GSF paying particular attention to the role of banks' climate sentiments; nonetheless, their analysis is confined to transition risks and no comparisons are made between the effects of the GSF and the DPF.

The aim of this paper is to provide the first integrated quantitative assessment of the potential effects of the GDCRs, with an explicit emphasis on their impact on both transition and physical financial risks. Our assessment is made using the DEFINE model (see Dafermos et al., 2017; Dafermos et al., 2018, which has been extended for the purposes of this paper in order to incorporate the role of capital requirements and green fiscal policy. DEFINE is one of the very few global climate-economy models that incorporates a detailed analysis of the interactions between climate change and the financial system and is, thereby, suitable for the evaluation of climate policies that can affect the stability of the financial system both through transition and physical risks.[2] A significant advantage of the model is that it takes explicitly into account feedback loops between the real economy and the financial system, which are crucial for a proper analysis of climate-related financial risks (see Stolbova et al., 2018).[3]

[1] Raberto et al. (2019) have investigated the potential impact of capital requirements on energy efficiency, but have not focused explicitly on the role of the green supporting and the dirty penalising factor. Esposito et al. (2019) have used data for the Italian economy to estimate how capital risk weights of banks could be adjusted to take into account the 'brownness/dirtiness' and the 'greenness' of different sectors of the economy. However, they have not explored the potential effects of such requirements on macroeconomic, financial and environmental variables.

[2] Dietz et al. (2016), Bovari et al. (2018a) and Lamperti et al. (2018) have also developed macroeconomic models about climate change in which finance plays a role. However, in these models the financial system is less detailed compared to DEFINE. Monasterolo and Raberto (2018), Monasterolo and Raberto (2019) and Dunz et al. (2020) have developed similar models with DEFINE in which the transition risks can be analysed, but not the physical ones, since climate change and its financial effects are not incorporated.

[3] The analysis of both the physical risks and feedback loops comes at a cost: it requires the use of a large-scale model that is quite complex. However, without such a large-scale model an integrated assessment of the quantitative effects of GDCRs would not be possible.

We explore how a hypothetical implementation of the GDCRs at the global level within the next few years could affect a series of macroeconomic, financial and environmental variables. We focus on the fact GDCRs constitute a climate finance policy that could have feedback effects on financial stability. There are at least three reasons for that. First, these requirements could reduce physical financial risks. This is so because they can affect the mix of green and carbon-intensive investment, leading to lower carbon emissions and, hence, lower global warming. Lower global warming can, in turn, reduce the severity and the frequency of climate-related events that have adverse effects on the stability of the financial system (e.g. flood-related loan defaults). Second, GDCRs could generate transition risks since they can disrupt the financing of dirty activities or increase the financing of green activities. This has implications for the accumulation of debt and the level of macroeconomic activity, both of which can have feedback effects on the stability of the financial system. Third, as will be explained below, GDCRs can influence climate-related financial risks through their interaction with traditional environmental policies. This is so because they can affect, for instance, the access to credit for firms that are induced to undertake more green investment as a result of such policies.

Within our dynamic macrofinancial framework, GDCRs are analysed as a policy that affects financial resilience not only directly by determining the level of capital held by banks, but also indirectly via the impact that capital requirements have on credit conditions and macroeconomic activity. This is in line with the recent empirical literature that has shown that capital requirements affect the volume of credit and lending interest rates (e.g. Akram, 2014; De-Ramon et al., 2016; De Marco and Wieladek, 2015; Meeks, 2017; De Jonghe et al., 2020; Fraisse et al., 2020).[4] A key contribution of our paper is, therefore, that it assesses GDCRs via a macroprudential perspective that takes explicitly into account the impact of the financial system on climate risks.[5]

Our analysis is conducted as follows. We first extend the DEFINE model in order to introduce GDCRs and identify the various channels through which these requirements could affect climate change, financial stability and macroeconomic activity via their impact on credit supply and loan spreads. In our modelling approach we make a clear distinction between credit demand and credit supply and we incorporate both the price and the quantity rationing of credit. Second, we econometrically estimate or calibrate the key parameter values that are linked with the transmission channels of GDCRs. We also use data to identify the degree of dirtiness of the loans provided to different sectors of the economy. Finally, once the whole model has been calibrated, we run a series of simulations in which we compare the effects of the GSF and the DPF under the hypothetical scenario in which these policies are introduced at the global level within the next few years. We also analyse the effects of the combined implementation of the GSF and the DPF as well as the effects of a combined implementation

[4] It is often argued that differentiated capital requirements might not be an effective measure of enhancing the credit that is provided to specific sectors of the economy. In most cases, this argument is based on a study conducted by EBA (2016), according to which the small and medium-sized enterprises (SME) supporting factor that was introduced at a European level in 2014 did not improve to a great extent the credit conditions for SMEs compared to large firms. However, it is not clear-cut that this impact was negligible. Mayordomo and Rodríguez-Moreno (2018) have shown that credit rationing imposed on medium-sized enterprises has actually declined as a result of this measure, although this has not been the case for the credit rationing imposed on small enterprises. They have also argued that the effectiveness of this measure has potentially be undermined by the uncertainty that exists about its duration. Moreover, Dietsch et al. (2019) have shown that the SME supporting factor had a positive impact on credit supply in France. Thus, although the impact of differentiated capital requirements is clearly uncertain, it is not reasonable to assume that it is necessarily negligible. In our study, we run our own econometric estimations about the impact of capital ratios on credit conditions (which actually shows that capital ratios affect lending and loan spreads) and we conduct a sensitivity analysis in order to deal with the uncertainty that exists about the effects of differentiated capital requirements.

[5] As Berenguer et al. (2020) have recently pointed out, there are two approaches that can be adopted for the design of GDCRs: the 'risk approach' and the 'economic policy approach'. According to the risk approach, capital requirements should be adjusted to capture climate risks, while the economic policy approach posits that capital requirements should be used as a tool that supports the transition to a low-carbon economy. The way that GDCRs are modelled in this paper is in line with the 'economic policy approach': risks weights are adjusted based on the greenness and dirtiness of the underlying assets, not based on their estimated risks. Therefore, from a risk perspective, the aim of this paper is not to analyse the risk differential between green and dirty loans and show how capital requirements can incorporate climate risks, but rather to explore how an 'economic policy' design of GDCRs can affect system-wide climate-related financial risks.

of carbon taxes/green subsidies and GDCRs.

We derive four key results. First, GDCRs can reduce the pace of global warming and decrease thereby the physical financial risks. This reduction is quantitatively small, but is enhanced when the GSF and the DPF are implemented simultaneously or in combination with green fiscal policies. Second, DPF reduces banks' credit provision and leverage, making them less fragile. Third, both DPF and GSF generate some transition risks: the GSF increases bank leverage because it boosts green credit and the DPF increases loan defaults since it reduces economic activity. These effects are small in quantitative terms and are attenuated when there is a simultaneous implementation of the DPF and the GSF. Fourth, fiscal policies that boost green investment amplify the transition risks of the GSF and reduce the transition risks of the DPF; the combination of green fiscal policy with the DPF is thereby a potentially effective climate policy mix from a financial stability point of view.

The remainder of the paper is organised as follows. Section 2 describes how we introduce GDCRs in the DEFINE model and analyses the transmission channels of these requirements. It also explains how green subsidies and carbon taxes are incorporated in the model and how they affect carbon emissions. Section 3 outlines how the model is overall calibrated and presents our econometric estimations linked with GDCRs. Section 4 describes our simulation results and analyses the effects of different policy scenarios about the implementation of GDCRs. Section 5 summarises and concludes.

2. Modelling the effects of green differentiated capital requirements

2.1. The DEFINE model: general features

The DEFINE 1.1 model, which has been developed for the purposes of this paper, introduces GDCRs and green fiscal policy (including carbon taxes and green subsidies) into the DEFINE 1.0 model (see Dafermos et al., 2018). DEFINE 1.1 is a global model that formulates the macrofinancial system using stock-flow consistent (SFC) techniques.[6] Its macroeconomy consists of households, firms, banks, the government sector and central banks. Households decide about the level of their consumption based on their income and wealth. They also take portfolio decisions since they allocate their wealth to deposits, government securities and (green and conventional) bonds. Firms rely on retained profits, bonds and loans in order to finance their investment expenditures. They invest in two types of capital: green capital and conventional capital. Banks provide a proportion of loans demanded by firms and decide about the interest rate on all types of loans. Their decisions are affected, amongst others, by the capital requirements imposed by financial regulators. Central banks provide advances on demand to banks and set the base interest rate. The government sector collects taxes (including carbon taxes), decides about the level of government consumption and government investment (which can be green or conventional), provides green subsidies and can implement bailout programmes, if there are financial problems in the banking sector.

In line with agent-based and SFC models (see e.g. Caiani et al., 2016; Monasterolo and Raberto, 2019), we assume that agents make decisions under fundamental uncertainty in which microeconomic variables are determined via macroeconomic interactions. The complexity of the macroeconomic system does not allow the agents to optimise intertemporally. Hence, it is assumed that they are bounded rational and take decisions based on heuristics.

Regarding climate-related processes, the model assumes that the use of fossil energy generates carbon emissions. Cumulative emissions influence the atmospheric temperature and lead to climate change that has feedback effects on the economy via climate damages. In particular, climate change results in capital destruction, reduction of labour force and a fall in capital and labour productivity. Climate change also affects the confidence of households and firms, which has implications for their consumption, investment and portfolio decisions.

[6] For the SFC approach to macroeconomic modelling, see Godley and Lavoie (2012).

For a given level of output, a higher use of non-fossil energy and a higher energy efficiency reduces carbon emissions, slowing down climate change. This can be achieved via green investment that has a non-linear impact on ecological efficiency due to learning processes. The cost of generating non-fossil energy declines at a higher rate as the use of renewables increases, reflecting endogenous technical progress. Carbon emissions are also reduced via the use of carbon sequestration technologies.

A detailed description of DEFINE 1.1 and its differences with DEFINE 1.0 is available in Appendix E. In what follows we concentrate on how GDCRs are introduced in the DEFINE 1.0 model, since the analysis of such requirements is the focus of this paper. We also explain briefly how green subsidies and the carbon tax affect the decisions of firms, which is a new feature of DEFINE 1.1 compared to DEFINE 1.0.

2.2. Modelling approach

The investigation of the effects of GDCRs requires (i) a detailed modelling of the credit demand and credit supply process through which the investment of the non-financial sector is financed and (ii) a clear analysis of the environmental footprint of different types of loans. Regarding (i), a considerable amount of theoretical and empirical work has been conducted over the last decade primarily as a response to the need of understanding better the role of credit in the run-up to the global financial crisis. Most Dynamic Stochastic General Equilibrium (DSGE) models have used the financial accelerator approach focusing on how the loan interest rate might affect credit. Jakab and Kumhof (2019) have departed from this approach by analysing explicitly both the quantity and the price rationing of credit and focusing on the endogenous creation of money. In addition, various empirical studies have explored the drivers of credit growth paying attention to both demand and supply factors (e.g. Bridges et al., 2014; Aiyar et al., 2016).

Our modelling approach draws on this literature. Like Jakab and Kumhof (2019), we pay attention to both the quantity and the price rationing of credit and we assume that money is endogenously created. In line with the empirical literature, we make an explicit distinction between the demand and the supply of credit. As will be explained below, this is particularly important for the understanding of the various channels through which differentiated capital requirements affect the economy and the financial system. The key parameters of the equations that are linked with GDCRs are selected based on econometric estimations that we make using panel data for a large number of countries.

Regarding the distinction between loans with different environmental impact, we first differentiate between green and conventional loans as in the previous version of DEFINE. Green loans are the loans which are used by firms in order to invest in green capital, which improves ecological efficiency, for example by being conducive to a higher use of non-fossil fuel and a higher energy and material efficiency. Conventional loans are loans provided to finance investment in conventional capital. These loans are then differentiated based on the 'degree of dirtiness' of the underlying investment. The higher the degree of dirtiness of an investment the higher its adverse contribution to global warming. We calibrate the degree of dirtiness by utilising global data for the level of carbon emissions per gross value added (GVA) in different sectors of the economy.

2.3. Key equations

In our model the timeline of credit-related events can be summarised as follows. Initially, firms decide about their overall desired investment based on a number of factors which are primarily related to their profitability and expected demand. A part of this investment is green. If their retained profits are not enough to cover the desired investment, firms issue bonds and apply for bank loans. Banks then decide about the level of interest rates and the proportion of loans that will be provided. If GDCRs are in place, these bank decisions are affected by the anticipated environmental impact of the loans: banks might impose higher interest rates and higher quantity rationing on dirty/conventional loans compared to green loans. The decisions of banks affect both the level of investment (and hence economic activity) and the level of carbon emissions which influences the dynamics of global warming.

Banks' decisions also have an impact on their own financial position; for example, a higher provision of credit might increase their leverage.

In what follows we describe the key equations linked with these events (for a more detailed description, see Appendix E). Total desired private investment ($I^D_{(PRI)t}$) is primarily driven by the profit rate and the rate of capacity utilisation: these variables affect desired investment in a positive way since firms wish to invest more when profits and sales are high. Investment is also allowed to be affected by the scarcity of labour and the scarcity of energy and material resources.[7] Most of the parameters of our investment equation are estimated econometrically; in our estimations the coefficients of the independent variables are statistically significant and exhibit the expected signs.

We explicitly take into account that within the firm sector there exist different types of investment and capital stock linked with different sectors of the economy that generate different levels of emissions. We consider four broad sectors: 'mining and utilities' (*S1*), 'manufacturing and construction' (*S2*), 'transport' (*S3*) and 'other sectors' (*S4*).[8] The total desired investment is allocated to these sectors based on their relative gross value added (GVA).[9] This is shown in eq. (1), where the desired investment of each sector ($I^D_{(PRI)it}$) is a proportion ($sh_{(GVA)i}$) of total desired investment ($i = S1, S2, S3, S4$). We calibrate this proportion based on the GVA of each sector.

$$I^D_{(PRI)it} = sh_{(GVA)i} I^D_{(PRI)t} \tag{1}$$

In each sector, both energy and non-energy investment is undertaken. Energy investment has to do, for example, with investment in power plants, fossil fuel supply and the energy efficiency of buildings. Non-energy investment includes the rest of the investment which affects, amongst others, material efficiency and recycling.

Hence, the private capital stock in each sector ($K_{(PRI)it}$) is overall given by:

$$K_{(PRI)it} = K_{G(PRI)it} + K_{C(PRI)it} \tag{2}$$

where $K_{G(PRI)it}$ is the green capital stock and $K_{C(PRI)it}$ is the conventional capital stock. Green and conventional capital stock are then subdivided into energy and non-energy private capital stock:

$$K_{G(PRI)it} = K_{GE(PRI)it} + K_{GNE(PRI)it} \tag{3}$$

$$K_{C(PRI)it} = K_{CE(PRI)it} + K_{CNE(PRI)it} \tag{4}$$

where $K_{GE(PRI)it}$ is the green energy capital stock, $K_{GNE(PRI)it}$ is the green non-energy capital stock, $K_{CE(PRI)it}$ is the conventional energy capital stock and $K_{CNE(PRI)it}$ is the conventional non-energy capital stock. The proportion of energy capital stock in total green capital stock (γ_{Ei}) is fixed and is calibrated using global data on energy investment. This proportion is the same for green and conventional capital. Hence:

[7] The implicit assumption is that, as the unemployment rate becomes too low and the scarcity of natural resources increases, the wage rate and the cost of using matter and energy increase, respectively. Since this affects adversely the production cost, investment might go down.

[8] This disaggregation relies on ISIC (International Standard Industrial Classification of All Economic Activities) rev. 3.1. The 'mining and utilities' sector includes ISIC C ('mining and quarrying') and ISIC E ('electricity, gas and water supply'), the 'manufacturing and construction' sector includes ISIC D ('manufacturing') and ISIC F ('construction'), the 'transport' sector corresponds to ISIC I ('transport, storage and communications') and the 'other sectors' include ISIC A, B, G, H and J-P. The main purpose of the disaggregation into these four sectors is to identify different degrees of 'dirtiness' for the loans given to these sectors based on the carbon emissions that they generate (see Section 3.3). All the sectors included in the 'other sectors' category have a low carbon intensity and their contribution to overall emissions is low. Hence, although the 'other sectors' represent a large part of total GVA, a further disaggregation would not change the essence of our analysis since this would only marginally change the degree of dirtiness assigned to these sectors.

[9] The share in total GVA has been used instead of the share in total investment, solely because of the lack of adequate investment data at the global level. Based on data for European countries, we find that the sectoral share of investment is close to the share of GVA. Thus, we do not expect that the use of GVA shares creates a significant bias in our analysis.

$$K_{GE(PRI)it} = \gamma_{Ei} K_{G(PRI)it} \tag{5}$$

$$K_{GNE(PRI)it} = (1 - \gamma_{Ei}) K_{G(PRI)it} \tag{6}$$

$$K_{CE(PRI)it} = \gamma_{Ei} K_{C(PRI)it} \tag{7}$$

$$K_{CNE(PRI)it} = (1 - \gamma_{Ei}) K_{C(PRI)it} \tag{8}$$

In the case of green private capital, an additional category of capital is the private capital linked to carbon sequestration technologies. Sequestration investment is undertaken only in sectors *S1* and *S2*. Sequestration private capital ($K_{SEQ(PRI)it}$) is modelled as a proportion (γ_{SEQi}) of total green energy private capital. This proportion is calibrated by using global data about sequestration investment. For $i = S1, S2$, we hence have:

$$K_{SEQ(PRI)it} = \gamma_{SEQi} K_{GE(PRI)it} \tag{9}$$

Green energy private capital and sequestration private capital contribute differently to the reduction of industrial carbon emissions. The latter are given by:

$$EMIS_{INt} = \omega_t (1 - seq_t) E_{Ft} \tag{10}$$

where E_{Ft} is the level of fossil energy, ω_t is the amount of emissions produced per unit of fossil energy and seq_t is the sequestration rate, i.e. the fraction of emissions that are captured and stored through carbon sequestration technologies. In our model, the share of non-fossil energy increases as the green energy capital rises compared to total conventional energy capital; also, the sequestration rate increases as sequestration capital increases relative to total conventional energy capital.[10] Sequestration capital can therefore reduce emissions by increasing seq_t while the rest of green energy capital can reduce emissions by causing a decline in E_{Ft}.

In each sector, a decision has to be made about the overall level of desired green private investment ($I^D_{G(PRI)it}$), which is set as a proportion, β_{it}, of the total desired private investment of each sector:

$$I^D_{G(PRI)it} = \beta_{it} I^D_{(PRI)it} \tag{11}$$

Eq. (12) shows how β_{it} is determined:

$$\begin{aligned} \beta_{it} = \beta_{0it} &- \beta_1 sh_{(EMIS_{IN})i} (tucr_{t-1} - tucn_{t-1}) \\ &- \beta_2 [sh_{Lt-1} (int_{Gt-1} - int_{Cit-1}) + (1 - sh_{Lt-1}) (yield_{Gt-1} - yield_{Ct-1})] \end{aligned} \tag{12}$$

β_{it} is affected by three factors. The first one is captured by the term β_{0it} which reflects exogenous developments, such as environmental preferences or institutional changes linked with environmental regulation. It also captures the idiosyncratic nature of investment in each sector. In our simulations β_{0it} is allowed to increase at a declining rate in the next decades in order to capture the gradual shift of firms to 'greener' practices.

The second factor reflects the cost of green capital compared to conventional capital. This cost differential has been proxied by the total unit cost of producing renewable energy ($tucr_t$) compared to the total unit cost of generating non-renewable energy ($tucn_t$).[11] We let $tucr_t$ be equal to $ucr_t (1 - gov_{SUBt})$, where ucr_t is the pre-subsidies levelised cost of producing renewable energy and

[10] For a more detailed description, see Appendix E.

[11] Because of the heterogeneity of both green and conventional capital, the cost differential between these two types of capital is in reality affected by a large number of factors, apart from the cost of energy. We have focused on the latter for two reasons. First, the energy cost arguably affects directly or indirectly the cost related with a large part of capital

gov_{SUBt} is the subsidy rate, namely the proportion of this cost that is funded by the government. $tucn_t$ consists of two components: (i) ucn_t which is the pre-taxes levelised cost of generating non-renewable energy and (ii) $\tau_{Ct}\omega_t(1 - seq_t)$ which is the carbon tax cost per unit of energy; τ_{Ct} is the carbon tax measured in US\$/kgCO_2 (or US\$trillion/GtCO_2). We assume that ucn_t rises every year to reflect the fact that costs increase as fossil fuel reserves are depleted.[12] On the other hand, we let ucr_t decline every year, assuming at the same time that the rate of decline is more rapid as the share of non-fossil energy goes up. This captures endogenous green technical progress.

The importance of the relative cost of energy differs between the different sectors. We assume that this cost differential is more important for those sectors that produce a higher amount of carbon emissions. We do so by multiplying β_1 by the share of each sector's carbon emissions, $sh_{(EMIS_{IN})i}$, in Eq. (12).

The third factor that affects β_{it} is the relative cost of external funding.[13] There are two sources of external funding: bonds and bank loans. Thus, when firms decide about their desired green investment, they compare the interest rate on green loans with the interest rate on conventional loans and the yield of green bonds with the yield of conventional bonds. The third factor is, therefore, captured by the term $\beta_2\left[sh_{Lt-1}\left(int_{Gt-1} - int_{Cit-1}\right) + \left(1 - sh_{Lt-1}\right)\left(yield_{Gt-1} - yield_{Ct-1}\right)\right]$ where int_{Gt} is the interest rate on green loans, int_{Cit} is the interest rate on conventional loans, $yield_{Gt}$ is the yield on green bonds, $yield_{Ct}$ is the yield on conventional bonds and sh_{Lt} is the share of loans in the total liabilities of firms (loans plus bonds).

Conventional desired investment ($I^D_{C(PRI)it}$) is given by:

$$I^D_{C(PRI)it} = I^D_{(PRI)it} - I^D_{G(PRI)it} \tag{13}$$

Once firms have decided about their desired green and conventional investment, they have to specify the amount of loans that they will demand from banks. This is done via their budget constraint:

$$NL^D_{Git} = I^D_{G(PRI)it} + repL_{Git-1} - sh_{(GVA)i}\beta_{it}RP_t - \delta_t K_{G(PRI)it-1} - sh_{(GVA)i}\bar{p}_G\Delta b_{Gt} \tag{14}$$

$$NL^D_{Cit} = I^D_{C(PRI)it} + repL_{Cit-1} - sh_{(GVA)i}\left(1 - \beta_{it}\right)RP_t - \delta_t K_{C(PRI)it-1} - sh_{(GVA)i}\bar{p}_C\Delta b_{Ct} \tag{15}$$

Firms need to cover the cost of their desired investment and repay part of their outstanding loans. These financing needs are covered via their retained profits, the issuance of bonds and new loans. We assume that loans are the residual source of finance. This is captured by eqs. (14) and (15) which say that firms' new desired loans are equal to their financing needs ($I^D_{G(PRI)it} + repL_{Git-1}$ and $I^D_{C(PRI)it} + repL_{Cit-1}$) minus the funding that comes from their retained profits ($sh_{(GVA)i}\beta_{it}RP_t$ and $sh_{(GVA)i}\left(1 - \beta_{it}\right)RP_t$), the money that firms set aside to cover depreciation ($\delta_t K_{G(PRI)it-1}$ and $\delta_t K_{C(PRI)it-1}$) and the issuance of new bonds ($sh_{(GVA)i}\bar{p}_G\Delta b_{Gt}$ and $sh_{(GVA)i}\bar{p}_C\Delta b_{Ct}$). NL^D_{Git} denotes the desired new green loans, NL^D_{Cit} denotes the desired new conventional loans, RP_t is firms' retained profits, rep is the principal repayment ratio, L_{Cit} is the amount of conventional loans, L_{Git} is the amount of green loans, $K_{C(PRI)it}$ is the private conventional capital, $K_{G(PRI)it}$ is the private green capital, $\bar{p}_C$ is the par value of conventional bonds, $\bar{p}_G$ is the par value of green bonds, b_{Ct} is the number of conventional bonds and b_{Gt} is the number of green bonds.

Banks impose both price and quantity credit rationing. This means that they supply only a fraction of demanded loans and change endogenously the loan spread. The assets of banks consist of green loans, conventional loans, government securities and high-powered money. The capital of banks (CAP_t),

stock in the economy. In the case of energy capital, the cost of energy has a direct impact on the return on this capital; in the case of non-energy related capital (such as capital that affects material efficiency and recycling), the cost of energy is relevant because it affects indirectly the cost of raw materials. Second, the cost differential between renewables and non-renewables can be calibrated relatively easily and is likely to follow a similar trend in the next decades as the broader cost differential between green and conventional capital.

[12] See e.g. Van der Ploeg and Rezai (2019) for a similar assumption.

[13] We have implicitly not included the cost of borrowing in ucn_t and ucr_t.

which equals bank assets minus liabilities, increases due to retained profits and declines as a result of defaults. The capital adequacy ratio (CAR_t) is equal to the capital of banks over their risk-weighted assets:

$$CAR_t = CAP_t \Big/ \left[w_{Gt} L_{Gt} + \sum w_{Cit} L_{Cit} + w_S SEC_{Bt} + w_H HPM_t \right] \tag{16}$$

where w_{Gt} is the risk weight on green loans, w_{Cit} is the risk weight on conventional loans, w_S is the risk weight on government securities, w_H is the risk weight on high-powered money, CAP_t is the capital of banks, L_{Gt} is the total amount of green loans, SEC_{Bt} is the government securities held by banks and HPM_t is high-powered money. A risk weight equal to zero is assigned to high-powered money and government securities. Under the current financial regulation framework, $w_{Gt} = w_{Cit}$. However, the introduction of green differentiated capital requirements would make w_{Gt} lower than w_{Cit}.

The risk weight on total loans (w_{LTt}) is defined as:

$$w_{LTt} = sh_{(LG)t-1} w_{Gt} + \sum sh_{(LC)it-1} w_{Cit} \tag{17}$$

where $sh_{(LG)t}$ is the share of green loans in total loans given by $sh_{(LG)t} = L_{Gt}/L_t$, and $sh_{(LC)it}$ is the share of the conventional loans of each sector given by $sh_{(LC)it} = L_{Cit}/L_t$; L_t is the total amount of loans.

The degree of credit rationing (CR_t) shows the proportion of demanded loans that are provided by banks. Hence, it lies between 0 and 1. The degree of credit rationing increases as the debt service ratio of firms goes up, since banks are less willing to lend when the financial position of borrowers deteriorates; the debt service ratio (dsr_t) is defined as the ratio of the sum of the interest and principal of firms to their profits. The degree of credit rationing also depends negatively on the capital adequacy ratio. In particular, credit rationing declines as the capital adequacy ratio increases relative to a minimum acceptable value, $CAR^{\min}$, which is determined by regulatory authorities (and is set equal to 8%). The incorporation of the capital adequacy ratio is in line with the recent empirical literature that has documented a negative effect of capital requirements and a positive effect of capital-to-assets ratios on bank lending (see Bridges et al., 2014; De Marco and Wieladek, 2015; Aiyar et al., 2016; De-Ramon et al., 2016; Meeks, 2017; Gambacorta and Shin, 2018; Gropp et al., 2019). There is also empirical evidence that shows that there is a negative effect of debt service ratio on bank lending (see Juselius and Drehmann, 2020). Moreover, our credit rationing function relies on our econometric estimations, described in Section 3.2, which verify the importance of the financial position of both firms and banks in the determination of loans.

Overall, the credit rationing function is as follows:

$$CR_t = f\left(\overset{+}{dsr_{t-1}}, \overset{-}{\left(CAR_{t-1} - CAR^{\min}\right)} \right) \tag{18}$$

This function is non-linear, reflecting the fact that credit rationing is bounded.

Eq. (18) refers to the total credit rationing on firm loans. In our baseline scenario banks do not treat green and conventional loans differently, so total credit rationing coincides with the credit rationing on different types of loans. However, credit rationing on green loans (CR_{Gt}) and conventional loans (CR_{Cit}) can become different once GDCRs are introduced. This is captured by the following equations:

$$CR_{Gt} = \left[1 + l_1 \left(w_{Gt-1} - w_{LTt-1}\right)\right] CR_t \tag{19}$$

$$CR_{Cit} = \left[1 + l_1 \left(w_{Cit-1} - w_{LTt-1}\right)\right] CR_t \tag{20}$$

where $i = S1, S2, S3$, w_{Gt} is the risk weight on green loans and w_{Cit} is the risk weight on conventional loans provided to sector i. When $w_{Cit} = w_{LTt}$ and $w_{Gt} = w_{LTt}$, the credit rationing on green loans and

conventional loans is the same with the total credit rationing. When $w_{Gt} < w_{LTt}$, the credit rationing on green loans becomes lower than total credit rationing.[14] When $w_{Cit} > w_{LTt}$, the credit rationing on conventional loans is higher than total credit rationing; this difference becomes larger as the degree of dirtiness of conventional loans is large, which is, for example, the case with the conventional loans provided to the 'mining and utilities' and 'transport' sectors (the degree of dirtiness is defined in Section 3.3). The parameter l_1 captures the responsiveness of credit rationing to changes in relative risk weights.

The total credit rationing is given by the weighted average of the credit rationing on the different types of loans:

$$CR_t = sh_{(NLG)t-1}CR_{Gt} + sh_{(NLC)S1t-1}CR_{CS1t} + sh_{(NLC)S2t-1}CR_{CS2t} + sh_{(NLC)S3t-1}CR_{CS3t} + sh_{(NLC)S4t-1}CR_{CS4t} \tag{21}$$

The credit rationing for the loans linked with the 'other sectors' ($S4$), which is denoted by CR_{CS4t}, is determined as a residual. Hence, by solving (21) for CR_{CS4t}, we get:

$$CR_{CS4t} = \frac{CR_t - sh_{(NLG)t-1}CR_{Gt} - sh_{(NLC)S1t-1}CR_{CS1t} - sh_{(NLC)S2t-1}CR_{CS2t} - sh_{(NLC)S3t-1}CR_{CS3t}}{sh_{(NLC)S4t-1}} \tag{22}$$

where $sh_{(NLG)t}$ is the share of desired green loans in total desired loans and $sh_{(NLC)it}$ is the share of desired conventional loans in total desired loans.

The lending interest rate is set as a spread over the base interest rate which is determined by central banks. This loan spread (spr_t) depends on the capital adequacy ratio and the debt service ratio:

$$spr_t = spr_0 - spr_1 \left(CAR_{t-1} - CAR^{\min}\right) + spr_2 dsr_{t-1} \tag{23}$$

The negative impact of the capital adequacy ratio on the lending spread is in line with the related empirical literature (see Slovik and Cournède, 2011; Akram, 2014; Meeks, 2017; Barth and Miller, 2018). The inclusion of the debt service ratio in eq. (23) reflects the fact that, as firms become more financially fragile, banks impose a higher spread to capture the higher risk of default.

As in the case of credit rationing, in our baseline scenario the loan spread is the same for all types of loans. However, the introduction of GDCRs can affect that. This is shown in the equations below:

$$spr_{Gt} = \left[1 + spr_3 \left(w_{Gt-1} - w_{LTt-1}\right)\right] spr_t \tag{24}$$

$$spr_{Cit} = \left[1 + spr_3 \left(w_{Cit-1} - w_{LTt-1}\right)\right] spr_t \tag{25}$$

where $i = S1, S2, S3$, spr_{Gt} is the spread on green loans and spr_{Cit} is the spread on conventional loans. The spread on the loans linked with the 'other sectors' ($S4$), denoted by spr_{CS4t}, is determined as a residual. The total loan spread is equal to:

$$spr_t = sh_{(LG)t-1}spr_{Gt} + sh_{(LC)S1t-1}spr_{CS1t} + sh_{(LC)S2t-1}spr_{CS2t} + sh_{(LC)S3t-1}spr_{CS3t} + sh_{(LC)S4t-1}spr_{CS4t} \tag{26}$$

Thus, if we solve for spr_{CS4t}, we get:

$$spr_{CS4t} = \frac{spr_t - sh_{(LG)t-1}spr_{Gt} - sh_{(LC)S1t-1}spr_{CS1t} - sh_{(LC)S2t-1}spr_{CS2t} - sh_{(LC)S3t-1}spr_{CS3t}}{sh_{(LC)S4t-1}} \tag{27}$$

[14] Although green loans are differentiated by sector, the credit rationing on these loans is the same for all sectors.

The overall way that green investment has been formalised in our model departs from traditional Integrated Assessment Models (IAMs) (see e.g. Nordhaus, 2018) on two key aspects. First, abatement costs (which in our model are captured by investment expenditures on green energy and sequestration capital) do not just represent an outflow for the firm sector as a whole; they represent, at the same time, an inflow to those firms that produce the related capital. Hence, in our model abatement costs do not reduce GDP and the net flows of the firm sector (see also Dafermos and Nikolaidi, 2019; Mercure et al., 2019). Second, in our model a part of the abatement expenses are covered though bank loans and bond finance and the amount of financial resources is not finite at a specific point in time (i.e. money is endogenous). Therefore, the banking sector and the financial markets play an active role in determining the level of abatement activities and, hence, the level of emissions generated by the economy. This role is neglected in traditional IAMs.

2.4. Transmission channels of GDCRs and their dynamic effects

Let us now summarise the channels through which GDCRs can affect the credit process in our model (see Fig. 1). There are two channels related to the provision of credit.[15] The first one is what we call the *credit volume channel* and refers to the impact that a change in the way that the capital adequacy ratio is estimated affects total credit rationing. In particular, if the GSF is introduced, the weight on green loans (w_{Gt}) declines and this increases the capital adequacy ratio (according to eq. (16)), causing a decline in credit rationing, according to eq. (18). On the contrary, under the DPF, the weights on conventional loans (w_{Cit}) increase, causing a decline in capital adequacy ratio and thereby a rise in credit rationing. The significance of the credit volume channel depends on the responsiveness of credit rationing to the capital adequacy ratio in eq. (18).

The second channel is the *credit reallocation channel*. This channel reflects the impact of relative risk factors on the allocation of credit between green loans and conventional loans. With everything else given, both the GSF and the DPF induce banks to support green loans more compared to conventional loans (see eqs. (18), (19) and (20)). Quantitatively, the credit reallocation channel is stronger when the responsiveness of green and conventional credit to their relative risk weights is high. This responsiveness is captured by the parameter l_1 in eqs. (19) and (20).

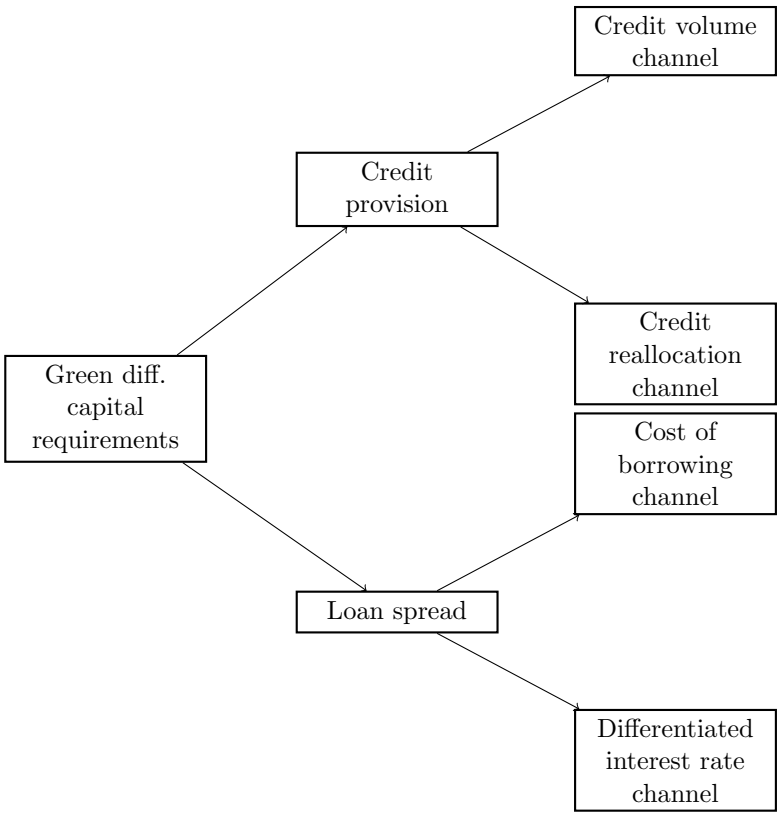
Although the GSF always increases green loans, its effect on conventional loans cannot be determined a priori. If the credit reallocation channel is less strong than the volume channel, conventional credit will be positively affected. Otherwise, conventional credit might decline. Likewise, the effect of the DPF on green loans is ambiguous. However, the DPF will always reduce conventional credit since both the volume and the reallocation channel operate in the same direction.

There are two additional channels that refer to the impact of GDCRs on the loan spread: the *cost of borrowing channel* and the *differentiated interest rate channel*. The cost of borrowing channel is straightforward: any change in the risk weights that leads to a lower (higher) capital adequacy ratio causes a rise (decline) in the total loan spread and, thus, the lending rate (for a given base interest rate). This in turn affects the profits of firms and thus their desired investment which determines the demand for credit. Therefore, the GSF reduces the interest rates and tends to increase the demand for credit. The DPF does the opposite. The strength of this channel depends primarily on the parameter spr_1 in eq. (23).

The differentiated interest rate channel operates via eqs. (24) and (25). Any change in financial regulation that makes w_{Gt} lower than w_{Cit} leads to a lower interest rate on green loans than the interest rate on conventional loans. Why is this important? According to eq. (12), firms wish

[15] In reality a change in capital requirements can also lead banks to change the proportion of their retained profits. Although this is not explicitly incorporated in our model (since banks' retention rate is exogenous), it is implicitly reflected in our econometric estimations about the effect of capital on credit. Note that an endogenous change in the retention rate has conflicting effects on economic activity. For example, if banks respond to an increase in capital requirements by increasing their retention rate investment could go up since banks can improve more quickly their capital adequacy ratio. However, consumption could at the same time decline since households would receive less distributed profits. Therefore, incorporating an endogenous retention rate in our model would most likely not change our results significantly.

Figure 1: Transmission channels of green differentiated capital requirements (GDCRs)



to invest more in green loans if the cost of borrowing on green loans compared to conventional loans declines. Hence, the GSF and the DPF increase the demand for green credit compared to conventional credit. This channel is more significant when the parameters spr_3 in eqs. (24) and (25) and β_2 in eq. (12) are high.

The transmission channels described above capture the direct effects of GDCRs. Once these transmission channels have been materialised, a dynamic process begins that involves the following steps: (i) GDCRs exert an indirect impact on various macroeconomic, financial and environmental variables; (ii) these variables have feedback effects on credit availability, since they affect the capital adequacy ratio and the debt service ratio of firms; and (iii) a new round of effects takes place.

This dynamic process affects both transition and physical risks. As far as the transition risks are concerned, the change in credit provision and loan spread induces a change in overall investment and, hence, economic growth. Economic growth, in turn, has an impact on the profitability and the liquidity of firms, causing a change in the default rate and thereby the capital of banks. This captures the effects on financial stability as a result of a GDCRs-induced transition to a lower carbon economy. These effects can be magnified as time passes because any change in the capital of banks and the debt service ratio of firms induces a new round of changes in credit availability and interest rates.

Regarding physical risks, the *credit reallocation channel* and the *differentiated interest rate channel* affect the level of green investment compared to conventional investment. This causes changes in energy efficiency and the use of non-fossil energy which, in turn, affects the path of carbon emissions and atmospheric temperature. The overall result is that GDCRs affect climate damages. These damages influence a large number of macroeconomic variables that ultimately affect firms' default rate and bank capital with feedback effects on credit availability and loan spread.

3. Model calibration and econometric estimations

3.1. General strategy

Our model has been calibrated using global data. In particular, some parameter values have been selected based on previous studies and relevant data. If we cannot directly rely on such studies and data, we select values from a reasonable range and a sensitivity analysis might be conducted. Some parameters have also been indirectly calibrated such that the model produces the baseline scenario described below or matches the initial values of endogenous variables obtained from the data. Furthermore, a few key parameters values have been estimated econometrically utilising panel data regressions for a large number of countries. This is the case for the parameter values in our investment, consumption, labour productivity, credit rationing and loan spread functions.[16] The related details are reported in Appendix E.

We run our model for the period 2018-2100. The reason why such a long horizon has been selected is because we wish to examine the long-run effects of GDCRs on climate change, which are particularly important for the physical financial risks. We use a scenario analysis in which first a baseline scenario is identified, and then GDCRs and higher carbon taxes/green subsidies are introduced to examine how they affect the pathway of key environmental, macroeconomic and financial variables.[17]

For the identification of our baseline scenario we draw on the Shared Socioeconomic Pathways (SSPs) framework that has been recently developed in the climate research community (see Riahi et al., 2017). In particular, we use as a reference the SSP2 and SSP3 mitigation scenarios that correspond to radiative forcing levels of 6.0 W/m^2 in 2100 (these levels give an atmospheric temperature slightly higher than 3^oC at the end of the century).[18] In both scenarios there is a transition to a low-carbon economy, but this transition is slow. In the SSP2, social, economic, and technological trends do not shift significantly from historical patterns and there is a moderate growth in global population. The SSP3 is characterised by a resurgent nationalism and regional conflicts that have a negative impact on global economic growth; population growth is low in high-income countries and high in low-income countries.

In our baseline scenario (see Table 1), the population growth, the energy intensity improvement, and the increase in the share of non-fossil energy until 2050 are in line with the SSP3. Global economic growth is consistent with the SSP2: it gradually declines over the next decades causing an increase in the unemployment rate. At the end of the century the atmospheric temperature is equal to 3.2^oC, as is the case both in the SSP2 and the SSP3. Annual green energy investment (both private and public) is on average equal to about 0.8% of GDP over the period 2018-2050.[19] We also posit that the loan default rate and the bond yields do not deviate significantly from their current values. Moreover, in broad line with the June 2020 World Bank projections, we have assumed that the COVID-19 crisis leads to a reduction of global economic growth by 5% in 2020; we have also assumed that the global economy bounces back partially in 2021, but the growth rate in 2021 is lower in our baseline scenario compared to the World Bank projections (World Bank Group, 2020). A potentially more realistic assumption would be that the economic impact of COVID-19 lasts for a longer period and is more severe. However, this would only marginally change the long-run trends that are the main subject of our analysis in this paper.

[16] Ideally, these econometric regressions should have been run using aggregate data at the global level. However, the number of observations that is available for the macroeconomic variables under investigation is not large enough in order for us to be able to do so. Thus, we have resorted to panel data regressions using country weights. The use of country weights ensures that the countries that have a higher contribution to global GDP play a more important role in the determination of the estimated parameters.

[17] The R code used for the simulations of the model is available at: https://github.com/marianikolaidi/DEFINE-1.1.

[18] The higher the levels of radiative forcing the higher the atmospheric temperature.

[19] This is slightly lower than the figure for green energy investment in the Nationally Determined Contributions (NDC) scenario in McCollum et al. (2018). Our baseline scenario is a bit more pessimistic about the path of carbon emissions compared to the NDC scenario.

The carbon tax pathway for the period 2030-2100 is the same as in the SSP3 6.0 W/m^2 scenario.[20] The carbon tax revenues are recycled: they are provided to firms in the form of green subsidies, covering part of the cost of generating non-fossil energy.[21] Our model is calibrated such that the elasticity of the industrial carbon emissions intensity with respect to the carbon tax in the baseline scenario is close to the elasticity derived in the SSP3 6.0 W/m^2 scenario.[22]

Table 1: Key features of the baseline scenario

Variable	**2018 value**	**2050 value**	**Mean (2018-2050)**	**St. deviation (2018-2050)**
Economic growth (%)	3.04	2.19	2.69	1.54
Unemployment rate (%)	5.40	7.01	6.56	1.26
Population (billion people)	7.63	10.01	8.87	0.72
Share of non-fossil energy in total energy (%)	15.0	23.0	18.6	2.7
Energy intensity as a ratio of 2018 energy intensity	1.00	0.71	0.86	0.10
Material intensity as a ratio of 2018 material intensity	1.00	0.90	0.95	0.04
Carbon emissions ($GtCO_2$/year)	42.13	51.43	47.46	3.18
Carbon tax (2018 US\$/tCO_2)	1.24	36.10	20.36	11.25
Annual green energy investment (% of GDP)	0.58	0.97	0.83	0.12
Default rate on corporate loans (%)	3.70	3.94	3.75	0.24
Yield of conventional bonds (%)	5.00	4.91	4.14	0.47
Yield of green bonds (%)	5.00	4.82	4.22	0.51

We conduct a few validation exercises to check whether the model has the potential to generate time series with properties close to the properties of actual time series data. For this purpose, we use a stochastic version of the model. This stochastic version is developed by including randomised variables in our investment and credit rationing functions. The inclusion of randomised variables allows us to consider the impact of exogenous factors that are not part of the endogenous structure of our model, but in reality affect the behaviour of time series. These randomised variables are assumed to follow an AR(1) process and the related parameter values have been calibrated such that the volatility of GDP and its components is close to the volatility observed in the actual data.[23] Table A.1 in Appendix A shows the standard deviations observed in the simulated data of the stochastic version of the model and the standard deviations in actual data.

We then compare the auto-correlation structure of our simulated time series with the auto-correlation structure of actual time series. Fig. A.1 shows that the auto-correlations in our simulated data are, broadly speaking, close to their empirical counterparts. We also report the cross-correlation between output and other macroeconomic variables both for the actual and the simulated time series (see Fig. A.2). We can see that the position of the peak, as well as the dimension and the shape of the simulated cross-correlation functions fit quite well to those of actual data. Based on the above, it can overall be argued that the stochastic version of our model can generate time series with empirically reasonable properties.

The stochastic version of our model is also used to illustrate the range of trajectories that the model can produce in the baseline scenario. Appendix B reports the cross-run standard deviations for some key variables in the baseline scenario when 200 Monte Carlo simulations are run, considering also the

[20] The data for the SSP2 and the SSP3 have been downloaded from the International Institute for Applied System Analysis (IIASA); for the period 2020-2100 the data are provided with a 10-year time step. In the SSP3 6.0 W/m^2 scenario the carbon tax value that is implicitly given for 2018 is too high compared to its actual value (the latter has been estimated by dividing carbon tax revenues by emissions at the global level); the value for 2020 is also too optimistic. Thus, we have used the actual value of the carbon tax for 2018 and the SSP3 value for 2030 and have interpolated the values between 2018 and 2030.

[21] In the SSP3 scenario the carbon tax revenues are recycled as well, but this happens via lump-sum transfers to households (see Fujimori et al., 2017) not via green subsidies as is the case in our model.

[22] Over the period 2030-2100, this elasticity is 0.7% in the SSP3 6.0 W/m^2 scenario, while it is 0.8% in our model. The desired elasticity is primarily achieved by adjusting the value of β_1 in eq. (12).

[23] An alternative way of introducing stochasticity in the model would be to include some agent-based structures in the model whereby agent-based variables take values from specific distributions. However, this would make our model much more complex without necessarily change the essence of our results.

hypothetical case in which climate damages do not exist.

Note that in our scenario analysis in Section 4 we use the deterministic version of the model. We could, alternatively, use the stochastic version, run Monte Carlo simulations and report the cross-run average values. However, when a sufficiently large number of Monte Carlo simulations are run, the cross-run averages do not differ from the values obtained from the deterministic version of the model. We have, therefore, opted for presenting the results from the deterministic version to reduce the execution time of our code.

3.2. Estimating and calibrating the key parameters of the transmission channels of GDCRs

We will now describe how the parameters linked with the transmission channels presented in Section 2.4 are estimated and calibrated. We will begin with the *credit volume channel*. The parameter that captures this channel is the responsiveness of credit rationing to the capital adequacy ratio. The challenge with the estimation of this parameter is the lack of sufficient and suitable data at the global level for the degree of credit rationing that would allow us to estimate it directly.[24] Hence, we estimate the impact of the capital adequacy ratio on credit rationing indirectly, following three steps. First, we run the following regression using panel data for 28 countries over the period 1995-2018:[25]

$$\Delta CREDIT_{it} = \gamma_0 + \gamma_1 CA_{it} + \gamma_2 DOS_{it} + \gamma_i + u_{it} \tag{28}$$

where i refers a country and t to a year, $CREDIT_{it}$ is the logarithm of the credit provided to the non-financial corporations, CA_{it} is the capital-to-assets ratio of banks, DOS_{it} is the debt-to-operating surplus ratio of non-financial corporations, γ_i is a country fixed effect and u_{it} is the error term.[26] The data sources, key summary statistics and the results are reported in Appendix C. Our estimations have been made using a variety of panel data techniques: Fixed effects, Random effects, Feasible Generalised Least Squares (FGLS) and Instrumental Variable Two-Stage Least-Squares (IV-2SLS). The Hausman test indicates whether the fixed-effects or the random-effects method is the preferred one. FGLS tackles the problems of autocorrelation and heteroskedasticity that appear to be present in our regressions.[27] IV-2SLS deals with endogeneity issues that might arise in our regressions because of the fact that in reality a change in credit might affect *CA* and *DOS*. The Sargan-Hansen J test is used to test the null hypothesis, according to which the instruments and the error term are not correlated. The Cragg-Donald statistic checks whether the instruments are weak (if this statistic is higher than the critical value, the instruments are not weak). The endogeneity test is utilised to test the null hypothesis that the regressors are exogenous.

We have selected to use a variety of methods in order to increase our confidence for the values of the estimated coefficients, as well as because each method has different advantages and disadvantages and it is not clear-cut what the most appropriate econometric model is. Based on the mean value of the statistically significant coefficients across the four models, we have that an increase in the capital-to-assets ratio by 1 percentage point leads to an increase in credit growth by about 0.53%, which is broadly consistent with the estimations in the related literature; see, for example, Gambacorta

[24] A database that can be used to proxy the degree of credit rationing is the Survey on the Access to Finance for Enterprises (SAFE), which refers to the credit conditions of enterprises in the European Union (see ECB, 2018). However, the coverage of this database is relatively small for our global model and, most crucially, there is no direct way to connect the financing conditions for firms with the financial position of banks. We use, though, the results of this survey for 2017 as a basis for the calibration of the value of the degree of credit rationing.

[25] The countries are Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, UK and US.

[26] We have opted to use the capital-to assets ratio instead of the capital adequacy ratio in our regressions. This is due to the lower data availability for the capital adequacy ratio as well as due to the fact that the latter is very sensitive to changes in bank credit (by definition, these changes affect substantially the value of risk-weighted assets). This sensitivity makes very likely the existence of reverse causality problems, which are much less likely to occur in the case of the capital-to-assets ratio (since the latter is not affected by risk weights).

[27] The results for these tests are reported in Appendix C.

and Shin (2018) whose analysis relies on a sample of global banks. Moreover, an increase in the debt-to-operating surplus ratio by 1 percentage point brings about a decline in the growth rate of credit by approximately 1.75%.

Second, the parameters estimated in the regression are adjusted since the capital-to-assets ratio (CA_{it}) and the debt-to-operating surplus ratio (DOS_{it}) are not identical, respectively, to the capital adequacy ratio and firms' debt service ratio, which are used as variables in eq. (18). Assuming a constant relationship between the capital-to-assets ratio and the capital adequacy ratio, the adjusted value of γ_1 is estimated as follows:

$$\gamma_{1-adj} = \gamma_1 \frac{\bar{CA}}{\bar{CAR}} \tag{29}$$

where $\bar{CA}$ is the cross-sample average of the capital-to-assets ratio and $\bar{CAR}$ is the cross-sample average of the capital adequacy ratio.

The parameter for the debt service ratio is simply estimated by multiplying γ_2 by the interest rate (int_t) plus the principal repayment ratio (rep):

$$\gamma_{2-adj} = \gamma_2 \left(int_t + rep\right) \tag{30}$$

Third, we incorporate the adjusted parameters in the model equations. The change in loans in the model is given by:

$$\Delta L_t = (1 - CR_t) NL_t^D - rep L_{t-1} - def_t L_{t-1} \tag{31}$$

where CR_t is the total credit rationing (which is the same for green and conventional loans in the baseline scenario), def_t is the default rate and NL_t^D is the change in the demanded loans which is equal to $\sum NL_{Cit}^D + \sum NL_{Git}^D$. Dividing both sides by L_{t-1}, yields:

$$\frac{\Delta L_t}{L_{t-1}} = \frac{(1 - CR_t)\, NL_t^D}{L_{t-1}} - rep - def_t \tag{32}$$

We then take the partial derivative of the growth rate of loans with respect to the capital adequacy ratio (recall that the credit rationing is a function both of the capital adequacy ratio and the debt service ratio according to eq. (18)):

$$\frac{\partial \left(\Delta L_t / L_{t-1}\right)}{\partial CAR_{t-1}} = -\frac{\partial CR_t}{\partial CAR_{t-1}} \frac{NL_t^D}{L_{t-1}} \tag{33}$$

Setting $\frac{\partial(\Delta L_t / L_{t-1})}{\partial CAR_{t-1}} = \gamma_{1-adj}$ and solving eq. (33) for the partial derivative of CR_t with respect to CAR_t, we get:

$$\frac{\partial CR_t}{\partial CAR_{t-1}} = -\gamma_{1-adj} \frac{L_{t-1}}{NL_t^D} \tag{34}$$

Similarly, the responsiveness of credit rationing to the debt-service ratio is given by:

$$\frac{\partial CR_t}{\partial dsr_{t-1}} = -\gamma_{2-adj} \frac{L_{t-1}}{NL_t^D} \tag{35}$$

In our simulations the value of $\frac{L_{t-1}}{NL_t^D}$ is estimated based on the initial values of loans and new loans demanded for 2018.

Let us now turn to the *cost of borrowing channel*. The parameters for this channel can be directly estimated using the following regression for the same time period and a similar sample of countries as the one employed for the estimation of eq. (28):

$$SPREAD_{it} = \mu_0 + \mu_1 CA_{it} + \mu_2 DOS_{it} + \mu_i + \varepsilon_{it} \tag{36}$$

where $SPREAD_{it}$ is the difference between the lending interest rate and the deposit interest rate, μ_i is a country fixed effect and ε_{it} is the error term. The data sources and the results are reported in Appendix C. The same panel data estimation techniques have been used as in the case of the econometric estimations for loans. Based on the mean values of the statistically significant coefficients across the four models, an increase in the capital-to-assets ratio by 1 percentage point produces a decline in the loan spread by 5.8 basis points. Moreover, an increase in the debt-to-operating surplus ratio by 1 percentage point leads to a rise in the loan spread by 13.5 basis points.

In order to introduce this estimation in our simulations, we make an adjustment similar to the one that we did for loans. This gives:

$$\mu_{1-adj} = \mu_1 \frac{\bar{CA}}{\bar{CAR}} \tag{37}$$

$$\mu_{2-adj} = \mu_2 \left(int_t + rep\right) \tag{38}$$

Regarding the *credit reallocation* and the *differentiated interest rate* channel, there is no straightforward way to estimate l_1, spr_3 and β_2 based on available data. Thus, we have opted to use some reasonable values and then to conduct a sensitivity analysis in order to cover a sufficiently large range of potential values.[28] In our Central Case, an increase in the difference between the weight of a specific type of loan and the risk weight on total loans by 1 percentage point leads to an increase in credit rationing and spread of this type of loan by 1% compared to total credit rationing and total loan spread (i.e. $l_1 = 1$ and $spr_3 = 1$).[29] In addition, a decline in the borrowing cost of green loans compared to conventional loans by 100 basis points increases the desired proportion of green investment in total investment by 1 percentage points (i.e. $\beta_2 = 1$). In our sensitivity analysis we consider Case I in which l_1, spr_3 and β_2 decrease by 50% and Case II in which these parameters increase by 50%.

In addition, in Case I the values of γ_1 and μ_1 are those obtained from the econometric model (Fixed effects, Random-effects, FGLS or IV-2SLS) that reflects the lowest responsiveness of credit and loan spread to the capital-to-assets ratio. In Case II the values of γ_1 and μ_1 correspond to those obtained from the model that gives the highest responsiveness of credit and loan spread to the capital-to-assets ratio. All the related values are reported in Table 2. Accordingly, we can overall interpret Case I as the case in which the transmission channels of GDCRs are relatively weak and Case II as the case in which the transmission channels of GDCRs are relatively strong.

3.3. Calibrating the degree of dirtiness of conventional loans

We calibrate the degree of dirtiness of conventional loans by utilising global data for the level of carbon emissions per gross value added (GVA) in different sectors of the economy. A loan is considered to be 'dirtier' when it corresponds to an investment it is undertaken by a sector that has a higher

[28] Our sensitivity analysis in the current paper covers only this small subset of the model parameters. A complete understanding of the properties of the model would require a much more extensive sensitivity analysis. However, this is beyond the scope of this paper. For some additional sensitivity analyses of previous versions of this model, see Dafermos et al. (2017) and Dafermos et al. (2018).

[29] Note that $l_1 = 1$ is a quite conservative value compared to the one that can be derived implicitly by the estimations in Mayordomo and Rodríguez-Moreno (2018).

Table 2: Values of parameters linked with the transmission channels of GDCRs

	Case I	Central Case	Case II
γ_1	0.33	0.53	0.8
μ_1	-0.03	-0.06	-0.08
l_1	0.50	1.00	1.50
spr_3	0.50	1.00	1.50
β_2	0.50	1.00	1.50

Note: γ_1: responsiveness of credit growth to the capital-to-assets ratio; μ_1: responsiveness of loan spread to the capital-to-assets ratio; l_1: responsiveness of green/conventional credit rationing to the difference between the weight on green/conventional loans and total loans; spr_3: responsiveness of green/conventional loan spread to the difference between the weight on green/conventional loans and total loans; β_2: responsiveness of the desired green investment share to the interest rate differential between green loans/bonds and conventional loans/bonds

carbon-GVA intensity.[30] We estimate carbon-GVA intensities for different sectors using data from UNCTAD (for gross value added) and IEA (for carbon emissions). The higher the carbon-GVA intensity of a specific sector compared to the carbon-GVA intensity of the total economy, the higher the degree of dirtiness. If a sector has a carbon-GVA intensity equal to the carbon-GVA intensity of the total economy, the degree of dirtiness of the loan provided to this sector is set equal to 1. The degree of dirtiness (dd_i) is thereby given by:

$$dd_i = \frac{\frac{carbon_i}{GVA_i}}{\frac{carbon}{GVA}} \tag{39}$$

where $carbon_i$ denotes the carbon emissions of sector i, $carbon$ stands for the carbon emissions of the total economy, GVA_i is the gross value added of a specific sector and GVA is the gross value added of the total economy.[31]

4. Effects of green differentiated capital requirements

As mentioned above, the starting year of our simulations is 2018. In our policy scenarios we assume that climate-related policies are introduced in 2022. For each scenario we undertake a sensitivity analysis based on the values of the parameters linked to the transmission channels of GDCRs reported in Table 2.

As shown in Fig. 2, in the baseline scenario climate change has a negative impact on long-run economic growth and causes financial instability after a few decades. In particular, since the transition to a low-carbon economy is slow, the large reliance of economic activity on fossil fuels keeps carbon emissions at a high level over the next decades (Fig. 2c), bringing about a global warming of about 3.2^{o}C in 2100 (Fig. 2d). The resulting climate damages reduce economic activity, especially after the 2°C threshold is passed (Fig. 2a). This leads to a decline in the profitability of firms (Fig. 2e)[32] that

[30] This draws on the related literature. For example, Monasterolo et al. (2017) have used greenhouse gas emissions in order to capture which sectors of the economy are more vulnerable to an abrupt transition to a low-carbon economy. Moreover, Esposito et al. (2019) have used carbon intensity to estimate the degree of dirtiness and greenness of different sectors of the Italian economy. However, the use of emissions has various limitations, including the fact that it does not take into account the complexity of the energy supply chain. A more consistent approach would be to use an approach similar to the 'climate policy relevant sectors' one developed by Battiston et al. (2017). However, this would require a much more granular version of our aggregate model and is therefore left for future research. An additional limitation of relying on emissions for capturing 'dirtiness' is that it only considers climate impacts, ignoring other non-climate aspects of dirtiness, such as high material intensity.

[31] An extension of this analysis would be to estimate a 'degree of greenness' for the investment of different sectors. In the current paper this has not been pursued since, based on the existing available data, it is not straightforward which variable should be used to capture the level of 'greenness' of the investment of each sector.

[32] Note that the decline in profitability is more pronounced compared to the decline in growth. There are two key reasons behind this result. First, the parameter that captures the responsiveness of investment to the profit rate is

increases their default rate (Fig. 2f). This rise in the default rate harms the profits of banks and thereby their leverage ratio (Fig. 2g). It also causes a decline in their capital adequacy ratio (Fig. 2h).

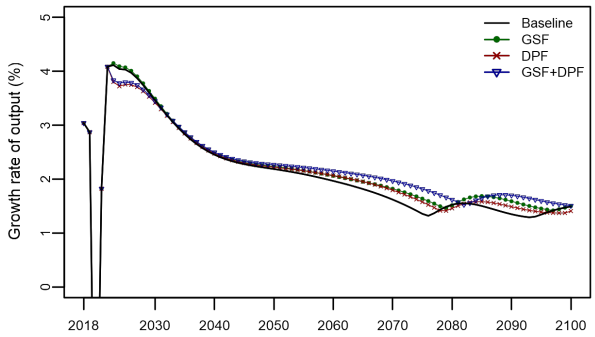
Accordingly, in the last decades of this century the leverage ratio and the capital adequacy ratio reach the thresholds imposed by financial regulation.[33] Although banks cut lending and increase interest rates as these thresholds are approached, this is not enough to prevent a significant decline in bank capital; this is due to the severity of climate damages. Consequently, the government steps in to bailout the banking sector. These bailouts prevent a collapse of the economic and the financial system. However, they affect adversely public indebtedness and are not enough to stabilise the economy since climate damages are continuously becoming more severe. These results illustrate that, without the implementation of ambitious climate policies, the financial system will be severely affected by physical risks in the long run.

relatively low based on our econometric estimations. Second, an important driver behind the reduction in the profit rate is the increase in the depreciation of capital as a result of climate damages. However, the money that firms put aside to rebuild climate-induced depreciated capital is used in order to increase gross investment (as part of a reconstruction process). Because of these two reasons, the decline in the profit rate is translated into a less significant decline in investment compared to what it would potentially be expected.

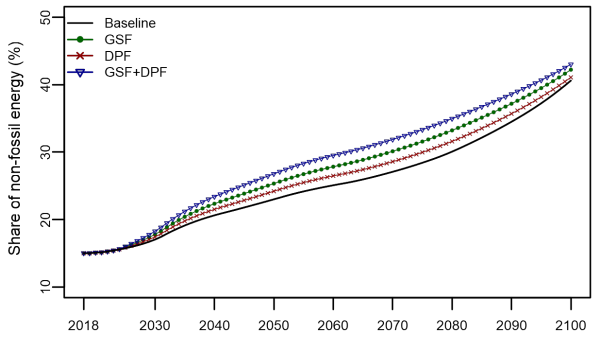
[33] These are 8% for the capital adequacy ratio and 1/0.03 for the leverage ratio, in line with Basel III (if we assume away the conservation and the countercyclical capital buffer). The leverage ratio is defined as the assets-to-capital ratio, which is the inverse of the Basel III leverage ratio. Note that in our model all bank capital is actually Tier 1 capital since it is accumulated via retained profits.

Figure 2: Effects of the implementation of green differentiated capital requirements (GDCRs)

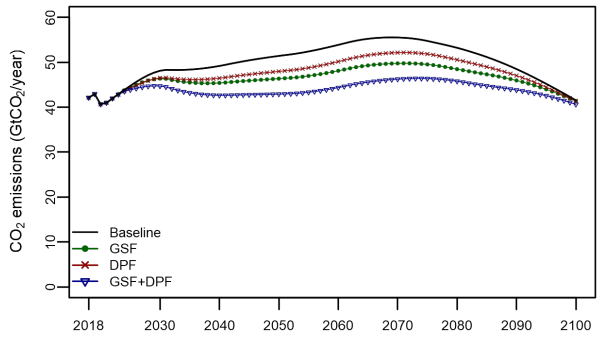
(a) Growth rate of output



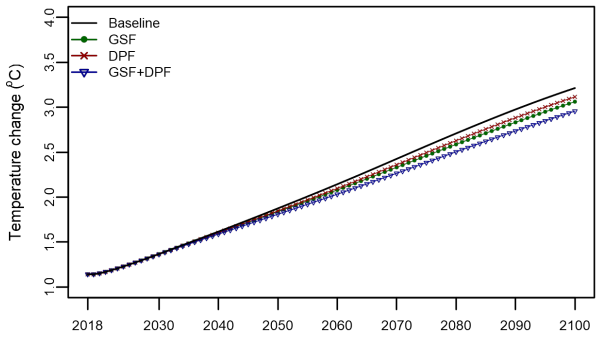
(b) Share of non-fossil energy in total energy



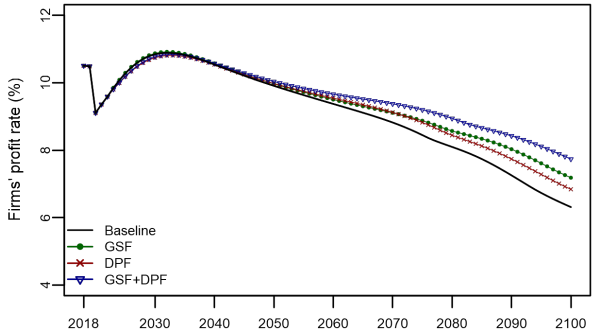
(c) CO_2 emissions



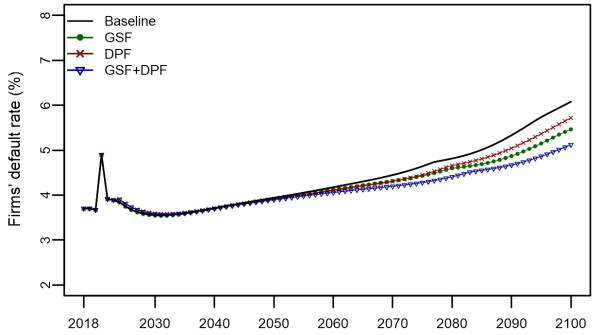
(d) Temperature change from the pre-industrial period



(e) Firms' profit rate



(f) Firms' default rate



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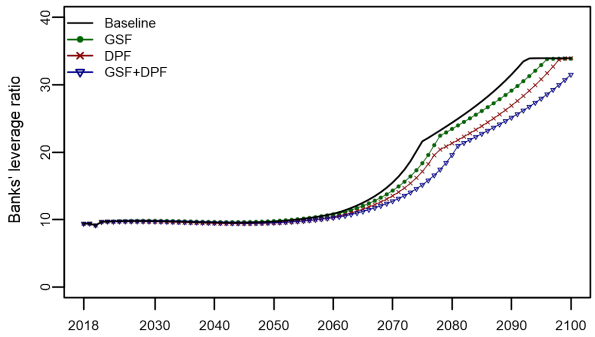
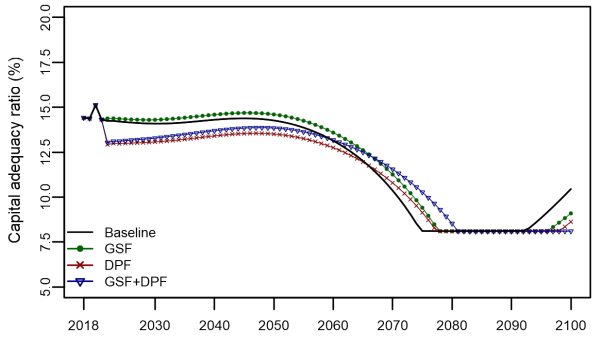
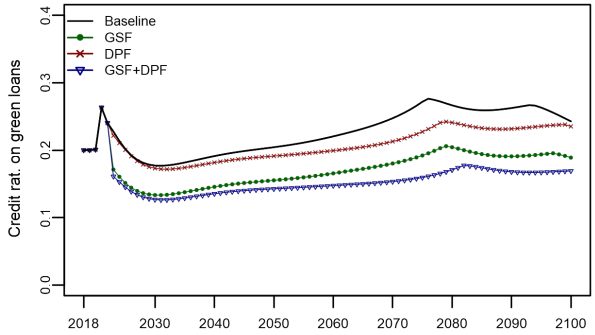
(g) Banks' leverage ratio



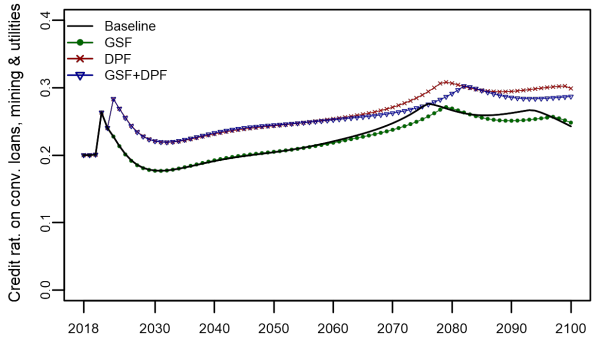
(h) Capital adequacy ratio



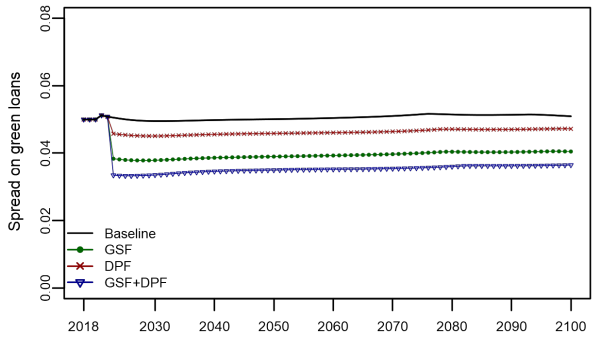
(i) Credit rationing on green loans



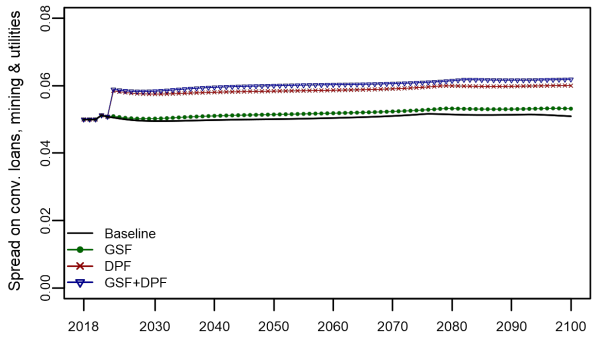
(j) Credit rationing on conventional loans, 'mining and utilities' sector



(k) Spread on green loans



(l) Spread on conventional loans, 'mining and utilities' sector



Note: All policy shocks take place in 2022. The values used in the baseline scenario are reported in Appendix E. In the GSF (Green Supporting Factor) scenario, the risk weight on green loans increases by 25 percentage points. In the DPF (Dirty Penalising Factor) scenario, the risk weight on conventional loans decreases by a maximum of 25 percentage points. In the GSF+DPF scenario, the GSF and the DPF are implemented simultaneously.

4.1. Comparing the green supporting factor with the dirty penalising factor

How can GDCRs affect the stability of the macroeconomic and the financial system? We first consider two policy scenarios according to which GDCRs are introduced in 2022. In the first scenario the GSF is implemented: the risk weight on green loans declines by 25 percentage points. In the second policy scenario financial regulators adopt the DPF: the risk weight on conventional loans increases by a maximum of 25 percentage points, depending on the degree of dirtiness of the underlying loan.[34]

Fig. 2 displays the effects of these policies. Under both the GSF and the DPF, green investment is boosted compared to conventional investment. This is so because of the *credit reallocation channel* and the *differentiated interest rate channel*: both policies make green loans more attractive since they reduce the risk weight on green loans compared to conventional loans. However, the GSF and the DPF differ with respect to their impact on overall credit rationing and loan spreads (*credit volume channel* and *cost of borrowing channel*). Since the GSF increases the capital adequacy ratio (Fig. 2h), it leads to lower overall credit rationing and loan spreads; in contrast, the DPF decreases the capital adequacy ratio (Fig. 2h), which results in higher overall credit rationing and spreads.

As a result of these channels, the GSF reduces the credit rationing and spread on green loans (Figs 2i and 2k), increases the loan spread on conventional loans (Fig. 2i) and leaves almost unchanged the credit rationing on conventional loans (Fig. 2j), since in our simulations the *credit volume channel* counterbalances the *credit reallocation channel*.[35] The DPF increases the credit rationing and spread on conventional loans (Figs 2j and 2l), reduces the loan spread on green loans (Fig. 2k) and does not change significantly the credit rationing on conventional loans due to the conflicting effects of the *credit volume channel* and the *credit reallocation channel*.

Overall, both the DPF and the GSF lead to an increase in the share of non-fossil energy (Fig. 2b) and energy efficiency, making climate change slightly less severe compared to the baseline scenario (Fig. 2d). The lower atmospheric temperature reduces climate damages in the long run. This results in higher economic activity (Fig. 2a), a lower default rate (Fig. 2f) and a lower bank leverage (Fig. 2g) in comparison with the baseline scenario. Note that in our simulations the GSF turns out to be slightly more effective in reducing global warming than the DPF, but the difference with the DPF is small.

Table 3 shows how these effects differ quantitatively when the transmission channels of GDCRs are weaker (Case I) or stronger (Case II). As expected, the decline that is caused in the long-run atmospheric temperature, compared to the baseline scenario, is more pronounced in Case II, while it is less significant in Case I. Accordingly, the beneficial impact of GDCRs on bank leverage and the loan default rate, which capture the physical risks, is more significant when the transmission channels of GDCRs are stronger.

How does the impact of the GSF differ from the impact of the DPF with respect to transition risks? First, the GSF and the DPF affect bank leverage – a proxy of the fragility of the banking system – in a different way. Since the DPF increases the overall credit rationing, it reduces the bank leverage in the first years after the introduction of this policy. On the contrary, under the GSF, the decline in credit rationing leads to a higher bank leverage in 2025 and 2030 compared to the baseline scenario (see Table 3).[36] Thus, it can be argued that the DPF is more conducive to the stability of banks than the GSF, when this is evaluated based on the effects on the bank leverage.

[34] The risk weight on the conventional loans of each sector i (w_{Ci}) increases by $0.25dd_i$ if $dd_i \leq 1$ and by 0.25 if $dd_i > 1$.

[35] In Fig. 2 we report the effects on the loans related with the 'mining and utilities' sector, which is the sector with the highest carbon-GVA intensity.

[36] In 2030 the increase in the bank leverage under the GSF compared to the baseline scenario is higher than in 2025 because more green loans are accumulated as time passes.

Table 3: Effects of policy shocks on selected variables, sensitivity analysis

	2025			2030			2050			2075			2100		
	Case I	Central Case	Case II	Case I	Central Case	Case II	Case I	Central Case	Case II	Case I	Central Case	Case II	Case I	Central Case	Case II
Growth rate of output (%)															
Baseline	4.061	4.033	3.997	3.481	3.464	3.444	2.190	2.187	2.180	1.488	1.356	1.186	1.383	1.492	1.573
GSF	4.083	4.072	4.061	3.497	3.493	3.491	2.208	2.235	2.274	1.583	1.637	1.724	1.391	1.498	1.572
DPF	3.887	3.757	3.588	3.443	3.416	3.393	2.200	2.221	2.249	1.572	1.575	1.606	1.346	1.407	1.494
GSF+DPF	3.907	3.797	3.663	3.459	3.447	3.445	2.217	2.266	2.330	1.663	1.816	2.001	1.345	1.505	1.831
CT+GS	4.063	4.035	3.999	3.497	3.479	3.459	2.409	2.419	2.428	2.393	2.367	2.333	2.219	2.204	2.182
CT+GS+GSF	4.102	4.103	4.107	3.535	3.536	3.537	2.417	2.434	2.458	2.392	2.367	2.339	2.220	2.216	2.216
CT+GS+DPF	3.898	3.775	3.613	3.470	3.444	3.420	2.407	2.425	2.445	2.398	2.382	2.367	2.227	2.221	2.216
Bank leverage															
Baseline	9.760	9.760	9.758	9.779	9.768	9.758	9.731	9.713	9.705	21.141	21.609	22.161	33.998	33.951	33.909
GSF	9.764	9.768	9.771	9.794	9.802	9.819	9.767	9.767	9.765	20.991	18.356	16.139	33.970	33.881	33.753
DPF	9.728	9.708	9.684	9.715	9.662	9.624	9.595	9.473	9.410	19.287	17.127	15.326	33.992	33.926	33.800
GSF+DPF	9.732	9.716	9.697	9.729	9.699	9.703	9.628	9.531	9.500	18.540	15.143	12.896	33.964	31.507	27.403
CT+GS	9.759	9.759	9.757	9.779	9.768	9.758	9.430	9.424	9.428	10.830	10.854	10.893	13.989	13.891	13.987
CT+GS+GSF	9.769	9.778	9.786	9.821	9.853	9.894	9.533	9.601	9.654	10.954	10.976	10.887	14.190	13.878	13.540
CT+GS+DPF	9.731	9.713	9.692	9.729	9.688	9.661	9.336	9.261	9.234	10.533	10.310	10.139	13.230	12.622	12.225
Default rate (%)															
Baseline	3.747	3.751	3.755	3.546	3.551	3.557	3.940	3.938	3.936	4.578	4.640	4.717	6.337	6.077	5.802
GSF	3.742	3.740	3.735	3.541	3.541	3.541	3.931	3.913	3.888	4.506	4.428	4.330	6.070	5.463	4.876
DPF	3.787	3.814	3.848	3.571	3.588	3.608	3.933	3.918	3.897	4.496	4.450	4.378	6.182	5.718	5.227
GSF+DPF	3.782	3.802	3.819	3.566	3.578	3.588	3.924	3.894	3.854	4.428	4.278	4.119	5.921	5.120	4.467
CT+GS	3.747	3.750	3.755	3.543	3.548	3.554	3.815	3.811	3.806	3.879	3.892	3.908	3.769	3.778	3.786
CT+GS+GSF	3.739	3.734	3.726	3.531	3.528	3.525	3.809	3.798	3.784	3.882	3.891	3.899	3.765	3.760	3.751
CT+GS+DPF	3.785	3.810	3.843	3.564	3.580	3.598	3.811	3.801	3.786	3.865	3.866	3.862	3.763	3.764	3.761
Atmospheric temperature (oC)															
Baseline	1.249	1.249	1.249	1.366	1.366	1.366	1.874	1.873	1.873	2.573	2.568	2.562	3.241	3.214	3.186
GSF	1.249	1.249	1.249	1.366	1.364	1.362	1.862	1.837	1.801	2.535	2.459	2.356	3.187	3.062	2.897
DPF	1.249	1.249	1.249	1.365	1.364	1.362	1.862	1.845	1.821	2.544	2.494	2.426	3.202	3.115	3.004
GSF+DPF	1.249	1.249	1.249	1.365	1.362	1.358	1.850	1.808	1.749	2.505	2.384	2.220	3.147	2.957	2.692
CT+GS	1.248	1.249	1.249	1.352	1.352	1.352	1.639	1.642	1.645	1.865	1.872	1.880	2.004	2.014	2.024
CT+GS+GSF	1.248	1.248	1.249	1.352	1.350	1.348	1.630	1.617	1.599	1.845	1.821	1.785	1.980	1.950	1.905
CT+GS+DPF	1.248	1.248	1.248	1.352	1.350	1.349	1.634	1.627	1.616	1.853	1.840	1.819	1.989	1.974	1.947

Note: The values used in the baseline scenario are reported in Appendix E. All policy shocks take place in 2022. The values for the Central Case, Case I and Case II, are reported in Table 2. In the GSF (Green Supporting Factor) scenario, the risk weight on green loans decreases by 25 percentage points. In the DPF (Dirty Penalising Factor) scenario, the risk weight on conventional loans increases by a maximum of 25 percentage points. In the GSF+DPF scenario, the GSF and the DPF are implemented simultaneously. In the CT (Carbon Tax) + GS (Green Subsidies) scenario, the carbon tax becomes equal to the carbon price in the SSP3 3.4 W/m^2 scenario and the green subsidies increase accordingly such that they are equal to the new carbon tax revenues. In the GSF+CT+GS scenario, the GSF and CT+GS policy are implemented simultaneously. In the DPF+CT+GS scenario, the DPF and CT+GS policy are implemented simultaneously.

Second, since the credit rationing and the spread on conventional loans increase under the DPF, there is a slowdown in economic activity (Fig. 2a). This has an adverse effect on the profitability and liquidity of firms and, thus, on their default rate in 2025 and 2030 compared to the baseline scenario (see Table 3). However, this slowdown is relatively modest. As a result, the impact on the default rate is quantitatively small.

4.2. Combining the green supporting with the dirty penalising factor

A combined implementation of the DPF and the GSF can reduce the adverse transition effects of these policies and increase their overall benefits. To begin with, the long-run impact on climate change is enhanced (Fig. 2d and Table 3). This is so because banks have a higher incentive to reduce the credit rationing on green loans compared to the credit rationing on conventional loans. As a result, the rise in green energy capital compared to the conventional energy capital is now much more pronounced. This results in a higher share of non-fossil energy (Fig. 2b), higher energy efficiency and thus lower carbon emissions (Fig. 2c). Importantly, the loan default rate in the long run is now lower (Fig. 2f), implying that the combined implementation of the DPF and the GSF maximises the favourable effects of GDCRs on physical risks.

Moreover, when the GSF is combined with the DPF, the GSF-induced rise in bank leverage does not materialise (actually the bank leverage becomes lower compared to the baseline scenario) and the DPF-induced increase in default is attenuated (see Table 3). Thus, although some transition effects are still in place, they become less significant and there are more benefits in terms of physical risks.

4.3. Combining green differentiated capital requirements with green fiscal policy

We now ask the question: how are the transition and physical risks affected if the DPF or the GSF are introduced in conjunction with some traditional fiscal policies? We examine this by considering a fiscal policy mix according to which an increase in the carbon tax is combined with an increase in green subsidies. More precisely, we assume that all the revenues that result from the increase in the carbon tax are recycled such that green subsidies are always equal to these revenues. There are two reasons why we have opted for such a policy mix instead of an isolated carbon tax policy. First, this policy mix can bring about more substantial outcomes in terms of an increase in green investment and carbon emissions reduction (see Dafermos and Nikolaidi, 2019; Bovari et al., 2018b; Bovari et al., 2020). Second, broadly speaking, the distribution of the carbon tax revenues to the economy via green subsidies is politically a much more realistic scenario given the significant distributional effects of a carbon tax policy (for these effects see e.g. Fremstad and Paul, 2019) and the negative effects of an isolated carbon tax policy on the financial position of firms and households.

We explore two alternative carbon tax trajectories. The first one, called the 'Medium carbon tax' trajectory, is taken from the SSP3 4.5 W/m^2 scenario and the second one, called the 'High carbon tax' trajectory, is taken from the SSP3 3.4 W/m^2 scenario. In the 'Medium carbon tax' trajectory the carbon tax becomes \$21/tCO_2 in 2022 and \$564/tCO_2 in 2100 (in 2018 prices).[37] In the 'High carbon tax' trajectory the carbon taxes becomes \$37/tCO_2 in 2022 and \$1474/tCO_2 in 2100 (in 2018 prices). Note that in the SSP3, the carbon tax trajectories are derived endogenously through the application of a recursive dynamic framework to an integrated assessment/computable general equilibrium model (see Fujimori et al., 2017). This is not the case in our model where it is assumed that the carbon tax is set exogenously by the government.[38] However, by using the carbon tax trajectories of the SSP3, we are able to examine the finance-related implications of widely used carbon tax policy trajectories; such implications are not explicitly considered in the SSPs and standard IAMs.

[37] We have used the US GDP deflator in order to make the adjustment.

[38] For an SFC model that follows more closely the approach of the standard IAMs, see Bovari et al. (2018a), Bovari et al. (2018b) and Bovari et al. (2020). In this model the emissions reduction rate is derived though a cost minimisation problem. However, the carbon tax trajectories are still exogenous.

The results for the 'High carbon tax' trajectory are displayed in Fig. 3, Fig. 4 and Table 3. In Fig. 3, the GSF is combined with the 'carbon tax+green subsidy (CT+GS)' policy, while in Fig. 4, CT+GS accompanies the DPF. The results for the 'Medium carbon tax' trajectory are reported in Appendix D (see Figs. D.1 and D.2).

In the CT+GS scenario a significant decline in carbon emissions is achieved (Fig. 3c), affecting favourably physical risks (Fig. 3f). This is so primarily because the desired green investment goes up, leading to higher energy efficiency and use of non-fossil energy. As expected, the decline in emissions and physical risks is higher under the 'High carbon tax' trajectory compared to the 'Medium carbon tax' trajectory.[39]

Let us now focus on the combined implementation of the GSF and the CT+GS policy. The boost of green investment caused by the green fiscal policy mix makes the level of green credit rationing relevant for a higher proportion of total desired loans. Since banks become more willing to finance green loans as a result of the introduction of the green supporting factor, the GSF leads to a higher increase in green investment, compared to the isolated CT+GS policy. As a result, the decline in physical risks is reinforced (see Fig. 3f and Table 3). Simultaneously, since the green credit expansion is now higher, economic growth increases slightly more (in comparison with the CT+GS scenario) and the leverage of banks in 2025 is now slightly higher compared to case where the GSF is put in place in isolation (see Table 3). This increase becomes more evident in 2030 since green investment has increased then even more compared to 2025. This overall suggests that the transition risks that stem from the GSF are higher when a green fiscal policy mix accompanies the GSF.

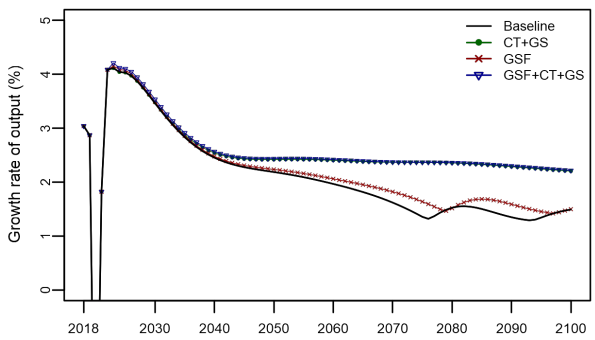
The opposite holds when the DPF is implemented in conjunction with the CT+GS policy: the combination of green fiscal policy with the DPF reduces the transition effects. As shown in Fig. 4a and Table 3, the growth rate of output in the DPF+CT+GS scenario is higher than what is the case in the DPF scenario. Since firms undertake less dirty activities and demand less dirty loans, the dirty penalty has weaker recessionary effects and this is beneficial for the transition risks: the default rate in the initial years is slightly lower than in the DPF scenario (Table 3). At the same time, the DPF reinforces the favourable effects of the CT+GS policy on atmospheric temperature and thereby on physical risks (Fig. 4f and Table 3).[40]

[39] In Fig. D.3 we show how the effects of the carbon tax policy differ when no recycling of carbon tax revenues is assumed. Interestingly, the difference in the carbon emissions path between the scenario in which recycling takes place and the scenario without recycling is lower than what would potentially be expected, given that when the carbon tax and the green subsidy are combined the increase in the use of renewables and energy efficiency is reinforced. The main reason why this difference is not very large is that an increase in the carbon tax that is not accompanied by recycling has contractionary effects. These contractionary effects place downward pressures on emissions. They also lead to financial instability.

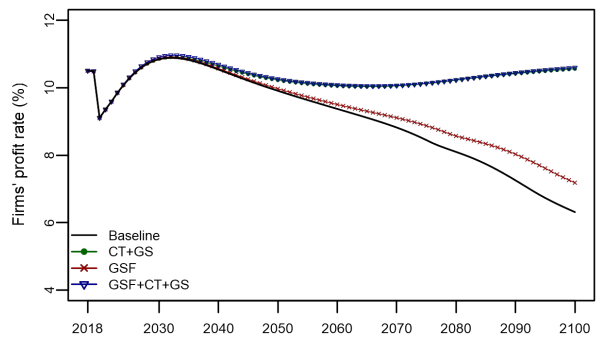
[40] As expected, the impact of green fiscal policy on the transition effects of GDCRs is smaller in the case of the 'Medium carbon tax' trajectory.

Figure 3: Effects of a combined implementation of the green supporting factor with an increase in carbon tax and green subsidies, 'High carbon tax' pathway

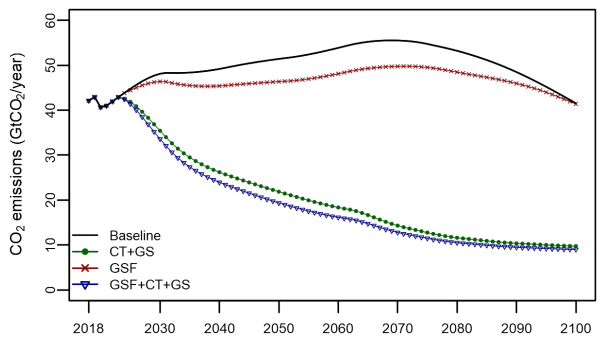
(a) Growth rate of output



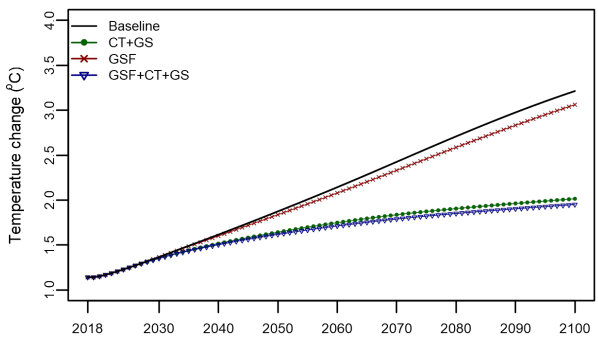
(b) Firms' profit rate



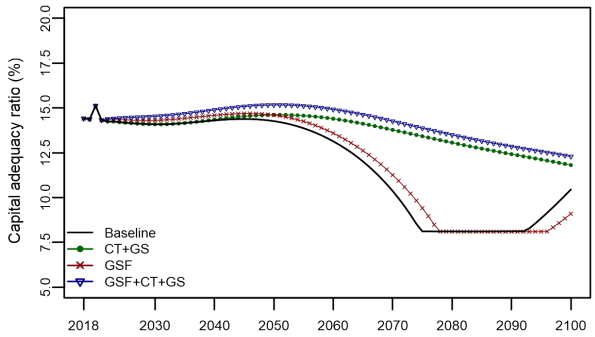
(c) CO_2 emissions



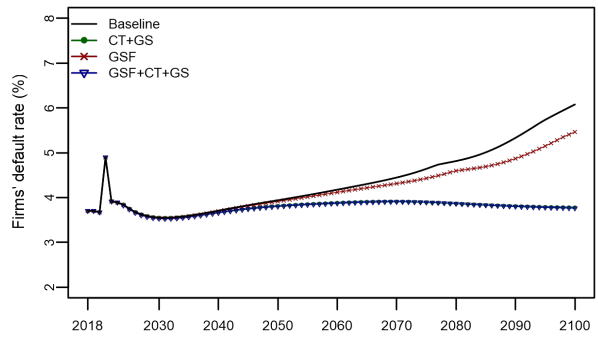
(d) Temperature change from the pre-industrial period



(e) Capital adequacy ratio



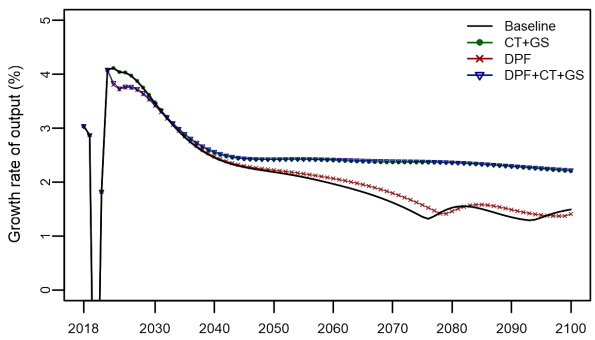
(f) Firms' default rate



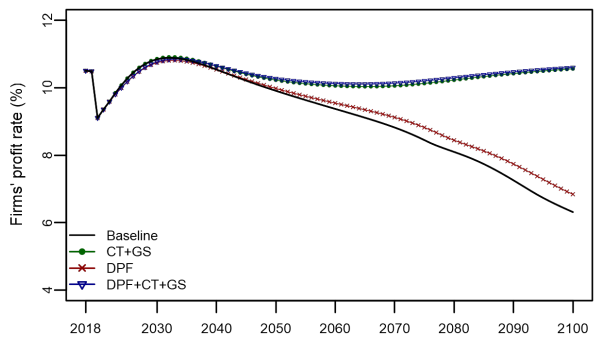
Note: The values used in the baseline scenario are reported in Appendix E. All policy shocks take place in 2022. In the CT (Carbon Tax) + GS (Green Subsidies) scenario, the carbon tax becomes equal to the carbon price in the SSP3 3.4 W/m^2 scenario and the green subsidies increase accordingly such that they are equal to the new carbon tax revenues. In the GSF (Green Supporting Factor) scenario, the risk weight on green loans decreases by 25 percentage points. In the GSF+CT+GS scenario, the GSF and CT+GS policy are implemented simultaneously.

Figure 4: Effects of a combined implementation of the dirty penalising factor with an increase in carbon tax and green subsidies, 'High carbon tax' pathway

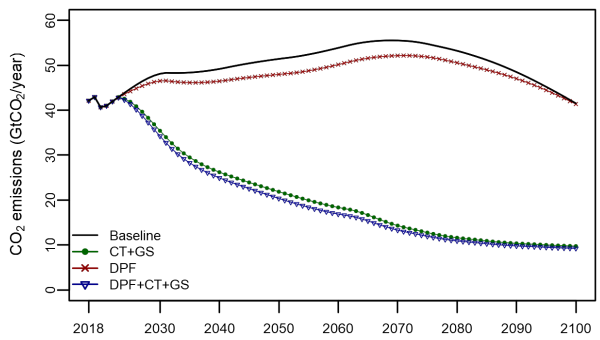
(a) Growth rate of output



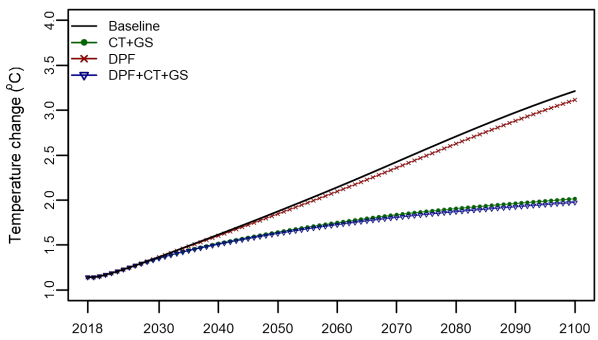
(b) Firms' profit rate



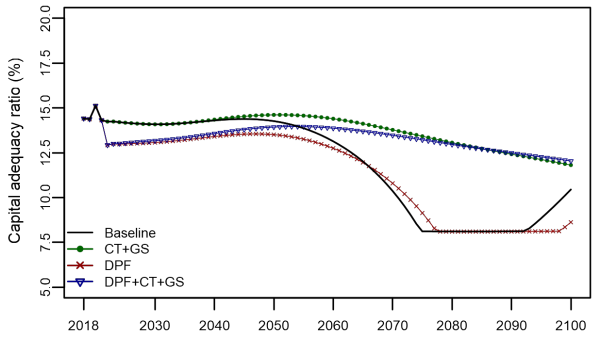
(c) CO_2 emissions



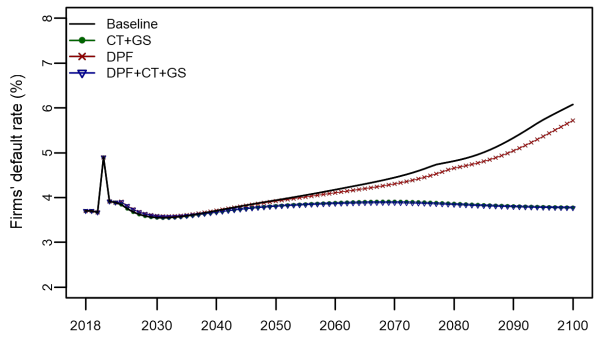
(d) Temperature change from the pre-industrial period



(e) Capital adequacy ratio



(f) Firms' default rate



Note: The values used in the baseline scenario are reported in Appendix E. All policy shocks take place in 2022. In the CT (Carbon Tax) + GS (Green Subsidies) scenario, the carbon tax becomes equal to the carbon price in the SSP3 3.4 W/m^2 scenario and the green subsidies increase accordingly such that they are equal to the new carbon tax revenues. In the DPF (Dirty Penalising Factor) scenario, the risk weight on dirty loans increases by a maximum of 25 percentage points. In the DPF+CT+GS scenario, the DPF and CT+GS policy are implemented simultaneously.

5. Conclusion

We have examined the effects of GDCRs on climate-related financial risks within a dynamic framework in which climate and macrofinancial feedback effects play a key role. We have shown that GDCRs can overall have a more beneficial effect on transition and physical climate-related financial risks, if they are implemented simultaneously. Although these effects do not turn out to be quantitatively very strong, they can play a supportive role in mitigating climate risks for the financial system. When GDCRs are put in place in conjunction with green fiscal policies, the transition risks of the GSF can increase, while the transition risks of the DPF can decline. In addition, the beneficial effects of green fiscal policies on physical risks are reinforced when they are accompanied by GDCRs.

Our analysis suggests that climate-related financial risks should not be viewed as being determined independently of the decisions of banks, including the decisions driven by changes in capital requirements. This is crucial because in the discussions about the role of GDCRs it is often implicitly assumed that these requirements should be set in a way that protects the banking system from *exogenously* determined risks. Recognising that risks are *endogenous* (in line with a macroprudential approach to financial regulation) opens up the possibility for adjusting these requirements in a way that induces the banking system to take decisions that reduce the climate risks posed to itself.

The step that we have made here by analysing GDCRs via a climate-enhanced macroprudential perspective opens an array of additional research questions. First, in this paper we have examined only a subset of transition risks. Although we paid attention to the transition risks that stem from the macro-level interaction between the real economy and the financial system and we considered different degrees of dirtiness for the investment of different sectors, we did not incorporate micro-based network effects that take explicitly into account the heterogeneity of firms and banks. The incorporation of such effects into our macrofinancial framework would significantly enhance the analysis of transition risks.[41]

Second, GDCRs do not constitute the only green finance policy that can affect climate-related financial risks. Future research could investigate the implications of additional green finance policies, as well as the interactions of other green finance policies with GDCRs. For example, it would be interesting to examine if the combined implementation of the DPF and a policy that links banks' access to central bank liquidity with the 'greenness' of their assets could lead to similar results, as those obtained in this paper when the DPF and the GSF are put in place simultaneously.

Third, our model abstracts from the housing market. The absence of this market is important. In many countries mortgages constitute a significant proportion of the assets of banks and it is well-known that mortgages can be significantly affected by physical and transition risks.

Fourth, in our simulations climate policies have been implemented at the global level. This implicitly assumes that GDCRs are, for example, introduced through the Basel framework and green fiscal policies are put in place in a coordinating manner around the world. In practice, it is more likely that these policies will be implemented at the national level (especially the fiscal ones). A national implementation of these policies requires the consideration of additional factors in the policy evaluation process. For instance, an isolated national implementation of the DPF would probably induce some 'regulatory arbitrage' whereby banks would move activities into countries in which the DPF is not in place. Similarly, an isolated introduction of a rise in carbon tax can cause carbon leakage effects. On the other hand, an isolated introduction of the GSF in a specific country could induce banks that engage in green finance to move activities into this country; and an increase in green subsidies could induce similar reactions in the non-financial sector. Hence, the impact of isolated national policies on the global transition and physical risks arguably depends on the nature of the policy. Our quantitative analysis might overestimate the effects of a nationally implemented DPF and carbon tax policy, but

[41] The methodologies and the modelling approaches developed by Battiston et al. (2017), Stolbova et al. (2018), Lamperti et al. (2018), Monasterolo and Raberto (2018) and Monasterolo and Raberto (2019) can be used in this direction.

potentially underestimates the effects of the GSF and green subsidies.

All the above-mentioned issues could be the subject of additional research. Such research could be part of a broader agenda that would explicitly adopt a dynamic macrofinancial approach to the analysis of climate-related financial risks.

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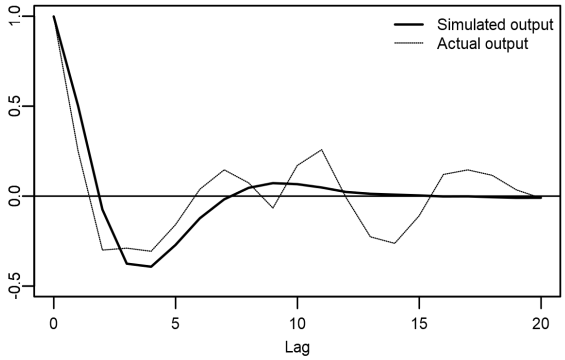
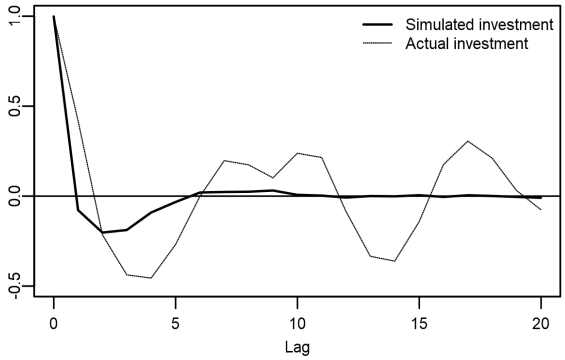
Appendix A Validation exercises for selected variables

Figure A.1: Auto-correlations of the cyclical components of selected variables, actual and simulated data

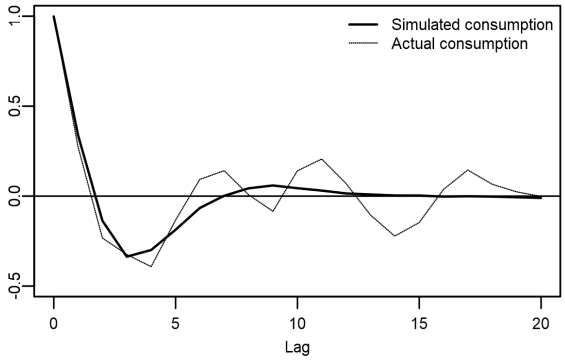
(a) Auto-correlation: output



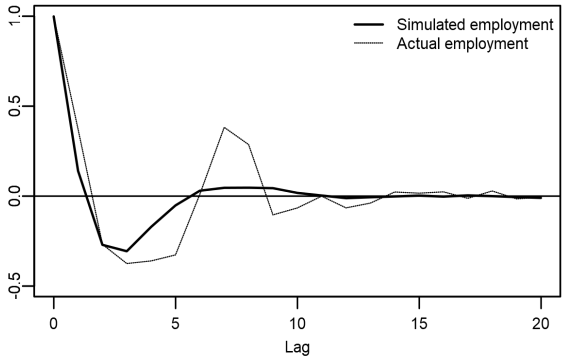
(b) Auto-correlation: investment



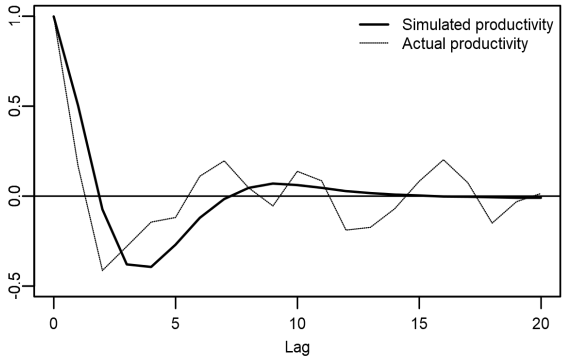
(c) Auto-correlation: private consumption



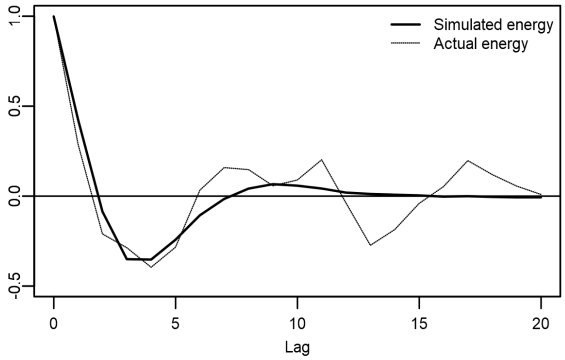
(d) Auto-correlation: employment



(e) Auto-correlation: productivity



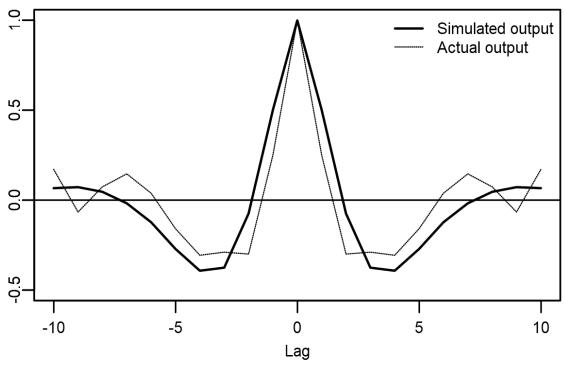
(f) Auto-correlation: energy



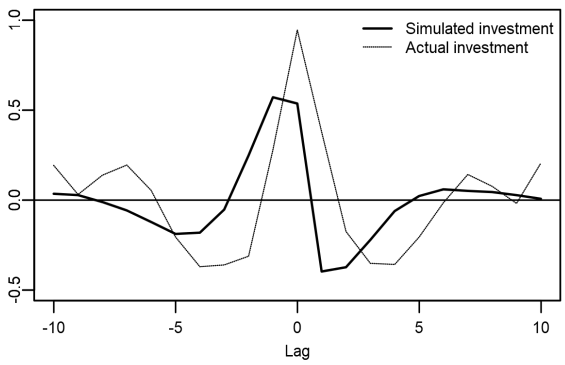
Note: The cyclical components have been obtained by applying the Hodrick-Prescott filter to the logarithm of the variables (smoothing parameter=6.25). The figures show the correlations between the cyclical component of each variable at time t and the cyclical component of the same variable at time t-lag, where lag=0, 1, 2,. . . ,20. For the simulated data, the cross-run average auto-correlations have been reported for the period 2023-2100 by using the baseline scenario without climate damages (stochastic version of the model; see Section 3.1); we have excluded the period 2018-2022 due to the high volatility linked to COVID-19. For the actual data, the time periods that have been used are: 1972-2018 (real output, real private consumption, real private investment), 1972-2017 (total primary energy supply) and 1991-2018 (employment and productivity). The data sources are: World Bank (real output, real private investment, real private consumption, employment and productivity) and IEA (total primary energy supply).

Figure A.2: Cross-correlations of the cyclical components of selected variables, actual and simulated data

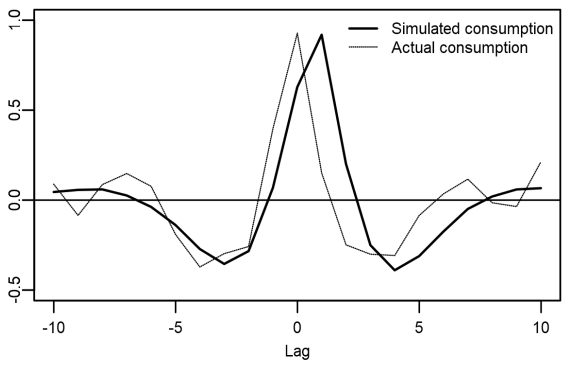
(a) Cross-correlation: output



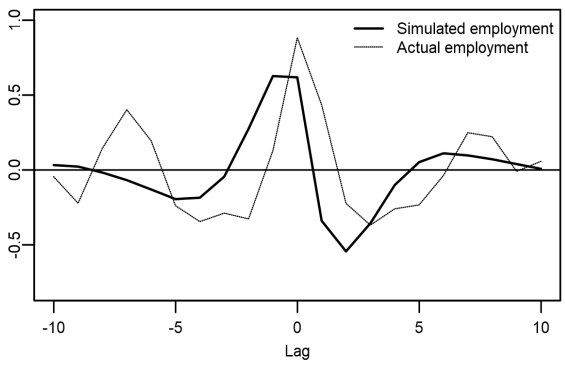
(b) Cross-correlation: investment



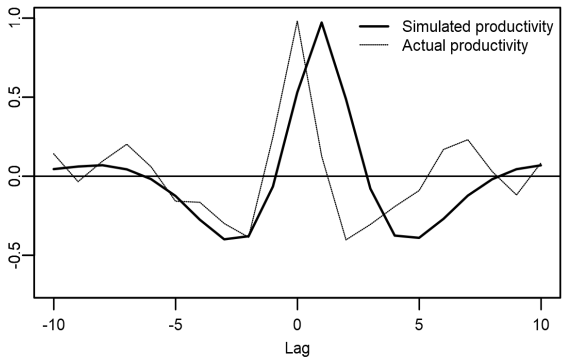
(c) Cross-correlation: private consumption



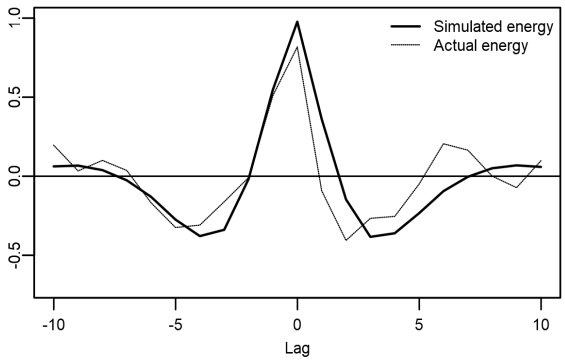
(d) Cross-correlation: employment



(e) Cross-correlation: productivity



(f) Cross-correlation: energy



Note: The cyclical components have been obtained by applying the Hodrick-Prescott filter to the logarithm of the variables (smoothing parameter=6.25). The figures show the correlations between the cyclical component of output at time t and the cyclical component of each variable at time t-lag, where lag=-10, -9, . . . ,9, 10. For the simulated data, the cross-run average cross-correlations have been reported for the period 2023-2100 by using the baseline scenario without climate damages (stochastic version of the model; see Section 3.1) we have excluded the period 2018-2022 due to the high volatility linked to COVID-19. For the actual data, the time periods that have been used are: 1972-2018 (real output, real private consumption, real private investment), 1972-2017 (total primary energy supply) and 1991-2018 (employment and productivity). The data sources are: World Bank (real output, real private investment, real private consumption, employment and productivity) and IEA (total primary energy supply).

Table A.1: Standard deviation of the components of GDP, simulated and actual data

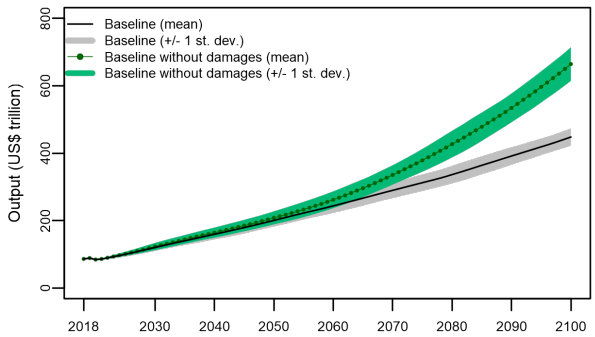
Variable	Simulated data	Actual data
Output	0.52	0.93
Investment	1.86	2.27
Private consumption	0.64	0.65
Government consumption	0.52	0.45

Note: All variables are in logarithms and have been detrended using the Hodrick-Prescott filter (smoothing parameter=6.25). For the simulated data, the cross-run average standard deviations have been reported for the period 2023-2100 by using the baseline scenario without climate damages (stochastic version of the model; see Section 3.1); we have excluded the period 2018-2022 due to the high volatility linked to COVID-19. For the actual data, the period 1972-2018 has been used. All data come from World Bank.

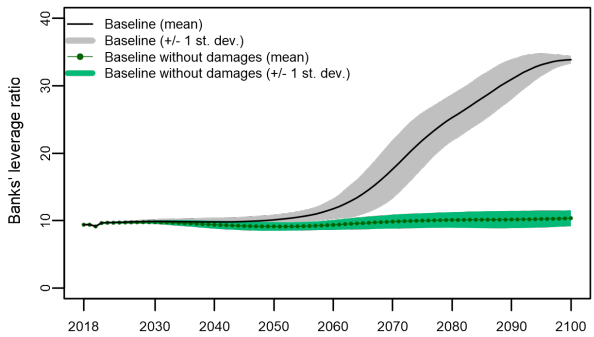
Appendix B Baseline scenario with and without climate damages

Figure B.1: Baseline scenario with and without climate damages

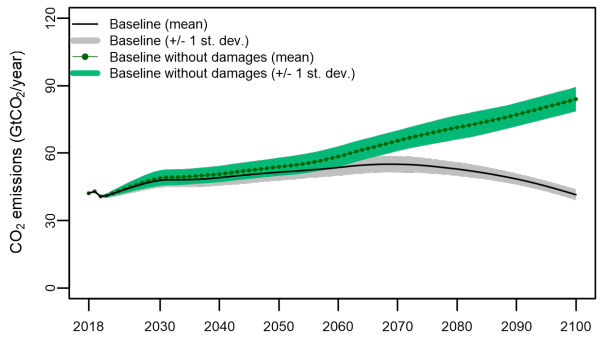
(a) Output



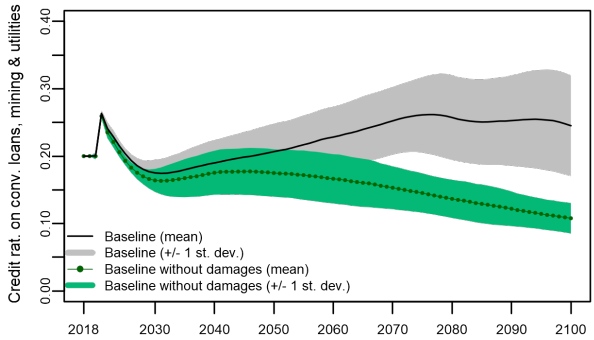
(b) Banks' leverage ratio



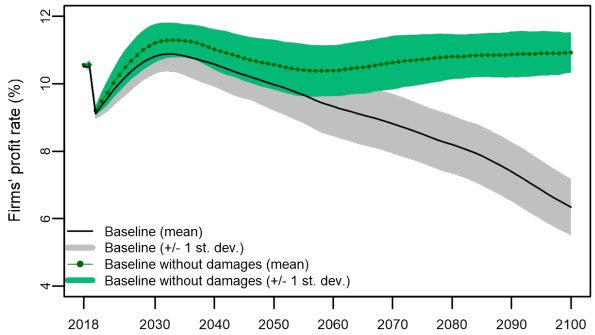
(c) CO_2 emissions



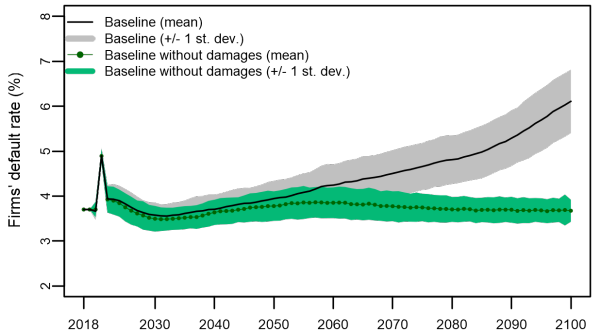
(d) Credit rationing on conventional loans, 'mining and utilities' sector



(e) Firms' profit rate



(f) Firms' default rate



Note: The figure reports cross-run averages and standard deviations from 200 Monte Carlo simulations (stochastic version of the model; see Section 3.1). The values used in the baseline scenario are reported in Appendix E.

Appendix C Data and econometric estimations for the determinants of non-financial corporate credit and loan spreads

Table C.1: Data sources

Variable	Description	Time period	Source
$\Delta CREDIT$	Logarithm of credit provided to non-financial corporations at market value (US$ billion), deflated using the GDP deflator	1995-2018	BIS (nominal credit), OECD (GDP deflator)
CA	Capital-to-assets ratio of the banking sector	1995-2018	OECD
DOS	Debt-to-operating surplus ratio for non-financial corporations	1995-2018	OECD
$SPREAD$	Interest rate spread (lending rate minus deposit rate)	1995-2018	World Bank
CAR	Capital adequacy ratio	2005-2018	IMF, Financial Soundness Indicators

Table C.2: Descriptive statistics

Variable	Mean	Max	Min	Std dev.
$\Delta CREDIT$	0.03	0.71	-0.66	0.13
CA	0.08	0.25	0.01	0.05
DOS	0.05	0.24	0.02	0.03
$SPREAD$	0.03	0.20	-0.01	0.02

Table C.3: Results from the estimation of panel data regressions, dependent variable: $\Delta CREDIT$, eq. (28)

	Fixed effects		Random effects		FGLS		IV-2SLS	
CA	0.644	***	0.332	***	0.331	***	0.800	***
	(0.135)		(0.061)		(0.075)		(0.294)	
DOS	-1.170	***	-0.518	***	-0.393	*	-3.223	***
	(0.454)		(0.192)		(0.203)		(1.219)	
Country weights	Yes		Yes		Yes		Yes	
Number of countries	28		28		28		28	
Observations	574		574		574		426	
Hausman test (p-value)	0.001							
Wooldridge test for autocorrelation (p-value)	0.003							
Modified Wald test for groupwise heteroskedasticity (p-value)	0.000							
AR(1) coefficient					0.118			
Instruments							CA_{-1}, DOS_{-1}, DOS_{-3}, DOS_{-4}, DOS_{-5}, DOS_{-6}	
Sargan-Hansen J test (p-value)							0.092	
Cragg-Donald statistic							71.902	
Cragg-Donald statistic: critical value							21.68	
Endogeneity test (p-value)							0.137	

*Note: ***, ** and * denote statistical significance at 1%, 5% and 10% significance level, respectively. Standard errors are reported in the parentheses. For the definition of variables, see Table C.1. FGLS: Feasible Generalised Least Squares; IV-2SLS: Instrumental Variables Two-Stages Least Squares; the critical values for the Cragg-Donald statistic are taken from Stock and Yogo (2005).*

Table C.3 reports the econometric estimations for the determinants of loans (see eq. (28)). The Hausman test suggests that the fixed effects model is preferred over the random effects one. The Wooldridge test and the Wald test imply that the null hypotheses of no heteroskedasticity and no autocorrelation are rejected; this leads us to run a FGLS model. The IV-2SLS approach allow us to address endogeneity issues that might arise in our regressions. The Sargan-Hansen J suggests that the instruments are valid. According to the Cragg-Donald Wald F test, our instruments are not weak, while the endogeneity test implies that our regressors are not exogenous, providing support for the use of a model that addresses endogeneity. However, experimentation with different instruments shows that the conlcusion about the existence of endogeneity might not be very robust. In all models the coefficients of our independent variables are statistically significant with the expected sign.

Table C.4: Results from the estimation of panel data regressions, dependent variable: *SPREAD*, eq. (36)

	Fixed effects		Random effects		FGLS		IV-2SLS	
CA	-0.080	***	-0.064	***	-0.031	**	-0.039	
	(0.015)		(0.016)		(0.013)		(0.029)	
DOS	0.283	***	0.181	***	-0.189	***	0.266	***
	(0.047)		(0.049)		(0.056)		(0.069)	
Country weights	Yes		Yes		Yes		Yes	
Number of countries	21		21		21		21	
Observations	282		282		282		243	
Hausman test (p-value)	0.481							
Wooldridge test for autocorrelation (p-value)	0.000							
Modified Wald test for groupwise heteroskedasticity (p-value)	0.000							
AR(1) coefficient					0.885			
Instruments							CA_{-1}, CA_{-2}, DOS_{-1}	
Sargan-Hansen J test (p-value)							0.325	
Cragg-Donald statistic							56.951	
Cragg-Donald statistic: critical value							13.430	
Endogeneity test (p-value)							0.835	

*Note: ***, ** and * denote statistical significance at 1%, 5% and 10% significance level, respectively. Standard errors are reported in the parentheses. For the definition of variables, see Table C.1. FGLS: Feasible Generalised Least Squares; IV-2SLS: Instrumental variables Two-Stages Least Squares; the critical values for the Cragg-Donald statistic are taken from Stock and Yogo (2005).*

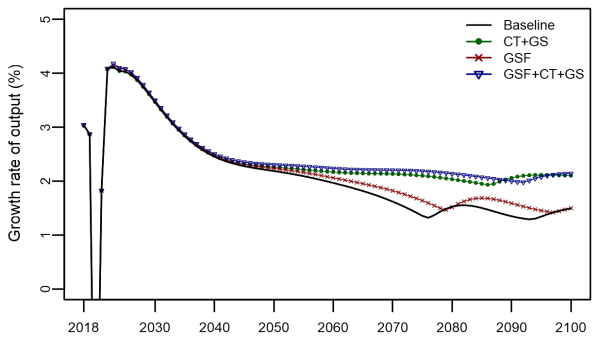
Table C.4 reports the econometric estimations for the determinants of the loan spread (see eq. (36)). The Hausman test shows that the random effects model is preferred over the fixed effects one. As in the case of the loan regressions, heteroskedasticity and autocorrelation exist (see the Wooldridge

test and the Wald test). In the IV-2SLS regression, the Sargan-Hansen J test suggests that the instruments are valid, while the Cragg-Donald Wald F test shows that our instruments are not weak. Based on the endogeneity test, the regressors are endogenous. The coefficient of the capital-to-assets ratio (CA) is always negative and is statistically significant in 3 out of 4 models. The coefficient of the debt-to-operating surplus ratio (DOS) is always statistically significant and it has the expected sign in 3 out of 4 models.

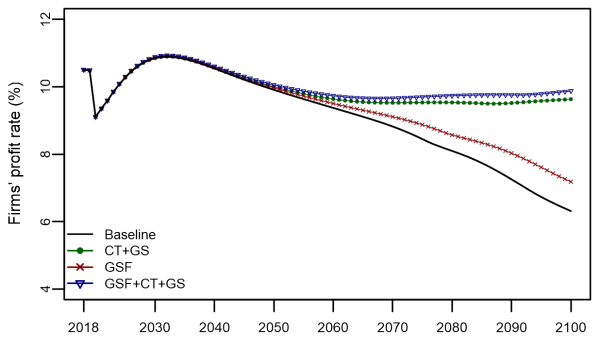
Appendix D Effects of green fiscal policy, 'Medium carbon tax' pathway

Figure D.1: Effects of a combined implementation of the green supporting factor with an increase in carbon tax and green subsidies, 'Medium carbon tax' pathway

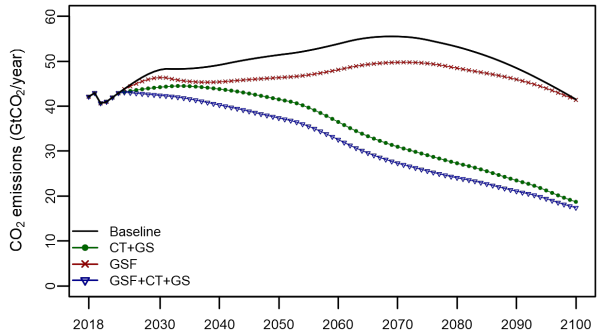
(a) Growth rate of output



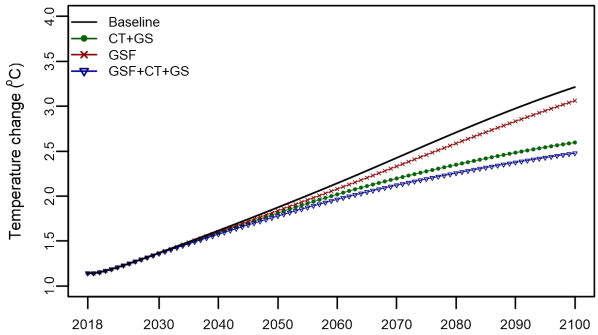
(b) Firms' profit rate



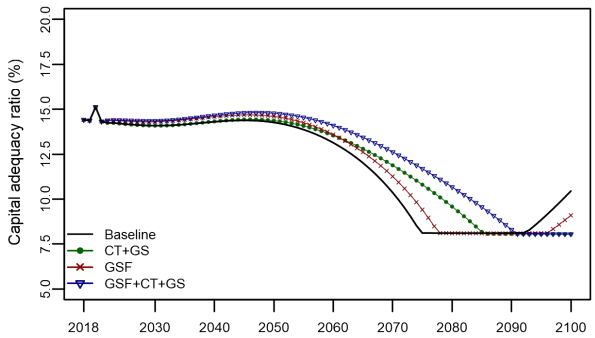
(c) CO_2 emissions



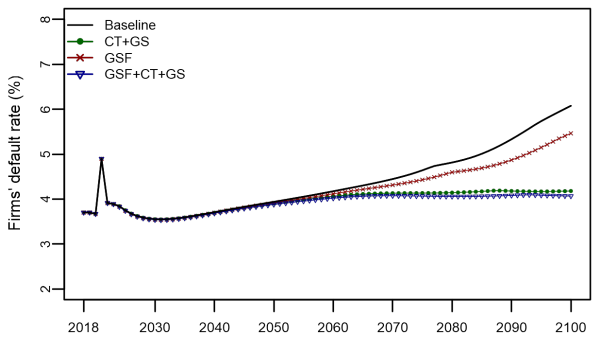
(d) Temperature change from the pre-industrial period



(e) Capital adequacy ratio



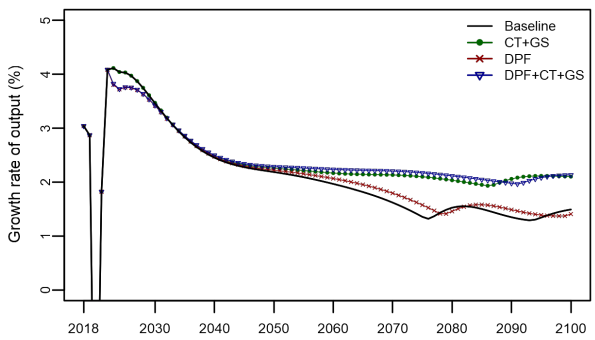
(f) Firms' default rate



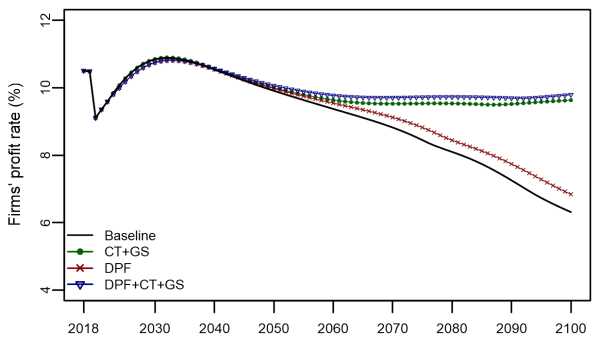
Note: All policy shocks take place in 2022. The values used in the baseline scenario are reported in Appendix E. In the CT (Carbon Tax) + GS (Green Subsidies) scenario, the carbon tax becomes equal to the carbon price in the SSP3 4.5W/m^2 scenario and the green subsidies increase accordingly such that they are equal to the new carbon tax revenues. In the GSF (Green Supporting Factor) scenario, the risk weight on green loans decreases by 25 percentage points. In the GSF+CT+GS scenario, the GSF and the CT+GS policy are implemented simultaneously.

Figure D.2: Effects of a combined implementation of the dirty penalising factor with an increase in carbon tax and green subsidies, 'Medium carbon tax' pathway

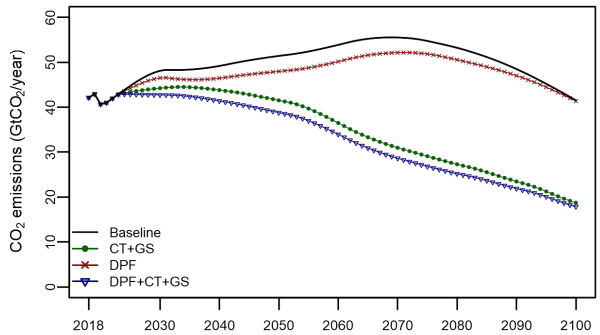
(a) Growth rate of output



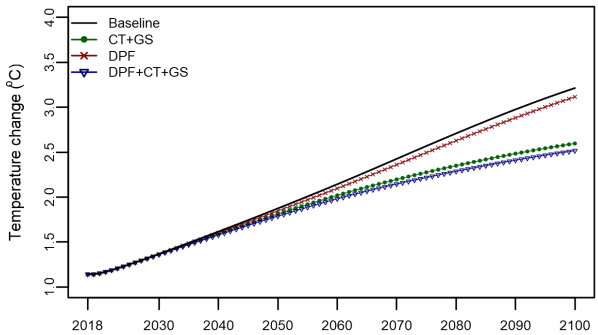
(b) Firms' profit rate



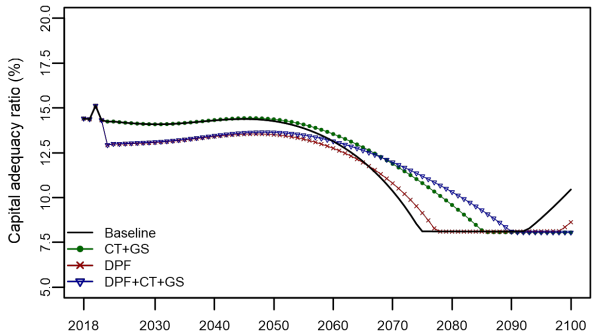
(c) CO_2 emissions



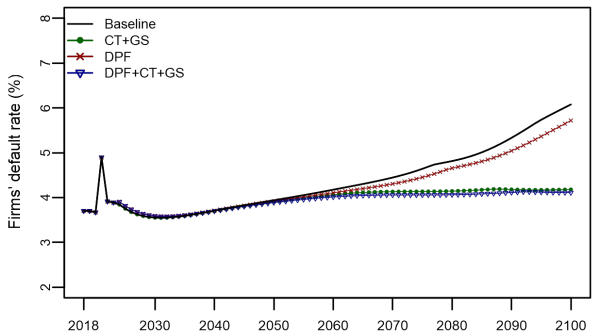
(d) Temperature change from the pre-industrial period



(e) Capital adequacy ratio



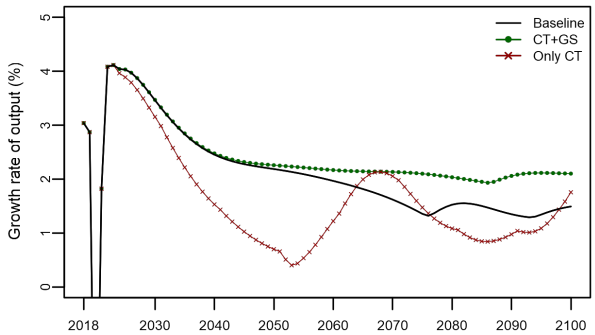
(f) Firms' default rate



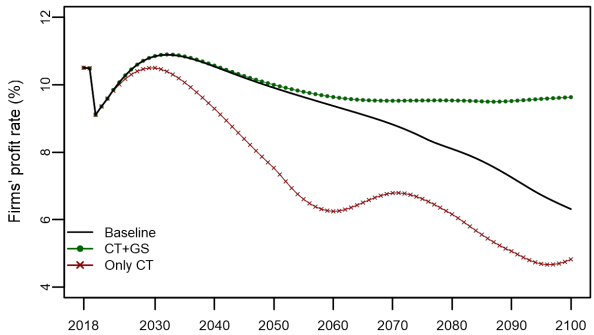
Note: All policy shocks take place in 2022. The values used in the baseline scenario are reported in Appendix E. In the CT (Carbon Tax) + GS (Green Subsidies) scenario, the carbon tax becomes equal to the carbon price in the SSP3 4.5W/m^2 scenario and the green subsidies increase accordingly such that they are equal to the new carbon tax revenues. In the DPF (Dirty Penalising Factor) scenario, the risk weight on dirty loans increases by a maximum of 25 percentage points. In the DPF+CT+GS scenario, the DPF and the CT+GS policy are implemented simultaneously.

Figure D.3: Effects of an increase in carbon tax with and without tax revenues recycling, 'Medium carbon tax' pathway

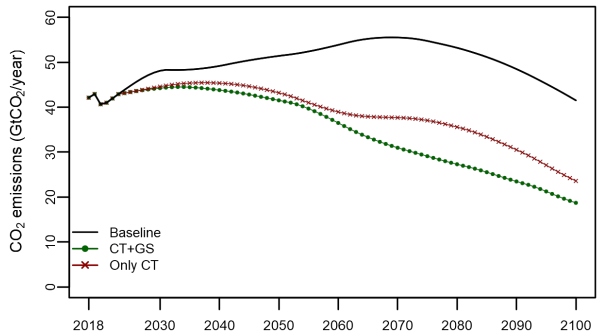
(a) Growth rate of output



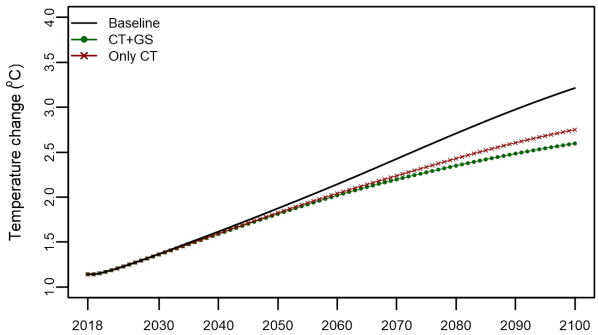
(b) Firms' rate of profit



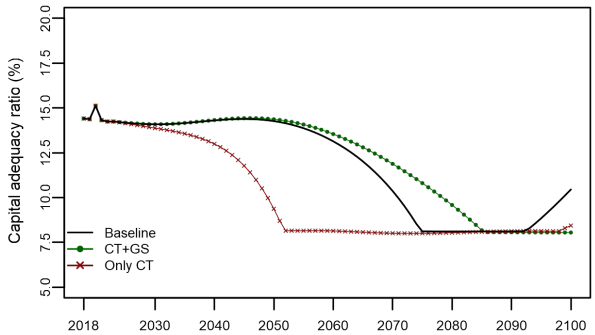
(c) CO_2 emissions



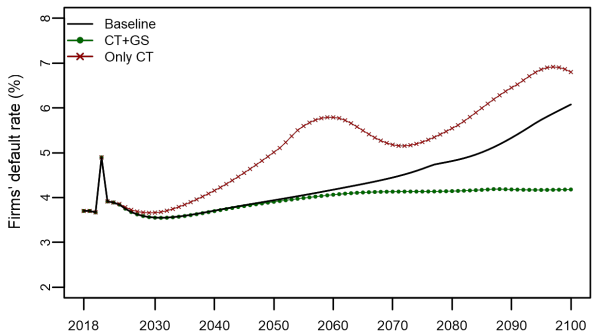
(d) Temperature change from the pre-industrial period



(e) Capital adequacy ratio



(f) Firms' default rate



Note: All policy shocks take place in 2022. The values used in the baseline scenario are reported in Appendix E. In the CT (Carbon Tax) + GS (Green Subsidies) scenario, the carbon tax becomes equal to the carbon price in the SSP3 4.5W/m^2 scenario and the carbon tax revenues increase accordingly such that they are equal to the new carbon tax revenues; in the 'Only CT' scenario, the carbon tax becomes equal to the carbon price in the SSP3 4.5W/m^2 scenario but the carbon tax revenues are not recycled.

Appendix E Supplementary Information

Supplementary information associated with this paper is available in the manual of DEFINE 1.1 which can be found at: www.define-model.org.