Can large-scale RDI funding stimulate post-crisis recovery growth? Evidence for Finland during COVID-19

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ABSTRACT

The COVID-19 pandemic and subsequent public health restrictions led to a significant slump in economic activities around the globe. This slump has been met by various policy actions to cushion the detrimental socio-economic consequences of the COVID-19 crisis and eventually bring the economy back on track. We provide an ex-ante evaluation of the effectiveness of a massive expansion of RDI funding in Finland to stimulate post-crisis recovery growth through an increase in RDI activities of Finnish firms. We make use of the fact that novel RDI grants for firms in disruptive circumstances granted in 2020 were allocated through established RDI policy channels. This allows us to estimate the structural link between RDI funding and economic growth for Finnish NUTS-3 regions based on pre-COVID-19 data. Estimates are then used to predict regional recovery growth out of sample and to quantify the growth contribution of RDI funding. Depending on the chosen scenario, our out-of-sample predictions point to a mean recovery growth rate of GDP between $-2.4\%$ in 2021 after a decline of up to $-2.5\%$ in 2020. RDI funding constitutes a significant pillar of the recovery process with mean contributions in terms of GDP growth of between 0.4 and 1 \%-points.

1. Introduction

In 2020, the Finnish economy plummeted, along with the rest of the world, due to COVID-19. The pandemic was met with public health measures to restrict mobility and social contacts (Banholzer et al., 2021), which led to a decrease in overall consumer demand for many goods and services along with supply restrictions. Consequently, by the time of this analysis, the volume of Finland’s GDP was estimated to shrink by around $-1.8\%$ in 2020 according to data from Statistics Finland. In 2021, the Finnish economy has started to recover as vaccinations have allowed to open up the society. As of October 2021, the Finnish employment rate had already recovered to its pre-crisis level and the volume of GDP has been growing again.\textsuperscript{1} Depending on the forecasting institution, predictions for the Finnish recovery growth rate of national GDP range from 2.9 to 3.7 \% for the year 2021.\textsuperscript{2}

In addition to the re-opening of the society, another important factor that has likely contributed to this recovery process is the massive public support given to the private sector: the amount of government subsidies to firms has grown significantly since 2020 compared to the pre-crisis situation. Besides standard instruments providing wage and cost subsidies, the Finnish government has also expanded its available support mechanisms for firms, among others, through the “Funding for business development in disruptive circumstances” program administered by Business Finland (BF). This program allocates research, development, and innovation (RDI) grants to firms with innovative ideas on tackling the detrimental effects of COVID-19 to their businesses. With an overall volume of €1740 M in 2020 (compared to €570 M in 2019) traditional and new BF funding channels are key fiscal policy measures used in Finland to stimulate economic activity during the COVID-19 crisis. This increase of public RDI funding in 2020 has been criticised in public debates in Finland. It was seen that the money would have been better spent for the direct support of firms that were the most affected by the...
2. RDI funding and regional growth

Innovation is considered as the key to economic development. There are naturally differences between the socio-economic conditions and the institutional capacity of regions to turn innovation inputs such as public RDI funding into economic growth (Oughton et al., 2002). Still, the impact of RDI on regional economic growth has been found to be significant, particularly, for more developed regions in Northern Europe (Sterlacchini, 2008), but there is also some recent evidence for innovation-led regional development in emerging economies (Rodriguez-Pose and Villarreal Peralta, 2015). Therefore, public RDI funding is commonly regarded as a promising effort to achieve long-term goals like facilitating regional and economic growth, competitiveness and employment as well as tackling environmental and social problems (Acciai, 2021).

The need for public RDI support rises from the averseness of private firms to invest on expensive and risky, but socially desirable, research due to knowledge spillovers that prevent them from fully cashing in on new potentially resultant new products and processes (Plank and Doblinger, 2018). On the contrary, public RDI funding programs are (or at least should be) designed to stimulate knowledge spillovers. As stated by Feldman and Kelley (2006: p. 1509), RDI “subsidies are an effective public policy instrument when knowledge spillovers exist”. As explained by Veugelers (2021) public RDI funding can, however, also substitute (if the RDI project would have been carried out in any case without public funding) or crowd-out private RDI activities (by increasing the demand for and, thus also, the costs of RDI). Further, not all public RDI funding will lead to successful innovations nor subsequent economic outcomes.

Nonetheless, at least in Finland the positive link between public RDI funding and innovation is relatively clear: Torregrosa-Hetland et al. (2019) have demonstrated – based on innovation output data – that out of the identified 2600 significant Finnish innovations, 35–55 % were stimulated by the public sector. Further, a recent impact study (Fornaro et al., 2020) found clear evidence that public RDI funding increased the recipient firms’ RDI intensity, job creation, collaboration with external partners and productivity, while Piekkola (2007) found clear RDI spillover effects in terms of regional productivity and employment growth in Finland. In short, despite the obvious country- and policy-specific variations, there is abundant evidence suggesting that public RDI funding and regional development are intertwined (e.g., Becker, 2015; Boeing et al., 2022) through the mediating role that the funding can have on economic growth. For example:

1. Public sector RDI funding has been shown to lead to employment growth (Link and Scott, 2013) and particularly increase the number of R&D employees (Czarnitzki and Lopes-Bento, 2013).
2. Public sector RDI funding has been shown to increase, rather than substitute or crowd-out, the private sector's RDI activities and investments (Almus and Czarnitzki, 2003; Cin et al., 2017).
3. Public sector RDI funding is related to realized patenting by private firms (Haapanel et al., 2017; Czarnitzki and Hussinger, 2018).

Therefore, a major threat to innovation during a times of crisis (Oughton et al., 2002) as the slowdown of RDI funding and investments. Governments struggle with diminishing tax revenues and budgets and are compelled to implement short-term solutions rather than long-term development (Pelless et al., 2018), while firms might be forced to enter a survival mode postponing future R&D expenses (Peschau and Schmuck, 2019). However, since innovation drives economic growth in the long run, governments are advised to find ways to increase, rather than decrease, their RDI funding in times of crisis (Makkonen, 2013).

As a specific reference to public RDI funding in times of crisis, Aristei et al. (2017) have indicated that public RDI funding has had at least a small positive impact on thwarting the reduction of firms’ own RDI efforts in the aftermath of the economic crisis of 2008. Contrarily, Hud and Hussinger (2015), while reporting overall positive effect of RDI...
subsidiaries on SMEs’ investment behavior, found evidence supporting the remarks that public RDI funding crowded out private RDI during the economic crisis of 2008. As such, the evidence on the impacts of public RDI funding during times of crisis is still mixed. However, the evidence is leaning more towards positive outcomes (e.g., Brautzsch et al., 2015; Cruz-Castro et al., 2018). For example, based on data on OECD countries, Rehman et al. (2020: p. 349) conclude that in the case of the economic crisis of 2008, public support to RDI “is a good strategy for an economy to confront economic crisis effectively by increasing the technological innovation in the private sector”.

While, the economic crisis of 2008 is very different from the contemporary crisis caused by the COVID-19 pandemic, the lessons learned from previous crises do, however, provide useful benchmarks when designating policy actions to mitigate the negative impacts of the contemporary one. The responses to tackling the COVID-19 pandemic indicate that governments have, at least partly, recognized that one of the best instruments for surviving and recovering from crises are related to supporting RDI (Barajas et al., 2021). In fact, several countries have included RDI policies into their efforts in tackling the negative effects of the COVID-19 pandemic (Braunerhjelm, 2022). We will utilize one such country, Finland, as the empirical case in this paper.

3. The case of Business Finland

Business Finland (BF) is the Finnish government organization for innovation funding and trade, tourism and investment promotion. It operates under the Finnish Ministry of Employment and the Economy. It was formed in 2018 by merging its predecessors Tekes (the Finnish Funding Agency for Technology and Innovation) and Finpro (Finland Trade Promotion Organization). Business Finland is the main funding agency for research and technology development in Finland. As such it is a key intermediary between the government and innovative organizations (Inkinen and Suorsa, 2010) and a vital part of the Finnish innovation system (Ramstad, 2009).

Business Finland funds universities, research institutes, firms registered in Finland as well as public bodies. In the case of firms, RDI funding through Business Finland is normally given to encourage companies to improve their ability to develop and apply new technologies and to transform research-stage ideas into viable businesses via (a combination of) direct unconditional grants as well as soft and guaranteed low-interest or capital loans conditional on the success of the resulting business (Piekkola, 2007).

As explained by Takalo et al. (2013: p. 260), the public decision criteria of Business Finland are based on the project’s estimated effects on the competitiveness of the applicant, the technology to be developed, the resources reserved for the project, the collaboration with other organizations and societal benefits. The applicants need to include the purpose and the budget of their intended RDI projects for which BF funding is needed together with the applied amount of funding (very large subsidies are rarely granted). The subsidy is granted as a share (depending on the size of the organization and the type of the project normally up to 40–65 %) of the total RDI costs and mostly given after the RDI investments are made.

In 2020, as a response to the COVID-19 pandemic, Business Finland launched a new funding program: “Funding for business development in disruptive circumstances”. The funding was channeled through two types of grants:

1. Preliminary funding for companies during business disruptions (max. €10,000 and 80 % of the project’s total costs, out of which up to 70 % can be paid in advance): to be used for investigating and planning new business, alternative subcontracting chains, and ways to organize production during and after the disruption caused by the coronavirus

2. Development funding for companies during business disruptions (max. €100,000 and 80 % of the project’s total costs, out of which up to 70 % can be paid in advance): to be used for carrying out development plans to improve the potential for success during and after the disruption caused by the coronavirus via the creation of new product- or production-related solutions

The funding criteria were uniform for all firms across all Finnish regions and based on competition, but the funding program was specifically designed to fit the needs of SMEs. The maximum funding level can be considered quite modest compared to the regular funding given by Business Finland: in 2020, the average of granted funding per firm was €30,000 smaller than in 2010-2019 (ca. €100,000). The application period for the program ran in 2020. The program received almost 30,000 applications out of which circa 20,000 were funded. The total amount of granted funding via this instrument surmounted to €990 M in 2020. The instrument was the largest of all COVID-19 support measures of the Finnish government that have, thus far, totaled up to €2400 M. The second largest support instrument, business cost support from the State Treasury amounted to €702 M, while the rest (such as the remuneration for business restrictions in the restaurant business) of the measures have been significantly smaller. Overall BF funding (established measures and the “Funding for business development in disruptive circumstances” program) reached a level of €1740 M in 2020 (compared to €570 M in 2019).

4. Data and stylized facts

We utilize data collected at the NUTS-3 level in Finland for our empirical estimations. There are 19 NUTS-3 regions in Finland: 18 in mainland Finland and one covering the autonomous region of Åland. Due to missing data in some of the key variables utilized in this paper, Åland has been excluded from the analysis. The remaining NUTS-3 regions correspond to the second tier of the administrative regional division in Finland – state, regions (maakunta) and municipalities.

Descriptive statistics and exact definitions of the utilized variables at the NUTS-3 level are given in Table 1. While most of the data were gathered from the database (and archives) of Statistics Finland, patent data were derived from the OECD RegPat database and data on RDI funding were provided by Business Finland. The overall database covers the time period from 1995 (when Finland joined the EU) up to 2018 (the latest year available for the full set of utilized variables at the time of data collection in August 2021), with the exception of BF funding data which is available until 2020.

Turning to some stylized facts of RDI funding through Business Finland, Panel A of Fig. 1 shows the evolution of funding volumes over time. While overall funding volumes have moderately grown over the period 1995 to 2010, thereafter funding levels have mainly stayed constant or slightly declined around 2016 to 2018. More strikingly however, BF funding has more than tripled in 2020 compared to its average pre-COVID funding level. As outlined above, this increase can mainly be attributed to the new funding program under the heading “Funding for business development in disruptive circumstances”. The latter amounts to approximately 57 % of total RDI funding of Business Finland in 2020.

In addition, Panel B of Fig. 1 (Boxplots) shows that the distribution of

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3 Information on the funding rules of Business Finland can be found from (Accessed 19 October 2021): https://www.businessfinland.fi/en/for-finnish-customers/services/funding/research-and-development

4 Information on funding rules for business support in disruptive circumstance can be found at (Accessed 13 October 2021): https://www.businessfinland.fi/en/for-finnish-customers/services/funding/disruptive-situations-funding

5 For an overview (in Finnish) on government support instruments see (Accessed 13 October 2021): https://yle.fi/uutiset/3-12115110
on socio-economic and innovation indicators. However, in terms of increases in BF funding intensities during the COVID-19 crisis, many of the firms located in the most economically developed and populous regions of Finland have done consistently well in attracting BF funding. The top-ranking regions in terms of received BF funding include the regions of Uusimaa, Pirkanmaa, North Ostrobothnia and Southwest Finland. These four regions are centered around the largest Finnish cities of 1) Helsinki capital region (including Espoo and Vantaa), 2) Tampere, 3) Oulu and 4) Turku respectively (see Fig. A1). The result is in line with earlier evidence on regional development (Makkonen and Inkinen, 2015) and innovativeness (Valovirta et al., 2009) in Finland: the indicated regions (and cities) have done consistently (and historically) well in various benchmarking exercises based on socio-economic and innovation indicators. However, in terms of increases in BF funding intensities during the COVID-19 crisis, many of the smaller regions (in terms of population), such as the regions of Kainuu (+156.8 %), South Savo (+153.9 %) and Päijät-Häme (+153.1 %), have significantly increased their funding intensities. When looking at the share of grants allocated through the new funding program (Panel C of Fig. 2), we can see that funding plays a major role particularly in those regions that have not historically done so well in attracting BF funding.

5. Estimation strategy

Our estimation/forecasting approach is organized as a two-stage process: First, we run a series of in-sample estimations for the pre-COVID sample period 1995 to 2018 (i.e., last available sample year for regional data at the time of this analysis). In this stage, we are mainly interested in consistently quantifying the structural relationship between regional RDI funding intensities by Business Finland and annual GDP growth rates, where the latter variable is chosen as broad regional performance measure. While BF funding is mainly directed towards enhancing the firms’ RDI performance (as outlined above), we argue that an analysis of regional GDP growth rates (including RDI input factors) not only covers these underlying supply side mechanisms, but also accounts for potential demand-side effects of BF funding in the short run, for example, in terms of using BF funding to hire R&D personnel, buy research and other equipment etc. To not over- or underestimate the overall funding effect, however, we also estimate auxiliary equations for (private and public) RDI inputs, i.e., regional R&D expenditure and...
patent rate, in which BF funding intensities enter as a determinant as well. These estimated links add to the total contribution of BF funding on regional GDP growth if RDI variables turn out to be a statistically significant determinant of regional growth.

To arrive at a consistent pre-COVID benchmark specification, in terms of estimator choice, we make use of recent advances in macroeconomic modelling for panel data together with the estimation of factor models utilizing (near-time) information from national timeseries development for regional GDP forecasts (Kopoin et al., 2013; Lehman and Wohlrabe, 2013). Specifically, available information on national GDP growth (or available growth predictions) are used as an essential scaling factor to predict regional GDP development in the course of the severe COVID-19 shocks throughout 2020 and 2021. In similar vein, we use other national macroeconomic data on employment and population levels as well as the aggregate unemployment rate to extrapolate the corresponding regional variable levels if they are needed for our regional growth model. Details are given below.

Formally, the main GDP growth equation to be estimated is specified as follows

$$\Delta gdp_{it} = \beta \Delta x_{i,t-m} + \lambda F_t + \phi x_{i,t-1} + \mu_t + \epsilon_{i,t}. \quad (1)$$

In Eq. (1), $\Delta gdp_{it}$ measures the annual growth rate of GDP per employee (i.e., labor productivity) in region $i$ at time $t$ defined as $\Delta gdp_{it} = \log (GDP_{it}) - \log (GDP_{i,t-1})$ and $\Delta x_{i,t-m}$ is a vector of lagged regional short-run determinants (where $m$ defines the lag length for these predetermined variables) including changes in regional gross fixed capital formation, changes in the regional unemployment rate, private and public R&D expenditures, patent applications and BF funding intensities. All variables included in $\Delta x_{i,t-m}$ that are used to estimate the growth model enter Eq. (1) as logarithmic transformed values. The vector of coefficients $\beta$ accordingly measure the % response of regional GDP per employee growth to % changes in these regional short-run determinants as elasticities. As indicated by the lag structure in Eq. (1), we rely on weak exogeneity (pre-determinedness) for effect identification. This clearly limits the interpretation of estimated effects with regard to their causal nature. We argue, however, that pre-determinedness together with a multi-factor panel estimation approach to reduce the risk of inducing an omitted variable bias may be regarded as a suitable estimation approach to obtain robust structural regression coefficients at the regional level.

Apart from the inclusion of regional short-run determinants, $F_t$ captures common factors whose values vary across time but not across regions. In our default specification, we include national GDP growth as essential contemporaneous, common scaling factor for the temporal development of regional GDP levels. This approach lends itself to the empirical literature on common correlated effects (CCE) estimators (Chudik et al., 2011). While the CCE literature typically employs cross-sectional averages of the dependent variable as a key proxy for unobserved common factors over time (Pesaran, 2006), the advantage of using the national GDP growth rate, particularly for out-of-sample forecasts, is that here observations are available beyond the maximum sample period at the regional level.

As we find that the correlation between both variables (national GDP growth rate and average regional GDP growth rate) is very high ($\rho = 0.86$), this indicates that both aggregate factors can be used interchangeably without loss of estimation power. The coefficient (also referred to as factor loading in the CCE literature) that measure the response of regional GDP growth rates to changes in the national aggregate GDP growth rate can either be modelled to be constant across all regions ($\lambda$ for all $i$) or to vary across regions by taking the form $\lambda_i \cdot (1) \cdot \phi_i$ (cf., Coakley et al., 2002; Pesaran, 2006). The latter heterogeneous common factor approach acknowledges the fact the national-regional linkages in GDP growth may be different for the included NUTS-3 region, for instance, mirroring different sectoral structures and, thus, local/national business cycle synchronization. We test if coefficient homogeneity for $\lambda$ holds in our data setting.

Fig. 2. Spatial distribution of BF funding intensities and funding types (overall; share of funds for business development in disruptive circumstances)
Notes: Own calculations based on data provided by Business Finland.
While the inclusion of short-run determinants ($\Delta x_{it-m}$) in Eq. (1) is expected to cover a significant share in the intra-regional variation of $\Delta GDP_{it}$, a pure short-run model of regional GDP growth may fail to account for relevant information contained in relationship between GDP levels and regional stocks of production factors such as the investment rate, the region’s human capital endowment and further knowledge stocks. We make use of this long-run relationship in regional labor productivity levels and knowledge production factors in a single-equation cointegration framework (Engle and Granger, 1987; Phillips and Moon, 2000). In this context, the error correction term $ec_{it-n}$ captures deviations in this long-run relationship as

$$ec_{it-n} = \log(GDP_{it}) - (\hat{\delta} x_{it} + \mu_i)$$

with GDP$_{it}$ being a measure of GDP per employee (labor productivity) in region $i$ at time $t$ and $x_{it}$ is a vector of regional knowledge production factors. The coefficient vector $\hat{\delta}$ captures the correlation between GDP and (knowledge) production factors in the long run, where the subscript "−n" in Eq. (2) indicates that these coefficients are estimated on the basis of a fixed effects panel model (FEM) for variables in log levels with $\mu_i$ being a vector of region-fixed effects. In Eq. (2), negative values of $ec_{it-n}$ indicate a mismatch between regional endowments and GDP per employee levels (a deviation from the estimated long-run co-integration path). We accordingly expect that an adjustment of GDP levels takes place over time, which implies that the regional economy will grow until the long-run cointegration relationship is restored. In this logic, the coefficient $\hat{\delta}$ in Eq. (1) will have a negative sign and that its magnitude measures the speed of adjustment of regional GDP levels towards the long-run cointegration relationship underlying Eq. (2). The time index $t - n$ describes the chosen lag length for $ec_{it-n}$ in Eq. (1) (see Table 2 for details how this is implemented).

We include region-fixed effects in the short- and long-run equations to avoid an estimation bias arriving from unobserved time-constant factors at the regional level correlating with regional GDP levels and growth rates. While Eq. (2) is estimated by means of ordinary least squares (OLS), we additionally also check for potentially auto- and cross-sectionally correlated errors in $\epsilon_{it}$ by applying generalized least squares (GLS) estimation to Eq. (1) next to the default FEM estimator. Finally, while our default econometric approach is to apply homogeneous (pooled) estimators to the vector of structural coefficients $\beta$, we also run model comparisons with heterogeneous mean group estimators (Pesaran and Smith, 1995; Eberhardt and Teal, 2010), which estimate separate coefficients for each cross-sectional unit (i) and then calculate average estimation coefficients. This comparison helps us to detect potential estimator inconsistencies. Similarly, we also test for coefficient differences across time periods as a means to detect structural breaks in the data.

As outlined above, next to the main GDP growth regression, we also estimate short-run auxiliary regressions for RDI inputs as

$$\log(R\&D_{it}^{\text{EXP BUS}}) = \sum_{k=1}^{K} \tau_k \log(R\&D_{it}^{\text{EXP BUS}}) + \pi \Delta x_{it-m} + \mu_i + \omega_{it} \tag{3}$$

$$\log(R\&D_{it}^{\text{EXP PUB}}) = \sum_{k=1}^{K} \tau_k \log(R\&D_{it}^{\text{EXP PUB}}) + \rho \Delta x_{it-m} + \mu_i + \omega_{it} \tag{4}$$

$$\log(\text{PATENT}_{it}) = \sum_{k=1}^{K} \psi_k \log(\text{PATENT}_{it}) + \theta \Delta x_{it-m} + \mu_i + \omega_{it} \tag{5}$$

The main purpose is to capture indirect effects of BF funding on regional GDP growth running through these RDI inputs. As no regional data are available for the out-of-sample forecasting period beyond 2018, short-run dynamics is captured as an autoregressive (AR) process with $\psi_k$, $\tau_k$ and $\varphi_k$ are the associated AR coefficients for lag $k$; $\theta$, $\pi$ and $\rho$ are coefficient vectors for the included short-run determinants $\Delta x_{it-m}$ (see Table 2 for an overview of included variables in each equation). As in Eqs. (1) and (2), $\mu_i$ are region-fixed effects and $\epsilon_{it}$, $\omega_{it}$ and $\omega_{it}$ denote the individual equations’ error terms. As for the case of Eq. (1), as default specifications, we estimate Eqs. (3) to (5) by both OLS and GLS to account for auto- and cross-sectional correlation patterns in the error term.

Based on the above-described set of estimates, we can compute the direct and indirect growth contribution of BF funding (in %) as

$$\text{Direct }: (\hat{\beta}_\text{PAT}\times \Delta BF)$$

$$\text{Indirect } : (\hat{\beta}_\text{R&D EXP BUS} \times \Delta BF); (\hat{\beta}_\text{R&D EXP PUB} \times \Delta BF); (\hat{\beta}_\text{PAT} \times \Delta BF).$$

where $\Delta \% BF$ measures the percentage change in the BF funding intensity on a yearly base. To give an example: We calculate the direct GDP growth contribution of BF funding by taking the estimated coefficient $\hat{\beta}_\text{BF}$ (expressed as an elasticity, which measures the percentage

Notes: AR(4) = Autoregressive panel model specification with a maximum of four time lags. All panel model specifications used to forecast variables shown in this table include region-fixed effects.

Table 2
Extrapolation of regional variables entering the GDP growth equation.

| Variables in Eq. (1) | Method of data extrapolation for out-of-sample predictions |
|----------------------|------------------------------------------------------------|
| $\Delta gdp$         | Calculated as $\log(GFCF_{it}) - \log(GFCF_{it-1})$ based on predicted values of GFCF (see below) |
| log(GFCF)            | AR(4) process (no national data available for out-of-sample period); prediction for 2019 and 2020 |
| $\Delta unemp$       | Calculated as $\log(UNEMP_{it}) - \log(UNEMP_{it-1})$ based on predicted values of UNEMP (see below) |
| $\Delta gdp$         | AR(4) process plus national development in unemployment rate; prediction for 2019 and 2020 |
| log(R&D$_{it}$ EXP BUS) | See Eq. (3); $k = 3, 4$ and included short-run determinants: change in gross fixed capital formation, change in employment rate, BF funding intensity; prediction for 2019 and 2020 |
| log(R&D$_{it}$ EXP PUB) | See Eq. (4); $k = 3, 4$ and included short-run determinants: change in gross fixed capital formation, change in unemployment rate, BF funding intensity; prediction for 2019 and 2020 |
| log(PATENT)          | See Eq. (5); $k = 3, 4$ and included short-run determinants; change in gross fixed capital formation, change in unemployment rate, BF funding intensity; prediction for 2019 and 2020 |
| log(BF)              | BF Funds available until 2020; funding intensity for 2019 and 2020 calculated on the basis of predicted EMPL levels (see below) |
| log(EMPL)            | AR(4) process plus national development in employment levels; prediction for 2019 and 2020 |
| $ec$ (error correction term) | Lag length set to $n = 3$ implies that no predictions of long-run variables beyond 2018 are needed to calculate GDP per employee growth rates until 2021. Available data from Statistics Finland are taken for 2019 and 2020; for 2021 we expect that the rebound growth is of the same magnitude as the decline in 2020, i.e., 1.8 % (baseline). Alternative scenarios also employ a lower rebound growth rate, e.g., a discount factor of $c = 0.5$. See empirical results section for further details. |
| $\Delta gdp$ (national) | Calculated as log(GFCF) − log(GFCF,−1) based on predicted values of GFCF (see below) |

6 The sets of regional determinants used for the long- (x) and short-run estimation ($\Delta x$) are allowed to differ from each other.

7 We are grateful to an anonymous referee for pointing to this additional type of robustness check.
Table 3
In-sample estimates of regional GDP growth model for Finnish NUTS-3 regions.

| Column | (1) OLS | (2) OLS | (3) OLS | (4) OLS | (5) GLS | (6) GLS |
|--------|---------|---------|---------|---------|---------|---------|
| Dep. Var.: | Δgdp | Δgdp | Δgdp | Δgdp | Δgdp | Δgdp |
| Sample: | 1998-2018 | 1998-2018 | 1998-2018 | 1998-2018 | 1998-2018 | 2008-2018 |
| Δgcf | -0.023*** | -0.006 | -0.005 | -0.006 | -0.009 | -0.006 |
| (0.0074) | (0.0057) | (0.0062) | (0.0070) | (0.0056) | (0.0057) |
| Δunemp | -0.036* | 0.060*** | 0.061*** | 0.058*** | 0.054*** | 0.062*** |
| (0.0187) | (0.0167) | (0.0175) | (0.0170) | (0.0122) | (0.0097) |
| log(R&D exp BUS) | -0.033*** | -0.008 | -0.010 | -0.006 | -0.004 | -0.025*** |
| (0.0070) | (0.0067) | (0.0070) | (0.0078) | (0.0056) | (0.0077) |
| log(R&D exp PUB) | 0.003 | 0.008*** | 0.009*** | 0.009*** | 0.009*** | 0.009*** |
| (0.0023) | (0.0019) | (0.0023) | (0.0025) | (0.0022) | (0.0033) |
| log(PATENT) | -0.003 | -0.003* | -0.003* | -0.003** | -0.003** | -0.003** |
| (0.0024) | (0.0016) | (0.0015) | (0.0013) | (0.0013) | (0.0015) |
| log(BF) | 0.016*** | 0.012*** | 0.012*** | 0.012*** | 0.008*** | 0.009*** |
| (0.0047) | (0.0031) | (0.0032) | (0.0040) | (0.0038) | (0.0039) |
| ec (error correction term) | -0.150*** | -0.167*** | -0.167*** | -0.167*** | -0.099*** | -0.099*** |
| (0.0296) | (0.0294) | (0.0361) | (0.0361) | (0.039) |
| Obs. (N = Regions, T – Years) | 378 (N = 18, T = 21) | 378 (N = 18, T = 21) | 378 (N = 18, T = 21) | 198 (N = 18, T = 11) | |
| Region-fixed effects | YES | YES | YES | YES | YES | YES |
| National GDP growth (common factor) | NO | YES (common coefficient) | YES (heterogenous coefficients) | YES | YES | YES |
| Wald χ2 – test for equal λj | 45.01*** | 495.33*** | 100.58*** | 87.31*** | 38.1 |
| Goodness-of-fit (R²) | 0.10 | 0.40 | 0.42 | 0.45 | 0.78 | 0.76 |
| Relative RMSE | 0.92 | 0.77 | 0.77 | 0.45 | - |

Notes: Robust standard errors are given in brackets. GLS estimates control for the presence of AR(1) autocorrelation (common to all regions) and heteroskedasticity in the error term. $R^2$ is calculated as squared correlation between predict regional growth rate and its observed value; RMSE is defined in the text.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.
change in GDP per employee growth for a 1% increase in RDI funding by Business Finland) and by multiplying it with the de facto percentage increase in the funding intensity for a given year, for example, for 2020 to calculate the growth contribution in 2021. Similar calculations are done for the indirect contribution of BF funding running through the included RDI variables, where the BF contribution to changes in these variables is calculated on the basis of reduced-form coefficients.

In the second out-of-sample forecasting stage, we forecast regional GDP development for the years 2019 to 2021 and compute the contribution of BF funding to the post-COVID regional recovery. While the imposition of a given lag structure facilitates the computation of out-of-sample predictions, we still need to extrapolate most of the included regressors (except BF funding for which we have data until 2020) in order to compute h-step ahead GDP growth forecasts on the basis of Eq. (1). To minimize the extent of extrapolation as a source for forecast biases, the lag structure in the short-run growth equation is set to \( m = 1 \) and \( n = 3 \), which implies that we do not need to extrapolate time-series entering the long-run equation shown in Eq. (2). Table 2 provides an overview of how we extrapolate the individual regressors included in Eq. (1) in the out-of-sample forecast period 2019–2021.

6. Empirical results

6.1. In-sample estimation

Table 3 presents the estimation results for regional GDP growth (per employee) in Finnish NUTS-3 regions as specified in Eq. (1). While Column (1) reports the result of a benchmark specification excluding common factors and the error correction mechanism from a long-run GDP level equation, these additional factors are gradually added to the model in Columns (2) to (5). Most importantly, as the results table shows, in all specification we observe a statistically significant and positive conditional correlation between the BF funding intensity and regional GDP growth. The range of estimated coefficient in Columns (2) to (5) of between 0.008 and 0.012 indicates that a doubling of BF funding intensities results in an increase in regional GDP per employee growth of 0.8–1.2 %-points. While funding intensities typically do not vary in such large magnitude, the increase in BF funding intensities between 2019 and 2020 varied between 50 % and 160 %. This already indicates that the growth contribution of this policy instrument to fight the economic consequences of the COVID-19 may be considerable at the NUTS-3 level if constant growth returns to changes in the BF funding intensity are assumed. We turn to these out-of-sample predictions further below.

In terms of specification choice, two observations can be made from Table 3: First, criteria related to the goodness-of-fit of the in-sample GDP growth predictions (both \( R^2 \) and relative RMSE) significantly improve once we include a common factor structure (proxied by the national GDP development) and add the error correction mechanism estimated from a long-run GDP equation.\(^8\) The latter has the expected negative sign indicating a medium-run adjustment process towards a long-run cointegration relationship specified in Eq. (2). Second, we obtain statistical evidence that the association between regional and national GDP growth rates is heterogeneously distributed across the Finnish NUTS-3 regions (as indicated by the Wald test for coefficient equality of \( \lambda_i \) reported in Table 2). Based on these observations, we argue that the most general and robust model specification is Column (5), which will be used as the basis for the out-of-sample forecasts.

A concern is, though, that the estimated link between regional BF funding intensities and GDP per employee growth rates may not be stable i) across cross-sectional units (regions) and ii) over time. To address the first issue, Table 4 reports the results of a Hausman-type test, which compares the estimated coefficient for the growth contribution of the BF funding intensity between the pooled GLS estimator from Column 5 of Table 3 and two mean group estimators. The idea of the Hausman test is that mean group (MG) estimators deliver consistent estimates but are potentially inefficient as they only use \( T \) observations to estimate the coefficient (Pesaran et al., 1996). The null hypothesis of the Hausman test for poolability is that the difference in coefficients between the consistent MG estimator and the more efficient pooled estimator is not systematic. If the null is not rejected, this would favor the pooled estimator. However, a rejection of the null hypothesis points to a systematic bias of the latter. As the results in Table 4 show, we do not find evidence for a systematic bias of pooled GLS compared to the applied MG estimators.

Similar to the case of cross-sectional heterogeneity, the existence of

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\(^8\) The relative Root Mean Square Error (RMSE) is defined as the ratio of the model’s RMSE and the corresponding RMSE of an autoregressive growth specification with a maximum of four lags (AR(4)). Relative RMSE values of below 1 thus indicate that the prediction error of the model is smaller than the one of the AR(4) benchmark specification.
structural breaks over time may potentially lead to an overestimation of the true BF funding effect on regional growth if the coefficient size declines over time. To test for coefficient instability, column (6) of Table 3 therefore reports the estimation results for a sample-split regression, which only includes years from 2008 onwards. These subsample results show no decline but a moderate increase in the coefficient for BF funding. Additionally, Fig. 3 plots estimation results of a time-varying coefficient approach for the full sample period, which captures potential time heterogeneity in the estimated BF funding coefficient by interacting the latter with separate time dummies covering three consecutive sample years (years before 2004 constitute the baseline period in this setup). As the results for the different estimators from column (1) to (5) in Table 3 show, coefficient size (except for model (1)) is very stable over time. Overall, the implemented robustness tests do not point to any in-sample parameter instability for the link between BF and regional GDP growth. Together with prior simulation evidence that favors homogeneous panel data estimators over heterogeneous type estimators in out-of-sample forecasts (Baltagi, 2008), we take the evidence presented here as a guideline to base our out-of-sample predictions on the pooled GLS model reported in Table 3.

Regarding the other included regional regressors, we find for most specifications in Table 3 that business sector R&D expenditures and the patent rate are either not or weakly negatively correlated with GDP growth. While this is likely due to i) the very volatile nature of patent applications at the Finnish NUTS-3 level and ii) the fact, that after the financial crisis of 2008, private R&D expenditures have increased steadily only in the region of Uusimaa, we find that public sector R&D expenditure flows are positively correlated with regional GDP development in the short run. Moreover, in the long run, we also find a positive relationship between the region’s patent stock, business sector R&D personnel, the physical capital investments, highly skilled labor, and regional growth. These positive long-run correlations are in line with most empirical contributions on growth and development at the Finnish national (Pohjola, 2017) and regional levels (Makkonen and Inkinen, 2015). The underlying structural parameters of the long-run GDP equation (with standard errors given in squared brackets) are estimated as

$$
\log(GDP_{it}) = 0.041 \log(GFCF_{it}) + 0.716 \log(HIGHEDU_{it}) [0.0099] + 0.0159 \log(UNEMP_{it}) - 0.182 \log(UNEMP_{it}) + 0.017 \log(PATSTOCK_{it}) + 0.045 [0.0130] \log(R&D^{EXP\ BCUS}) + 0.067 \log(R&D^{EXP\ PUB}) + 0.006 [0.0133] \log(PATENT) \log(R&D^{EXP\ PUB})
$$

$$R^2 = 0.63 \quad \text{Phillips-Perron} \ t - \text{statistic} = -3.91^{***} \quad (H_0: \text{No cointegration})$$

Moreover, we also find evidence for a significant cointegration relationship between variables included in the long-run equation in the reported test statistic for a Phillips-Perron t-test with the null hypothesis of no cointegration among regions (Pedroni, 1999, 2004).

In addition to the direct relationship between BF funding and regional growth, Table 5 shows positive conditional correlation between BF funding and RDI inputs included in Eq. (1) (except the very volatile patent rate). This finding is in line with the earlier literature on public RDI funding as already discussed in Section 2: BF funding affects private RDI investments positively. While these indirect transmission channels thus suggest that BF funding further increases regional GDP growth through a technological upgrading mechanism, in the short run, we have to be aware that the link between some of these RDI inputs, i.e., private-sector R&D expenditures and the region’s patent rate, was estimated to be absent and/or negative. This leaves the direction of the indirect growth contribution of BF funding unclear ex ante.

### Table 5

| In-sample estimates of auxiliary RDI equations. |
|-----------------------------------------------|
| Column (1) | (2) | (3) |
| Dep. Var. | $\log(R&D^{EXP\ BCUS})$ | $\log(R&D^{EXP\ PUB})$ | $\log(PATENT)$ |
| Sample: | 1998–2018 | 1998–2018 | 1998–2018 |
| $AR$ coefficients (jointly) | 0.406*** | 0.445*** | 0.103* |
| $\Delta gcf$ | (0.0394) | (0.0297) | (0.0598) |
| $\Delta unemp$ | −0.064 | 0.172*** | 0.373** |
| $\log(BF)$ | (0.0210) | (0.0215) | (0.0700) |
| Obs. (N = Regions, $T$ = Years) | 360 (N = 18, $T$ = 20) | 360 (N = 18, $T$ = 20) | 360 (N = 18, $T$ = 20) |
| Region-fixed effects | YES | YES | YES |

Notes: Standard errors are given in brackets. All estimates are on the basis of GLS estimation as in Column (5) of Table 3.

Estimation controls for the presence of $AR(1)$ autocorrelation (common to all regions) and heteroskedasticity in the error term.

- $p < 0.10$.
- $*** p < 0.05$.
- $** p < 0.01$.

### 6.2. Out-of-sample prediction (baseline)

Based on the in-sample estimation results shown in Tables 3 and 5, together with the forecast setup outlined in Table 2, we are finally able to compute and plot out-of-sample forecasts for regional GDP growth in Finland beyond the latest available regional observation in 2018. Reduced-form results for the in- and out-of-sample forecast period are shown in Fig. 4. The figure plots the observed mean GDP per employee growth rate together with its mean prediction growth across the 18 Finnish NUTS-3 regions and a 95 % forecast range based on $+/− 2$ standard deviations of the individual regional forecasts (see Fig. A2 for the individual forecasts for each NUTS-3 region). These baseline forecasts are produced for the following scenario:

1. a national rebound growth rate of 1.8 % in 2021 (after −1.8 % in 2020),
2. constant GDP growth returns to BF funding before and during COVID-19.

Alternative scenarios are presented further below.

If we compare the mean GDP growth rate (black solid line) with the in-sample prediction until 2018 (grey dashed line), Fig. 4 shows that our mean forecast accurately matches the de facto development (as also indicated by the RSME<1 in Table 3). Only during the period 2000–2004 we observe a tendency of over-/underprediction of growth rates. However, in all cases the predicted model correctly identifies turning points in the data. Importantly, the model prediction does a particularly good job to match mean regional development during the economic crisis of 2008, which can be seen as in-sample validation for the model’s ability to capture the 2020 slump during the COVID-19 crisis. This is shown in the right area of the figure depicting the out-of-sample forecast interval with regard to the magnitude of the crisis response of regional GDP levels, we find a decline in regional GDP growth rates of up to −2.5 % in 2020 (with a mean decline of $−1$ %) and recovery growth rates of between 2 and 6 % in 2021 (with a mean growth rate of $−4$ %). This prediction is slightly higher but comes close to aggregate forecasts for the Finnish economy ranging from 2.9 to 3.7 % (see Section 1). One
should note, though, that the mean growth rate reported here puts an equal weight on each region and, hence, does not take the region’s share in national GDP into account. Panels A to C of Fig. 5 show how the different components of the short-run growth equation contribute to the forecasted post-crisis recovery growth across Finnish NUTS-3 regions.

As Panel A of Fig. 5 shows, the largest total growth rate in 2021 is predicted for regions that are typically considered as the regional “growth engines” of Finland: Uusimaa, Pirkanmaa and North Ostrobothnia. Additionally, regions whose economies have been reported to experience significant growth, for example, Kymenlaakso, before the COVID-19 crisis (European Commission, 2020) are predicted to experience, respectively, higher and lower recovery than on average. As such, the COVID-19 pandemic seems to have had a relatively small impact on the overall picture of spatial development in Finland. Panel B of Fig. 5 shows the contribution of the predicted national GDP growth rate on regional GDP per employee growth rates running through $\frac{\Delta Y}{\Delta P}$. Here, national-regional linkages account for between 1% and 2.2% of the predicted regional growth performance in 2021. As the panels show – and in line with earlier evidence (Pekkala, 2000) – regions do not grow at the same pace as the aggregate economy. In our forecasts, the regions of Pirkanmaa and South Karelia are the most aligned with the national growth trend.

Panel C of Fig. 5 plots the growth contribution of the massive increase in BF funding intensities in 2020, which are estimated to have a significant impact on regional GDP per employee growth in 2021. The estimated contribution of BF funding varies between 0.4% and 1.4% points in terms of regional GDP per employee growth across Finnish NUTS-3 regions (mean growth contribution: ~1% point).9 Thus, on average, we find that the significant increase of BF funding in 2020 constitutes a major pillar of this recovery process as roughly one fourth of the overall regional GDP growth rate can be attributed to the increase in the BF funding intensity at the regional level (annual BF funding intensities increased by between 50% and 160% in 2020).

Especially many of the smaller (in terms of population) Finnish regions show significant positive growth due to BF funding. Regions – such as Kainuu, South Savo and Päijät-Häme – that have increased their BF funding intensity the most are the ones with the highest estimated BF funding contribution to their GDP growth rates. Additionally, in some cases the overall growth rate would even be negative, if not accounting for BF funding (and the national rebound effect discussed above). Contrarily in regions (including, for example, the already well-off Uusimaa) where the BF funding intensity has not grown as significantly, the contribution of BF funding on their estimated GDP per employee growth rate is more modest. Thus, the positive effect of BF funding seems to be more important for regions with less endogenous regional growth factors.

6.3. Out-of-sample predictions (alternative scenarios)

As pointed out above, the size of individual growth contributions and the overall GDP growth forecast depend on two key parameter settings in the baseline scenario. One is that the link between BF funding and regional growth (the return to BF funding) is considered constant even for significant higher funding levels and that this constant link also holds for the “Funding for business development in disruptive circumstances” – although the program deviates in some ways from the traditional BF funding (see Section 3). Earlier work on the effectiveness of regional funding for GDP growth has pointed to a potential maximum funding intensity after which no additional growth impulse can be observed (Mitze et al., 2015), which indicates a maximum absorptive capacity of regions to translate RDI (and other types of) inputs into outputs (Oughton et al., 2002). To accommodate this aspect, we run alternative scenarios that assume constant returns for traditional RDI funding from Business Finland but decreasing returns for the “Funding for business development in disruptive circumstances” program.

A key motivation for decreasing returns of BF funding is that we evidently observe a change in the sectoral composition of RDI subsidy recipients under the “Funding for business development in disruptive circumstances” program compared to pre-COVID-19 periods. In fact, as Table 6 shows, apart from computer programming (software) services, the largest individual sectors receiving RDI subsidies through the new COVID-19 BF funding program are low- to medium-tech industries. Similarly, the share of low- to medium-tech industries among the recipients was larger in 2020, than the average between 2010 and 2019, in all but one region.

Earlier studies (e.g., Ortega-Argilés et al., 2011, 2015; Lau and Lo, 2015) have shown that high-tech firms fair significantly better than low- to medium-tech firms in terms of the impact that RDI has on their productivity. In other words, there are sectoral differences in the rate of returns on RDI subsidies. To formally include the sectoral composition of regional RDI funding into our empirical analysis, we divide the recipient firms (per region) into 1) high- and 2) low- to medium-tech sectors following the classification of Castellani et al. (2019). We then re-estimate the short-run GDP growth model from Eq. (1) for these disaggregated BF funding intensities during 2010–2018 (no earlier data were available for sector-specific BF funding volumes). The in-sample estimation results in Table 7 support the earlier evidence and point to higher returns to RDI funding in high-tech sectors, while the estimate rate of return in low- and medium-tech sectors is below the average (aggregate) return.

Taking this tentative evidence for decreasing returns to RDI funding in low and medium-tech sectors into account we adjust our out-of-sample predictions in the following way: a discount factor $r$ is introduced, which captures decreasing returns by multiplying the estimated elasticity from our baseline estimates (Column 5 of Table 3) with this factor. While the in-sample estimates suggest a discount of about 15–20%, i.e., $r = 0.8$, we also consider larger discounts (i.e., $r = 0.7$ and $r = 0.6$) based on the consideration that the share of low- and medium-tech funding has substantially increased in 2020 beyond the average regional share used for the in-sample estimates reported in Table 7.
then use the discount factor $r$ to calculate the direct growth contribution of BF funding as

$$\text{Direct} = \left( \hat{\beta} \times \Delta \%_{\text{BF traditional}} \right) + \left( r \cdot \hat{\beta} \times \Delta \%_{\text{BF disruptive}} \right),$$

where $\Delta \%_{\text{BF traditional}}$ measures the change in traditional BF funding intensity and $\Delta \%_{\text{BF disruptive}}$ the change in the intensity of “Funding for business development in disruptive circumstances” on a yearly base. As BF funding intensities for the latter instrument vary across regions, this will also result in spatial differences in the direct growth contribution of BF funding when we compare the different scenarios – even if we assume that the discount factor $r$ is constant across regions. We further assume that the indirect BF funding channels running through the RDI input variables remain unchanged. Resulting forecasts for the BF

### Table 6
The “top-ten” recipient industry sectors of (a) Business Finland RDI funding during 2010–2019 and (b) “Funding for business development in disruptive circumstances” instrument in 2020.

| Standard Industrial Classification (TOL 2008) | RDI Category | N   | Amount (€)  |
|---------------------------------------------|--------------|-----|-------------|
| a) Computer programming (software) services (62) | High-tech    | 4426 | 416,699,411 |
| Manufacturing computer products (26)        | High-tech    | 748  | 216,463,903 |
| Manufacturing machinery and equipment (28)   | Low-to medium-tech | 897  | 203,572,285 |
| Architectural services and engineering (71)  | Low-to medium-tech | 1367 | 134,532,771 |
| Wholesale trade (46)                        | Low-to medium-tech | 1255 | 90,694,648  |
| Scientific research and development (72)    | High-tech    | 720  | 85,164,033  |
| Management consultancy services (79)        | Low-to medium-tech | 1279 | 63,854,514  |
| Manufacturing chemical products (20)         | High-tech    | 230  | 59,977,349  |
| Manufacturing electrical equipment (27)      | High-tech    | 296  | 59,969,398  |
| Manufacturing paper products (17)            | Low-to medium-tech | 93   | 55,933,373  |
| b) Computer programming (software) services (62) | High-tech    | 1261 | 78,831,310  |
| Wholesale trade (46)                        | Low-to medium-tech | 1247 | 75,543,289  |
| Specialized construction (43)                | Low-to medium-tech | 1004 | 61,990,263  |
| Retail trade (47)                           | Low-to medium-tech | 1173 | 56,713,819  |
| Food and beverage services (56)             | Low-to medium-tech | 1354 | 56,379,956  |
| Management consultancy services (79)        | Low-to medium-tech | 1150 | 48,161,255  |
| Manufacturing fabricated metal products (25) | Low-to medium-tech | 535  | 40,496,815  |
| Construction of buildings (41)               | Low-to medium-tech | 644  | 39,576,073  |
| Architectural services and engineering (71)  | Low-to medium-tech | 563  | 38,238,234  |
| Land transport and transport via pipelines (49) | Low-to medium-tech | 641  | 30,901,444  |

Notes: $N =$ number of firms receiving funding. In a) the funding amount is summed over the period 2010–2019 (Source: Business Finland). RDI categorization of high-tech and low-to medium-tech sectors is based on Castellani et al. (2019).
funding contribution to regional GDP per employee growth in 2021 are plotted in Fig. 6. As Fig. 6 shows, larger discount factors generally translate into a lower average growth contribution of between 0.4 and 0.7 %-points in terms of GDP growth (compared to an approx. 1 %-point mean contribution in the baseline scenario) and also result in smaller inter-regional variation in the growth contribution of RDI funding. Particularly those regions that have significantly increased their overall BF funding in 2020 through the new “Funding for business development in disruptive circumstances” program (see Panel C in Fig. 2) are now observed to have smaller BF growth contributions vis-à-vis the rest of the country. Moreover, regions which - at the aggregate level - mainly substitute traditional BF funding in favor of grants from the new program without significantly increasing their overall BF funding intensities now show to have a close to zero or even slightly negative BF growth contribution as shown in Fig. 6. Taken together, we argue that a moderate discount factor of \( r = 0.7 \) may be regarded as a reasonable choice given that i) the sectoral composition of funding changed to higher shares received by low- and medium-tech sectors and ii) the average BF funding volume per recipient firm is approx. 30 % smaller in the new “Funding for business development in disruptive circumstances” program compared to the traditional BF funding channel. Smaller or absent scale effects at the individual firm level may then accordingly translate into decreasing returns to BF funding at the regional level.

Finally, we use this setting to compute a more conservative (lower bound) overall growth scenario that additionally assumes a smaller national GDP growth impulse for regional recovery trends (running through the included common factor structure). Specifically, we discount the 2021 prediction for national GDP growth (1.8 %) by a factor of \( c = 0.5 \) (in other words, we bisect the national growth impulse in this conservative scenario). The resulting spatial distribution of the main components of GDP growth in 2021 are shown in Fig. 7. As the results in Panel A of Fig. 7 show, this lower-bound scenario predicts a moderate mean regional GDP per employee growth rate of \( \sim 2 \% \) in 2021 compared to the \( \sim 4 \% \) mean recovery growth rate in the baseline scenario. While some regions are still predicted to have annual growth rates between 3 % and 4 %, at the lower end of the regional growth distribution, in two cases, this scenario would now predict that regions continue to shrink in 2021.

### 7. Discussion and conclusion

Fighting the detrimental socio-economic consequences of the ongoing COVID-19 crisis is a major challenge for policy makers. Many countries have started to experiment with different demand and supply-
side oriented support schemes to assist individual workers and firms to survive in troubled times and to foster post-crisis recovery growth. One particular focus of the Finnish government was to provide public support to pursue RDI activities: BF funding increased from €570 M in 2019 to €1740 M in 2020. In this paper, we have collected empirical evidence to make first, scientifically grounded statements about likely effectiveness of this policy plan.

Since regional data for a comprehensive ex-post evaluation of BF funding effectiveness are not readily available yet, we have adopted a two-stage ex-ante evaluation design. In a first step, we have estimated the empirical link between RDI funding through Business Finland and regional GDP growth for Finnish NUTS-3 regions. Our results for the pre-COVID-19 sample period 1995–2018 point to a robust, positive correlation between the BF funding intensity and annual GDP growth. We additionally find that BF funding also affects the level of other R&D and output variables such as private and public R&D expenditure levels positively (although the link between these variables and GDP growth is found to be weaker in the short than in the long run). Based on these in-sample parameter estimates, we have then predicted regional GDP growth rates out-of-sample until 2021. An inspection of the out-of-sample prediction quality has shown that our regional forecasting system accurately predicts i) the COVID-related economic slump in 2020 and ii) the predicted national post-crisis recovery growth rate.

With regard to the role of RDI funding by Business Finland, we find that the massive increase in expenditure volumes is pivotal for this recovery growth rate. Based on our structural growth model estimates we find an overall growth contribution attributable of increased BF funding through Business Finland of between 0.4 and 1 %-points of regional GDP growth (per employee) for the individual Finnish NUTS-3 regions. While we have carefully assessed the statistical significance and robustness of this result in the paper, one remaining question that ultimately needs to be answered is: How plausible is the estimated magnitude of the BF funding contribution to regional GDP growth?

To provide an answer to this question, Table 8 summarizes key information on our two main forecast scenarios together with information on the relative financial importance of BF financial inflows into a NUTS-3 region as share of its regional GDP.

Table 8: Plausibility check – relating predicted BF contribution to financial importance of funding for regional GDP.

|                                | Mean  | S.D.  | Min.  | Max.  |
|--------------------------------|-------|-------|-------|-------|
| Share of BF funding in regional GDP (in %, in-sample period, 1998–2018) | 0.18  | 0.11  | 0.02  | 0.57  |
| Share of BF funding (2020) in regional GDP (2018) (in %) | 0.60  | 0.16  | 0.36  | 0.94  |
| Predicted BF contribution to GDP growth rate of BF funding (in %, baseline scenario) | 1.04  | 0.29  | 0.43  | 1.40  |
| Predicted BF contribution to GDP growth rate of BF funding (in %, conservative scenario with r = 0.7) | 0.52  | 0.34  | -0.20 | 1.02  |

Notes: Predicted BF contributions to regional GDP growth rate are based on forecast scenarios shown in Figs. 5 and 7.

Fig. 7. Spatial distribution of main components of GDP growth in 2021 (conservative scenario)

Notes: Own estimates based on parameters reported in Column (5) of Table 3 and forecast setup described in Table 2. The estimated vector of fixed effects has been ignored in the decomposition of GDP growth rates. The growth contribution of BF funding is calculated for a discount factor of r = 0.7. For the national GDP growth impulse, we use a discount factor of c = 0.5 compared to the baseline scenario; see text for further explanations.
levels, in fact lends further support to our forecasts. That is, while during the pre-COVID period the average percentage share BF funding in regional GDP was indeed only about 0.2 % (with a regional range of 0.02 % to 0.6 %), we observe a considerably higher average share of 0.6 % (with a range of 0.36 % to 0.94 %) once we relate BF funding levels in 2020 (i.e., under COVID-19) to 2018 regional GDP levels (last in-sample observation). The latter regional range, in fact, comes close to the range of growth contributions of BF funding in our different forecast scenarios. Hence, we can expect that even without any additionally private investments induced the additional monetary inflow of public RDI funding into the region during the COVID-19 crisis should raise regional GDP levels by a rate that is, by and large, within the dimension our model predictions. We take this back-of-the-envelope calculation as supportive evidence for the plausibility of our predicted growth contribution of Business Finland RDI funding.

Taken together, the results of this paper support the view that in addition to business cost support, governments should also support private sector R&D activities as a means to recover from crises even in times of budgetary constraints. While short-term business cost support for firm survival has previously been found to be important when a crisis hits an economy (National Audit Office of Finland, 2021), the situation may change if the crisis lingers (Vibriáš et al., 2020): it can hinder market exit and thus lead to the misallocation of public funding towards supporting unviable firms. Or to put it differently: surviving a crisis also requires governments to design policies that encourage innovation (Acemoglu, 2009).

As far as it can be said from an ex-ante perspective, the RDI funding through Business Finland including the “Funding for business development in disruptive circumstances” program seems to be a successful example of such policy implementations. The emphasis given to the innovative aspects of the proposed projects rather than just on firm survival (Fornaro et al., 2020) in the selection process has arguably contributed to the success of this particular BF funding instrument. The granted funding per firm was designed to remain rather modest (either €10,000 or €100,000), which has allowed the funding to be spread among over 20,000 firms of which the majority were SMEs. In this regard, the fact that Business Finland covers 80 % of the costs out of which 70 % can be paid in advance can be argued to be a definite improvement for SMEs. This is because, even favorable RDI policies can be inefficient for small firms, if they need to cover the costs up-front, which might lead to cash-flow problems (particularly) in times of crisis (Harris et al., 2020).

Obviously, our finding of a positive GDP growth contribution of RDI funding through Business Finland is conditional on the stability of the link between BF funding and regional growth during the COVID-19 crisis. If - instead - there is a maximum absorptive capacity of regions to translate publicly funded RDI inputs into outputs (Mitze et al., 2015), then the growth returns to BF funding may decrease with increasing funding intensities. The latter may also happen if the regional economy’s absorptive capacity is lower due to the overall economic slump.

We have accommodated this more conservative view in alternative forecasting scenarios, which point to a mean growth contribution of BF funding of between 0.4 and 0.7 %-points in terms of GDP per employee growth (compared to ~1 %-point in the baseline scenario). This prediction is accompanied by a forecast of about 2 % for the average regional GDP growth rate in 2021. These conservative scenarios especially consider a lower rate of return to RDI funding in the new “Funding for business development in disruptive circumstances” program due to i) a sectoral shift towards higher funding shares in low- and medium-tech sectors and ii) a declining average funding volume per recipient firm compared to the traditional BF funding.

Weighing the different scenario analyses against each other based on the observed funding developments and our structural estimates, overall, we judge that the lower bound prediction of a 0.4 %-point growth contribution of BF funding to regional recovery growth after the initial COVID-19 shock in 2020 can be regarded as the most reliable input for future policy debates about RDI support during crises. Next to these key aspects, there are three further assumptions underlying our identification approach whose validity should be checked in complementary ex-post evaluations: First, in the specification of the regional growth model we assume a relatively fast input-output transmission channel. That is, BF funding is assumed to show up in regional GDP figures in the following year. Although we find empirical support for this lag structure in our sample, there are also good reasons to believe that it takes further time until RDI activities fully translate into economic output. In this sense, our predictions may actually underestimate the mid- to long-run impact of BF funding on the Finnish economy.

Second, we assume that national economic development exogenously affects regional GDP growth trends. While this is needed in our short-run forecasting system to capture the COVID-19 shock, alternative approaches using spatial rather than national-regional dependences should be additionally explored in the future (see Baltagi et al., 2014). Similarly, our approach does not entertain the possibility that the pandemic has significantly changed the structure of the regional economic systems internally in terms of, for example, changes in the regional sectoral composition of firms or the self-selection of workers from heavily affected sectors to relatively unaffected sectors (Burzyński, 2020) and the subsequent shifts in labor costs. Investigating the potential impacts of these types of systemic (internal) changes, thus, remains a task to be undertaken once appropriate regional data becomes available.

Third, there is the issue of causality. As we have already pointed out in the paper, we identify effects under the assumption of weak exogeneity of regressors (including BF funding). That is, that they are predetermined with respect to current regional GDP growth rates. While this may be sufficient to estimate robust conditional correlations at the regional level as a means to produce reliable short-run GDP growth forecasts, we cannot make strong statements about the causality between BF funding and economic growth. Future studies on the effectiveness of public RDI funding under COVID-19 should thus consider alternative ways to identify causal relations, preferably on the basis of micro data for firms and institutions receiving public RDI funding. Ultimately, there are many unknowns and uncertainty that make forecasting such a complex crisis as the COVID-19 pandemic has caused extremely challenging (Luo, 2021). We, though, hope that our ex-ante assessment may nonetheless provide valuable priors for this endeavor and support policy makers with highly needed information to assess and finetune their policies during the ongoing COVID-19 crisis and for preparing for future crises.

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Declaration of competing interest

While the research was funded by Business Finland, the funder did not influence the results of the research. The work was conducted without any pressure from the funder, or the steering group appointed by the funder.

Data availability

Study data and replication codes (for STATA) can be downloaded from the publicly accessible Figshare data repository under the permanent DOI: 10.6084/m9.figshare.16945279.
Appendix A

Fig. A1. Map of Finnish regions (regional capitals in brackets).

Fig. A2. In- and out-of-sample forecasts for the individual NUTS-3 regions in Finland.

Notes: Estimates based on coefficients reported in Column (5) of Table 3 and forecast setup described in Table 2. National GDP growth in Finland in 2021 is set to 1.8%.

See Fig. A1 for region names associated with the displayed NUTS3 codes.
